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

Here is the abstract text. Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Start new paragraphs after a blank line and with 2 spaces indent. Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

# 1 INTRODUCTION

* This document supports the development of guidelines for defining LRPs for Pacific Salmon, as required by the recently revised Fisheries Act. Guidelines that have been informed by this work are available in the companion working paper “Guidelines for Defining Limit Reference Points for Pacific Salmon Stock Management Units.”
* Under the New Fisheries Act, Limit Reference Points (LRPs) that represent the level below which serious harm is occurring will be required for major fish stocks prescribed in regulation. LRPs define the trigger below which rebuilding plans will be required.
* For Pacific salmon, it is anticipated there could 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 Conservation Units (CUs) that are managed together with the objective of achieving a joint status. A CU is the fundamental unit of biodiversity that we are trying to maintain and manage.
* ~~While lower biological benchmarks under the Wild Salmon Policy delineate abundances below which CUs are considered at risk of extinction (DFO 2005).~~ Methods to assess status of CUs have been developed for a range of data types, and statuses across multiple metrics are grouped into a single status. These methods produce status results that largely align with COSEWIC. For example a Red status CU, generally aligns with an Endangered COSEWIC status. A key gap, however, is that these have not , ~~these benchmarks have not been identified for many data-limited~~ been aggregated to the SMU level, representing significant gaps in our ability to develop LRPs under the Fisheries Act.
* The suite of LRP estimation methods considered in this paper are specific to the case where a LRP is defined as a single aggregate abundance that is associated with a high probability of all component CUs being above lower benchmarks that are consistent with the WSP. Alternative approaches to identifying LRPs are discussed in t
* The overall goal of this working paper is demonstrate and evaluate LRPs for 3 case study stock management units. 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.
* In retrospective analyses, our objective is to demonstrate the sensitivity of the LRP to the removal of years or CUs to inform guidance about minimum numbers of years or CUs
* In simulation evaluation, our objectives are to:
  1. Identify the bias in LRP estimates by comparing LRP estimated from observed data to “true” LRP estimated from “true” population dynamics (without observation error)
  2. How robust are LRPs to different underlying scenarios (model formulations, covariance in CU dynamics, observation errors, time varying productivity and capacity)?
  3. How does LRP (and 95% CIs) vary with the number of years and proportion of CUs (and trade-offs), relative to the “true” LRP that includes all years and data?
* Estimates presented in this paper are not meant to be definitive LRPs, which require more thorough review of data and their use here with local analysts and partners. These case studies demonstrate various approaches for developing LRPs.

# 2 LRP ESTIMATION METHODS

## 2.1 Overview

studies. Detailed methods specific to each case study are provided in Sections 3 (Interior Fraser Coho), 4 (WCVI Chinook), and 5 (South Coast Chum, excluding Fraser).

We applied two approaches to assessing LRP status:

1. a proportion approach to assessing whether they are above an LRP. This is based on the proportion of CUs in an MU in the Red status zone.
2. We also applied an approach that looks at the aggregate abundance of an MU that looks at underlying CU statuses based on relative abundance metrics only; we used two analytical approaches to achieve this
   1. Logistic regression LRP’s
   2. Projection based LRPs

~~All LRP estimation methods first require the status of individual CUs with with an SMU to be assessed as being above or below a lower benchmark. The distribution of CU-level status estimates within a CU is then used as a basis for defining an LRP.~~

~~Under Canada’s Wild Salmon Policy (WSP), the lower benchmark is defined as a level of abundance high enough to ensure there is a substantial buffer between it and any level of abundance that could lead to a CU being considered at risk of extinction.~~ Explain multi-mertric approach, short- and long-term trends, absolute abundance, and relative abundance. Commen BM for short- and long-term trends and abs abs. Rel abundance BM unique for each CU. A variety of methods are available for estimating relative ab lower benchmarks depending on species and data availability (citation needed). A more thorough discussion of available benchmarks, as well as how these relate to WSP Integrated Status Assessments, is provided in the companion working paper *Guidelines for Defining Limit Reference Points for Pacific Salmon Stock Management Units* (Holt et al. in review).

## 2.1 LRP definition

The Limit Reference Points (LRPs) under the New Fisheries Act represent the level below which serious harm is occurring will be required for major fish stocks prescribed in regulation. LRPs define the trigger below which rebuilding plans will be required.

A management unit (MU) is the group level LRPs are evaluated on. For Pacific Salmon, an MU is comprised of one or more CUs, where a CU is a fundamental unit of biodiversity for Pacific salmon. It is ‘a group of wild salmon sufficiently isolated from other groups that, if lost, is very unlikely to recolonize naturally within an acceptable timeframe, such as human lifetime or a specified number of salmon generations.’ (DFO 2005).

An LRP can include either the proportion of CUs not in their Red (poor) status zone, or single abundance benchmarks for the MU aggregate. The former being a unique consideration for Pacific Salmon and the latter broadly applying to all fish species in Canada, which are largely marine species.

Pacific Salmon given their complex population structure, and freshwater and marine life stages, have unique considerations relative to marine species. For this reason, fisheries, which operate at the MU scale, is not the only management action that can be used to improve salmon production. In fact, catch has been considerably reduced in recent years (see SOPO Grant et al. 2021). Habitat management and hatchery management are playing an increasing role in actions required to support salmon adaptation to climate change, and these require CU considerations within habitat aggregations, or down to the population level for hatchery ones. For marine species, the only lever is fisheries, so a single aggregate MU that relates to this scale makes most sense.

Pacific Salmon have an existing approach to assessing salmon CU statuses through DFO’s Wild Salmon Policy (WSP) (DFO 2005). These approaches have been developed and implemented for several groups of Pacific Salmon CUs (Holt et al. 2009; Holt 2009; Grant 2011; Grant & Pestal 2012; DFO 2015; DFO 2016; Grant et al. 2020). This work can be used to support one approach for LRP development.

## 2.1 PROPORTION-BASED LRPS

~~A proportion-based LRP is simply the proportion of CUs required to be above CU-level lower benchmarks. For example, the LRP could be set at “100% of CUs with abundance > lower benchmark.” In this case, the LRP would be breached anytime a single CU dropped below its lower benchmark. Guidance on how to select the required proportion, including when it may be appropriate to consider proportions < 100%, is provided in the companion working paper~~ *~~Guidelines for Defining Limit Reference Points for Pacific Salmon Stock Management Units~~* ~~(Holt et al. in review).~~

We consider two types of proportion-based LRPs in our case studies. The first is based on the proportion of CUs with abundance above relative-abundance lower benchmarks. The second is based on the proportion of CUs for which a multidimensional rapid status assessment indicates that status is in either the Amber or Green Wild Salmon Policy status zones.

### 2.1.1 Proportion of CUs above abundance-based lower benchmarks

For SMUs in which CU-level abundance relative to abundance-based lower benchmarks is assessed annually, LRPs can be set at the required proportion of CUs with abundance above their abundance-based lower benchmarks.

proportion based approaches

For multi-dimensional status, we are using the term ‘lower benchmark’ to be Red status zone for the CU. Not entirely a correct usage of this term, but applies it to the language used for LRP triggers of rebuilding plans.

### 2.1.2 Proportion of CUs with multidimensional status > lower benchmark (i.e. Red status)

Canada’s Policy for Conservation of Wild Pacific Salmon (Wild Salmon Policy, WSP) sets out requirements for the assessment of status of salmon CUs ([*Canada’s policy for conservation of wild Pacific salmon*](#ref-canada_canadas_2005) ([2005](#ref-canada_canadas_2005))). Peer-reviewed, integrated status assessments require large amounts of time and work. The State of the Salmon program (Fisheries and Oceans Canada) is developing a method of assessing the status of CUs more rapidly ([Pestal et al.](#ref-pestal_algorithms_2021) ([2021](#ref-pestal_algorithms_2021)), in prep). Using the inputs and outcomes of status assessments for Fraser River sockeye, Interior Fraser coho, and Southern BC Chinook ([DFO](#ref-dfo_wild_2015) ([2015](#ref-dfo_wild_2015)), [DFO](#ref-dfo_integrated_2016) ([2016](#ref-dfo_integrated_2016)), [DFO](#ref-dfo_2017_2018) ([2018](#ref-dfo_2017_2018)), [Grant et al.](#ref-grant_2017_2020) ([2020](#ref-grant_2017_2020))), this method uses Classification and Regression Tree (CART) analyses to create algorithms that approximate the status of the integrated assessments. Essentially, it uses a decision tree to evaluate status based on data type, quality, abundance, and trends to assign a status to CUs (e.g., Figure 2.1). An expert review of these statuses is an intentional part of the process. 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.

This aligns with COSEWIC approaches and produces similar results for assessments conducted for IFC, FrSK, SBCCN.

Add in proportion of CUs above Red status.

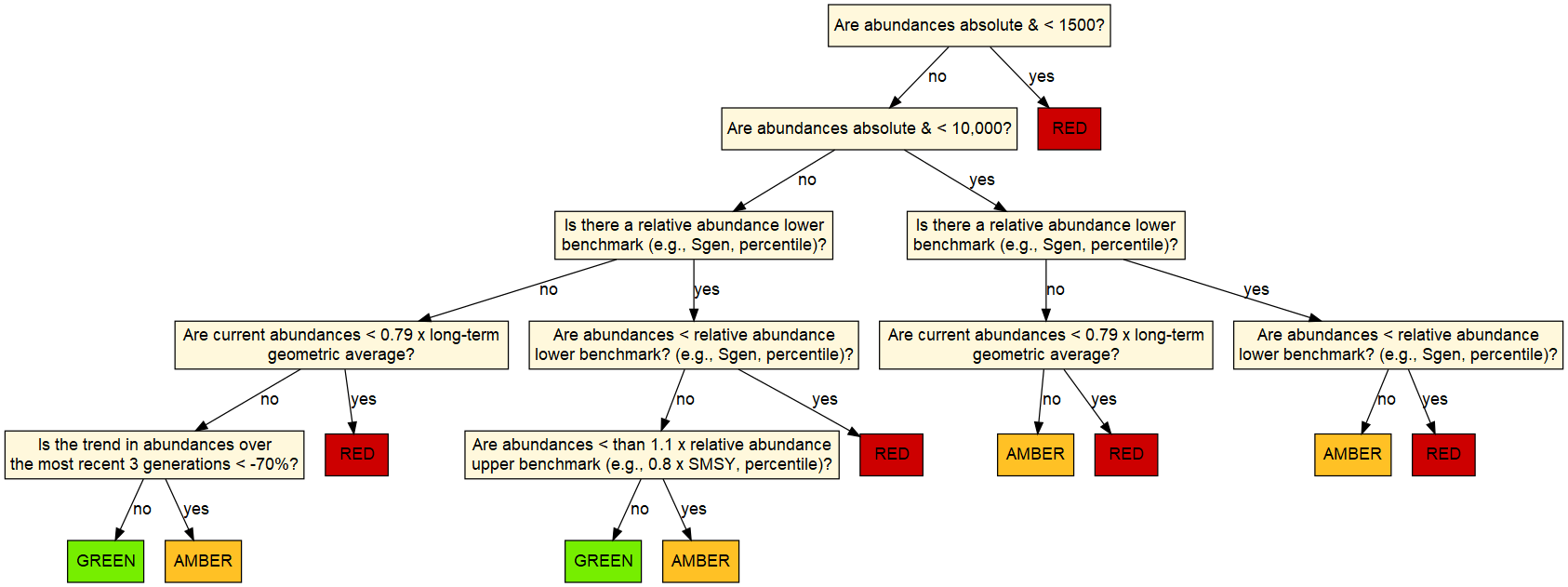


Figure 2.1: Decision tree to assess status of Conservation Units based on the Wild Salmon Policy, under development by State of the Salmon Program

## 2.2 AGGREGATE ABUNDANCE-BASED LRPS

Aggregate abundance-based LRPs represent the SMU-level abundance at which there is a sufficiently high probability that a required proportion of CUs will be above their individual benchmarks. This definition requires two decisions to be made.

We examined ‘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-frame_guidance_2010)): 50%, 66%, 90%, and 99%. The 50% value represents the mid-point of the “About as likely as not” category (33 - 66%), indicating that there is an equal probability that all CUs will be above their LBMs as there is that they will not. The 66% values represents the lower end of the “Likely” category (i.e., it is “Likely” that all CUs will be above their LBMs), the 90% value represents the lower end of the “Very Likely” category, and the 99% value represents the “Virtually Certain” category. A discussion of considerations for selecting the appropriate probability threshold when calculating abundance-based LRPs is included in the working paper *Guidelines for Defining Limit Reference Points for Pacific Salmon Stock Management Units* (Holt et al. in review). For our case studies, we focus on a 50% probability threshold for sensitivity analyses, but show sensitivity to other values.

We consider two types of aggregate abundance-based LRPs in our case studies: Logistic regression LRPs and Projected LRPs. Logistic regression LRPs are based on historical data, and thus represent conditions that have been previously experienced by a SMU. In comparison, projected 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.

### 2.2.1 Logistic regression LRPs

Logistic regression LRPs are derived from an empirically estimated relationship between CU-level status and aggregate SMU abundance. Using this approach, the LRP represents the aggregate abundance that has historically been associated with a pre-specified probability of a required proportion of CUs being above their lower benchmarks. In all three case studies, we assume that all CUs are required to be above their lower benchmarks (i.e., proportion = 100%). For each year of observed data, CU-level status is quantified as a Bernoulli variable: 1 (success) = all CUs have spawner abundance greater than their lower benchmark, , and 0 (failure) = all CUs did not have . A logistic regression is then fit to predict the probability that all CUs will have 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 calculate the LRP as the aggregate spawner abundance associated with the pre-specified probability threshold of ,

An example logistic regression fit is shown in Figure ([**ref?**](#ref-ref))(fig:example-logisticFit). 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 .

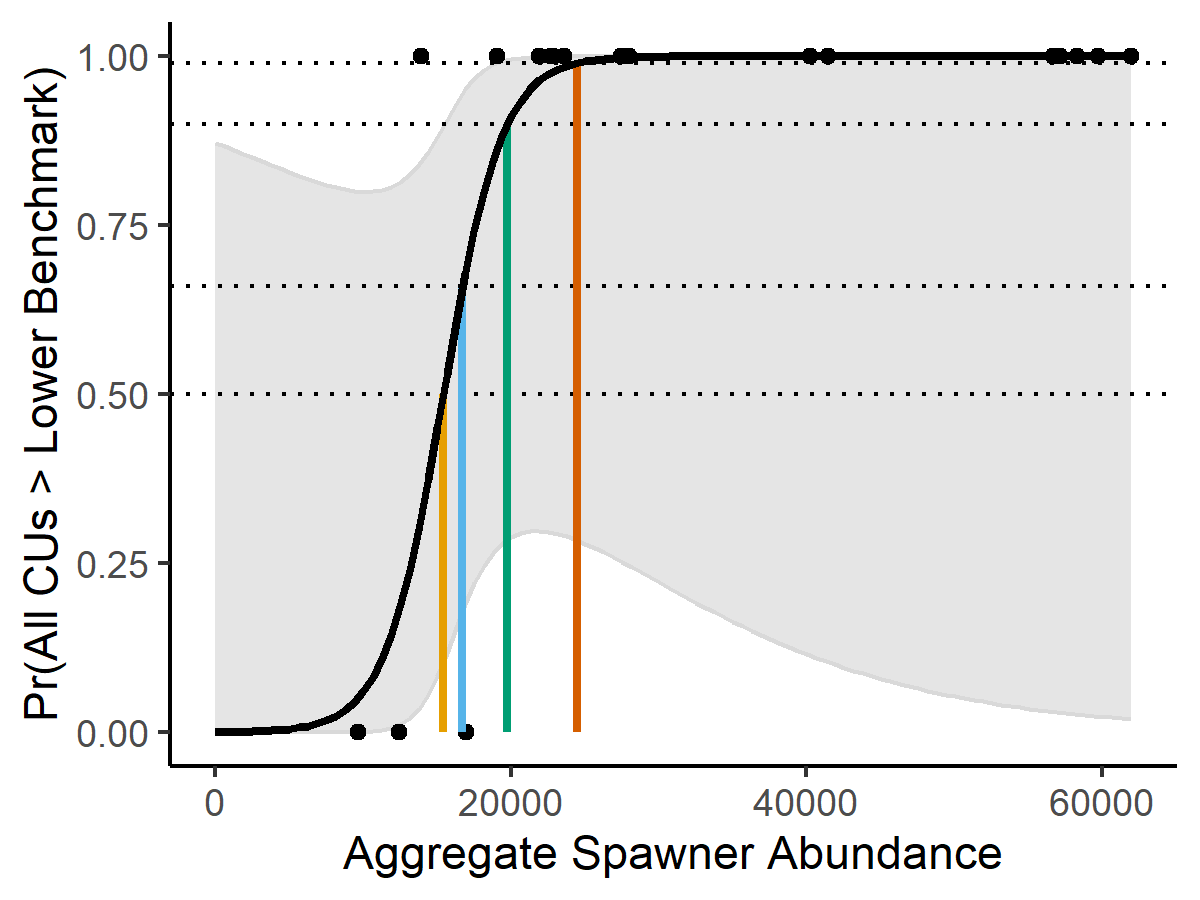


Figure 2.2: Logistic regression fit to annual Benroulli data to predict the probability of all CUs being above their lower benchmark (LBM) as a function of aggregate SMU abundance. Black dots are annual Benroulli indicators showing whether the requirement of all CUs above their LBM was met (success = 1) or not (failure = 0) in each year, the black solid line in 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 (, where i = a CU). Using this approach, CU-level status was quantified as the number or CUs with for each year of observed data. A logistic regression was then fit to predict the proportion of CUs with as a function of aggregate spawner abundance to the SMU (i.e., abundance from nCUs combined). We do not show 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.

To Do: mention uncertainty

##### 2.2.1.0.1 Logistic Regression Model Diagnostics

There are several assumptions associated with logistic regression, of which four are relevant for our application to LRPs, 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](#ref-r_core_team_r_2021)).

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.
4. The sample size is large. Logistic regression assumes that the sample size of the data set is large enough to draw valid conclusions from the fitted model.

**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-fox_applied_2016)).

**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 2016](#ref-fox_applied_2016)). Equation (2.4) reduces to,

when , and to,

when ([Ahmad 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)**

As a general rule of thumb, deviance residuals greater than 2 are considered to be to be outliers, since 95\% of the distribution is expected to be within 2 standard deviations of the mean. Further identifying influential outliers is recommended, but was not feasible for this application because TMB, the software used to estimate model parameters, does not provide the hat-matrix required to assess influence of individual points.

**Evaluating sample size (Assumption 4)**

A minimum of 10 data points for the least frequent outcome is recommended to avoid biases in model coefficients ([Peduzzi et al. 1996](#ref-peduzzi_simulation_1996)). 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. Although it is possible to estimate LRPs with lower sample sizes, the risks of biases in model parameters increases.

**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 et al. 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, the difference in the number of parameters between full and null models. P-values <0.05 indicate significant lack of fit ([Fox 2016](#ref-fox_applied_2016)).

In addition, the quasi- 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 quasi- 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.

**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 unrealistically good 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.

### 2.2.2 PROJECTION-BASED LRPS

Projected LRPs are estimated using stochastic projections of future CU abundances to characterize the relationship between aggregate SMU-level spawner abundance and the probability that the required proportion of CUs will be above their lower benchmarks (e.g. Sgen). We used the samSim 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; Freshwater et al. 2020). We created a modified version of samSim to support LRP estimation. The LRP version of samSim is described in detail in Appendix B ??, while model code is available on GitHub at: <https://github.com/Pacific-salmon-assess/samSim/tree/LRP>.

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. 2011, 2019a, 2019b; Grandin and Forrest 2017; Ohlberger et al. 2019; Olmos et al. 2019; Forrest et al. 2020, 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.
* Specification of variability in exploitation rates as a function of both variability among years and variability among CUs.

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, age-at-maturity, 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. Furthermore, we were only applying a simple fixed ER harvest strategy when projecting forward, so annual variability arising from observation error would be accounted for by our specification of between-year variability in ERs.

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 200 fish intervals. 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. 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 200 year-trial combinations that had a aggregate abundance in 10,000 - 12,000 fish bin.
   * Summarize the number of ‘successful’ year-trial combinations that occurred for that bin. For example, 50 of 200 year-trial combinations in the aggregate abundance bin of 10,000 - 12,000 fish are successes in which all CUs were above their lower benchmarks.
   * Calculate the probability that all CUs will be above their lower benchmarks for that bin as:
   * For example, if 50 of the 200 realizations that fell within the of 10,000 - 12,000 fish were ‘successes,’ there would be a 25% probability (50 / 200 = 0.25) that all CUs would be above their lower benchmarks when aggregate abundances are between 10,000 and 12,000 fish.
4. Identify the LRP as 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 shows in Figure ([**ref?**](#ref-ref))(fig:example-projectedCurve) 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 that LRP estimates should be presented as a range based on the bin size.

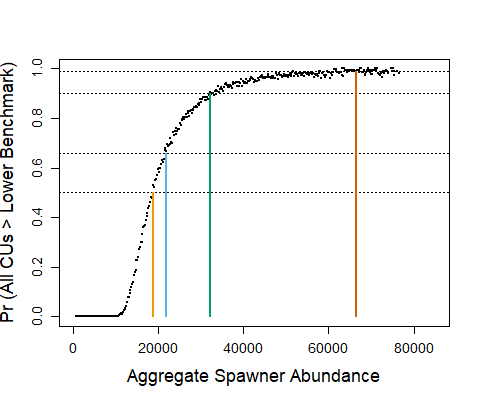


Figure 2.3: Example of projected probability curve derived from projections over 30 years and 10,000 MC trials. The curve shows the projected probability of all CUs being above their lower benchmark (LBM) as a function of aggregate SMU abundance, with each dot in teh curve representing a single combination of year and simulation replicate. 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 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-arbeider_interior_2020)). During their freshwater fry residence, IF coho are believed to migrate away from spawning sites and into small tributaries and off-channel habitat. 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-arbeider_interior_2020)).

;; WSP Conservation Units (CUs) have been identified for of Interior Fraser Coho based on genetics and geographic separation: Middle Fraser, Fraser Canyon, Lower Thompson, North Thompson, and South Thompson [[DFO](#ref-dfo_wild_2015) ([2015](#ref-dfo_wild_2015)); Figure 3.1]. Previous work by the Interior Fraser Coho Recovery Team also identified 11 subpopulations nested within the five CUs, and developed recovery objectives based on maintaining abundance in each of these smaller subpopulation units [[Fraser Coho Recovery Team)](#X830e4246a33c0126fa23b8a896db7c00660e6f5) ([2006](#X830e4246a33c0126fa23b8a896db7c00660e6f5)); 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 [Fraser Coho Recovery Team)](#X830e4246a33c0126fa23b8a896db7c00660e6f5) ([2006](#X830e4246a33c0126fa23b8a896db7c00660e6f5)). The Fraser Canyon CU is the only CU with a single subpopulation; this result is because most of the spawning for the CU occurs within a single river ([Arbeider et al. 2020](#ref-arbeider_interior_2020)).

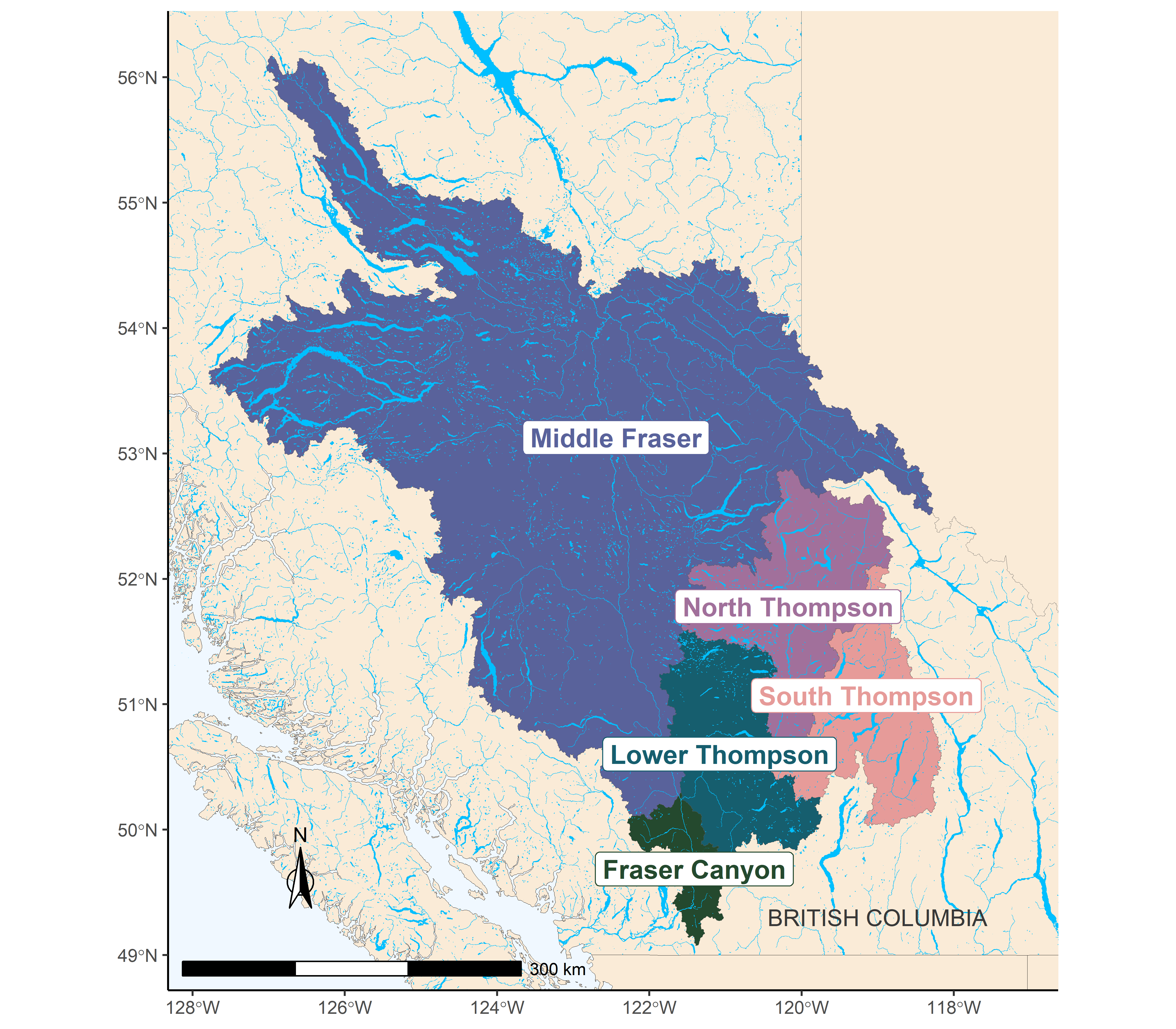


Figure 3.1: The five Conservation Units that make up the Interior Fraser Coho Stock Management Unit.

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 [Fraser Coho Recovery Team)](#X830e4246a33c0126fa23b8a896db7c00660e6f5) ([2006](#X830e4246a33c0126fa23b8a896db7c00660e6f5)).

|  |  |
| --- | --- |
| Conservation Unit | Sub-population |
| 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 |

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-decker_assessment_2014)). Evidence of a new, lower productivity regime starting in return year 1994 has been documented ([Decker et al. 2014](#ref-decker_assessment_2014)) 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 (COSWEIC) based on the stock unit being assessed as a single ‘Designatable Unit’ (DU). Subsequent work by the Interior Fraser Coho Recovery Team lead to a conservation strategy outlining recovery objectives for the management unit ([Fraser Coho Recovery Team)](#X830e4246a33c0126fa23b8a896db7c00660e6f5) ([2006](#X830e4246a33c0126fa23b8a896db7c00660e6f5))). Those recovery objectives were largely based on the distribution of spawning escapement among the 11 subpopulations in Table 3.1. A short-term recovery objective of 20,000 spawners was identified as a level that would maintain a minimum of 1,000 naturally spawning wild Coho Salmon in at least half of the 11 subpopulations, while a long-term recovery target of 40,000 spawners was identified as a level that would maintain 1,000 or more wild Coho Salmon in all 11 subpopulations. In 2014, [Decker et al.](#ref-decker_assessment_2014) ([2014](#ref-decker_assessment_2014)) assessed status relative to the 2006 IFCRT objectives, and concluded that IF coho had been above the short-term recovery target of 20,000 spawners in every year since 2008, and above the long-term recovery target of 40,000 spawners in the most recent two return years (2012 and 2013)

An updated COSEWIC assessment in 2016 upgraded the status designation for the IFC DU to ‘threatened’ ([COSEWIC 2016](#ref-cosewic_cosewic_2016)). In response to this COSEWIC status, DFO subsequently 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-arbeider_interior_2020)). As part of this RPA, the long-term DU recovery target for IF Coho was recommended was a 3-year geometric mean abundance of 35,935 natural-origin spawners. This target was based on the historically observed aggregate abundance that met a distributional goal of 1000 spawners in all subpopulations.

To Do: need to work in [Korman et al.](#ref-korman_evaluation_2019) ([2019](#ref-korman_evaluation_2019))

## 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; ([**ref?**](#ref-ref))(fig:coho-CU-timeseries-Combined)), (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.

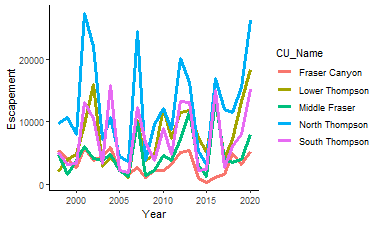


Figure 3.2: Escapement time series for five Interior Fraser Coho CUs

Data were similar to those previously described in [Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)); data treatments, assumptions, infilling, and data quality are described in detail in that document. More recent updates that are not described in [Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)) include the incorporation of three additional years of data (return years 2018-2020), 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 recruitment-at-age (M. Arbeider, pers. comm).

* Still to add:
* Caveats: e.g., recruitment estimated using common ER for all CUs; review Arbeider et al. for additional data caveats

## 3.3 METHODS

### 3.3.1 CU Status Estimation

We consider two types of CU benchmark to represent CU status when developing LRPs for Interior Fraser Coho.

**Sgen**

The first type is the WSP lower benchmark of , where Sgen is the number of spawners required to recover to SMSY (spawners maximum sustainable yield) within one generation, under equilibrium conditions in the absence of fishing ([Holt et al. 2009](#ref-holt_indicators_2009)). Four different formulations of stock recruitment model are used to estimate Sgen based on previous analyses. Key differences among the formulations centre around whether a hierarchical model structure is used when estimating Sgen and whether an informative prior distribution is applied to the spawner abundance level at which the stock replaced itself (SRep).

We primarily use the two model formulations that assume no hierarchical structure among CUs (IM and IM.cap) as a basis for comparing among LRP estimation methods, but have retained the two hierarchical model formulations (HM and HM.cap) for sensitivity analyses. Our rationale for focusing on the individual modelling approaches was two-fold. First, 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. Second, initial investigations of the hierarchical models fit to IF coho data showed that LRP estimates were sensitive to the choice of the assumed standard deviation on the hyper-distribution for the productivity parameter.

*Model 1: Individual Ricker (IM)*

Using this approach, we assumed that productivity was independent among CUs with a shared covariate for marine survival. The Individual 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) 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-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)), 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-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)):

*Model 2: Individual Ricker with High (IM.HiCap)*

The IM.HiSRep model is similar to model 1 (IM), but used an informative prior distribution to increase carrying capacity. This version of the Ricker model has been identified as a plausible alternative to the base Ricker model with a survival covariate (Equation 1) in recent science advisory processes for Interior Fraser Coho (([Korman et al. 2019](#ref-korman_evaluation_2019)), ([Arbeider et al. 2020](#ref-arbeider_interior_2020))).

[Korman et al.](#ref-korman_evaluation_2019) ([2019](#ref-korman_evaluation_2019)) suggested that the Ricker model with a survival co-variate 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](#ref-korman_evaluation_2019)). Furthermore, they observed that one brood line had persisted at a relatively higher and more stable spawner abundance than the other two brood lines, which they viewed as evidence for a higher capacity than the base Ricker model estimates. Based on these concerns, [Korman et al.](#ref-korman_evaluation_2019) ([2019](#ref-korman_evaluation_2019)) proposed an alternative Ricker model that used an informative prior distribution to increase carrying capacity (represented as the spawner abundance at which the stock replaces itself, ). [Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)) followed the approach of ([Korman et al. 2019](#ref-korman_evaluation_2019)) by considering both the base Ricker model and a version of the Ricker model with an informative prior distribution on (which they referred to as the Ricker\_priorCap model) to be plausible when providing management advice.

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 when evaluating LRP options for this SMU.

[Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)) (and Korman???) 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-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)). Note that the “” term is used to correct for scaling spawner abundance by 1/1000 when fitting models. [Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)) 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 3.3.

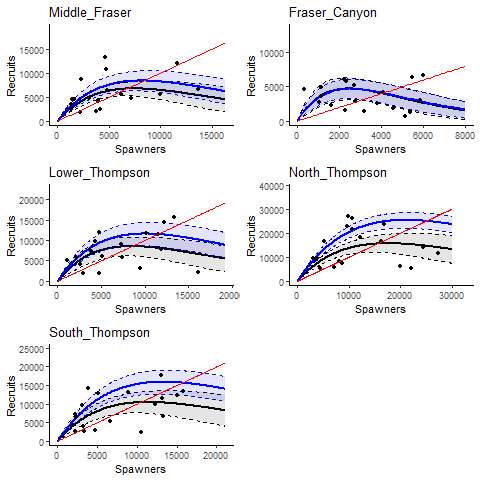


Figure 3.3: Stock recruit curves fit to spawner and recruitment data using individual models for each CU. Solid black lines shows the MLE fit for the IM model while solid blue lines shows the MLE fit for the IM.HiCap model. Associated black and blue shaded regions show the 95 percent confidence intervals on respective model fits. The red line show the replacement line.

*Model 3: Hierarchical Ricker (HM)*

The hierarchical Ricker model (HM) follows recent stock-recruitment analyses for Interior Fraser Coho that assume CU-level productivities are sampled from a common, normal distribution that is shared by all CUs (([Korman et al. 2019](#ref-korman_evaluation_2019)), ([Arbeider et al. 2020](#ref-arbeider_interior_2020))). The formulation of the hierarchical Ricker model is the same as that described above for the individual Ricker model, except we fit it as a mixed-effect model that treated CU-level parameters as random effects:

where, is the mean of the normal distribution and is the standard deviation. In addition to the likelihood constraints on and desribed for the IM, we included the following constraints on and to replicate the Bayesian model fitting routine of [Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)):

*Model 4: Hierarchical Ricker with High (HM.HiCap)*

The HM.HiCap model is the same as the IM.HiCap model, but with a hierarchical structure assumed for CU-level productivities. As with the HM model (model 3), CU-level productivities are sampled from a common, normal distribution that is shared by all CUs.

*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 (Scheurell 2016). was then calculated numerically by solving the following equation:

**Distribution among subpopulations**

The second type of CU benchmark is based on the distribution of spawning escapement among subpopulations nested within CUs (Table 3.1). We have based this benchmark on the short-term recovery objective identified by the [Fraser Coho Recovery Team)](#X830e4246a33c0126fa23b8a896db7c00660e6f5) ([2006](#X830e4246a33c0126fa23b8a896db7c00660e6f5)), which [Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)) summarized as: *“the 3-year geometric average, natural-origin escapement in at least half of the subpopulations within each of the five populations is to exceed 1000 spawning Coho Salmon, excluding hatchery fish spawning in the wild”*, where ‘populations’ is analogous to CUs. We selected the short-term recovery target to represent a lower CU benchmark in our study because, as noted by [Arbeider et al.](#ref-arbeider_interior_2020) ([2020](#ref-arbeider_interior_2020)), the short-term target was designed as an immediate target when the population was endangered. As such, it was interpreted as a level expected to prevent extinction or loss of genetic diversity. The “half of sub-populations within each CU” threshold required 2 out of 3 sub-populations to be above 1000 fish for the North Thompson and South Thompson CUs, 1 out of 2 sub-populations to be above 1000 fish for the Lower Thompson and Middle Fraser CUs, and the only sub-population in the Fraser Canyon to be above 1000 fish. This distributional benchmark is specific to the Interior Fraser Coho SMU. We have retained it as part of this case study to maintain consistency with previous work.

### 3.3.2 LRP Estimation: Proportion of CUs > Lower Abundance Benchmark

**Methods**

We looked at the proportion of CUs that dropped below Sgen (Figure 3.4) and the proportion of CUs that failed to meet the distributional target of 1000 fish in half of subpopulations 3.5) 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 was below their CU-level benchmark. Estimates of Sgen were based on all data available up to 2020, so our evaluation is not a true retrospective analysis.

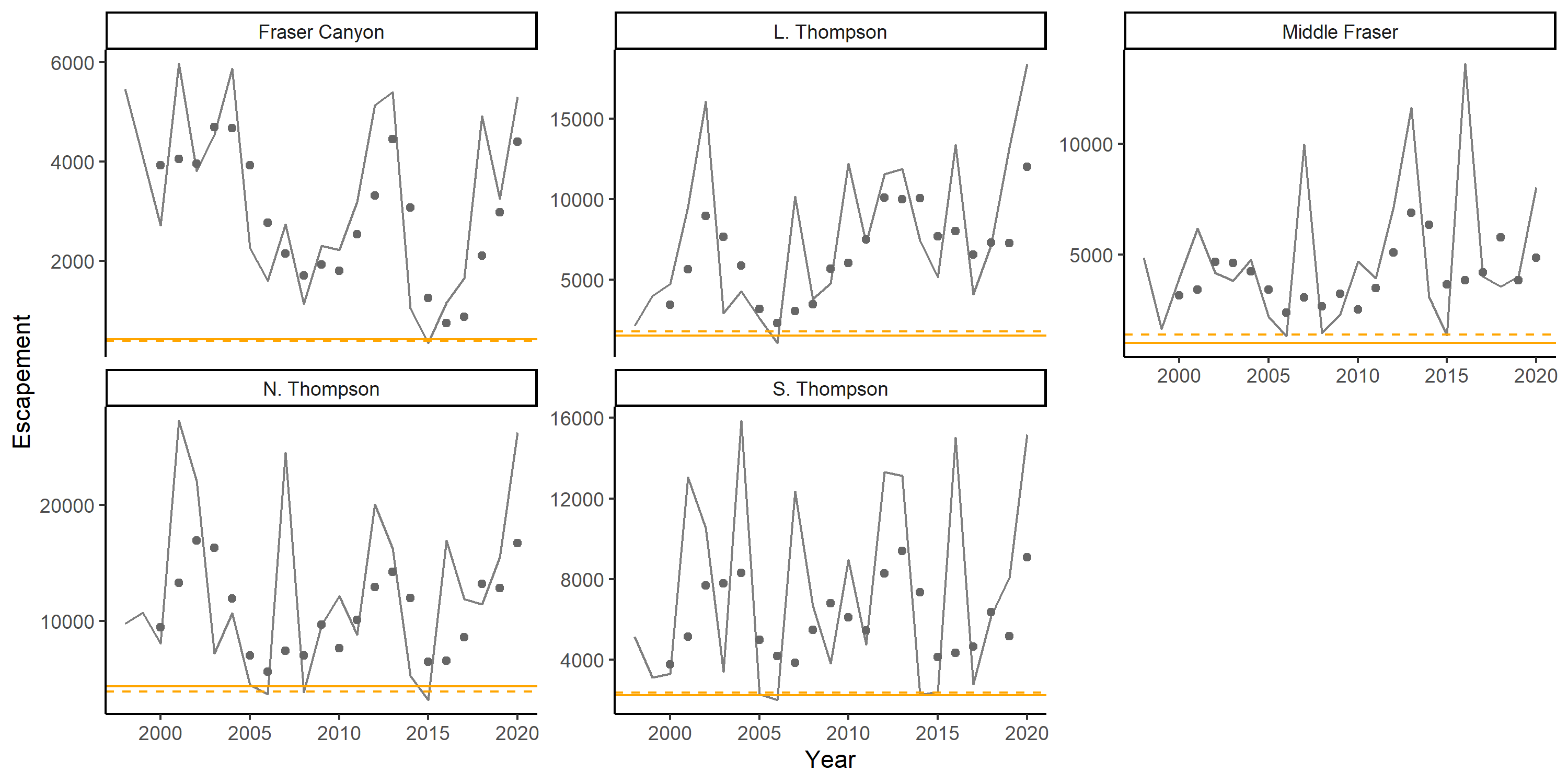


Figure 3.4: Escapement time series for five Interior Fraser Coho CUs shown as annual escapements (lines) and 3-year geometric mean escapements (dots). Solid orange lines show estimates of Sgen from the IM model, while dashed orange lines show estimates of Sgen from the IM.HiCap model.

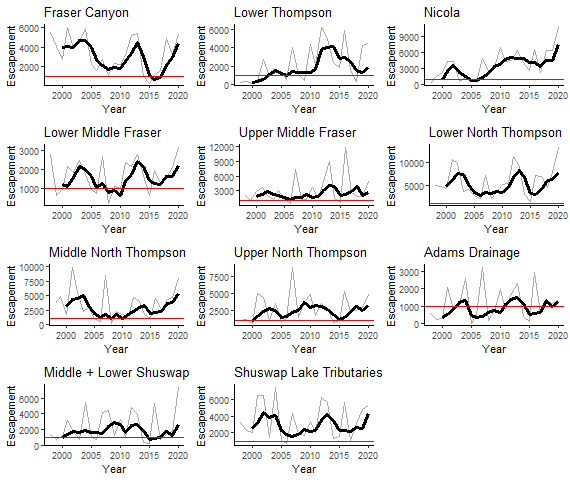


Figure 3.5: Escapement time series for 11 subpopulations of Interior Fraser Coho shown as annual escapements (grey lines) and 3-year geometric mean escapements (thick black line). CUs to which each subpopulation belong to are shown in Table —-

**Results**

For three of the five CUs,estimates of Sgen based on the IM.cap spawner recruit model were higher than those based on the IM model (Middle Fraser, Lower Thompson, and South Thompson CUs; Figure 3.4). The North Thompson CU showed the opposite pattern, with the Sgen estimate from the IM model higher than that from the IM.cap model. The fifth CU, Fraser Canyon, had almost equal estimates for the two approaches with Sgen estimates only differing by 32 fish.

For all five CUs, the generational (3-year) geometric average escapement between 2001 and 2020 remained above the estimated value of Sgen in 2020 (), regardless of which stock recruit model was used to estimate Sgen (Figure 3.4).Because the proportion of CUs above Sgen was always 100%, there were no years in the available time series that were below the proportion-based LRP.

Only 3 of the 11 sub-populations had their generational average escapement remain above the 1000 spawner threshold in all years (Figure 3.5). All other CUs dropped below 1000 spawners in one or more years.

[— more results summary to be added here —-]

All 11 subpopulations were above 1000 spawners in 2020, which means that the SMU would be well above the LRP based on the proportional LPR approach applied to the distributional benchmark in 2020 (Figure 3.5).

### 3.3.3 LRP Estimation: Aggregate Abundance Empirical LRPs

**Methods**

We evaluated aggregate abundance-based LRPs derived using logistic regressions for both types of Interior Fraser Coho benchmarks: Sgen and the distributional target of 1000 fish in half of sub-populations. See Section 2.2.1 for an overview of the approach used to calculate aggregate abundance-based LRPs using logistic regression.

When estimating logistic regression LRPs using Sgen, we used an integrated modelling approach in which CU-level Sgen 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 (3.4) - (3.6))
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))

***Retrospective Analysis***

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

***Effect of Missing CUs***

To examine the effect of missing CUs on 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 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 absolute LRP estimates because absolute LRP estimates vary with the number (and combination) of CUs used.

**Results**

Figure: Logistic model fit - IM in 2020

Figure: Logistic model fit - IM cap in 2020

Figure: Logistic model fit - distribution

Appendix: Maximum posterior density estimates (± standard error) obtained from fitting the ‘Individual Ricker’ (IM) version of the Integrated Sgen-LRP model to Interior Fraser Coho data.

Appendix: Maximum posterior density estimates (± standard error) obtained from fitting the ‘Individual Ricker with cap’ (IM.cap) version of the Integrated Sgen-LRP model to Interior Fraser Coho data.

Table: Comparison of all logistic LRP estimates in 2020

### 3.3.4 LRP Estimation: Aggregate Abundance Projection-Based LRPs

**Methods**

IM model

IM cap model

Model averaging

**Results**

### 3.3.5 Historical Evaluation of Status

### 3.3.6 Retrospective Analysis

***Effect of LRP Estimation Method***

***Effect of number of years***

***Effect of number of CUs***

# 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-holtby_conservation_2007)), 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-riddell_review_2002) ([2002](#ref-riddell_review_2002))). 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-withler_genetically_2018)). 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-withler_genetically_2018)). Only stocks with PNI values 0.5 were included in the development of LRPs and assessment against those LRPs (J. Bokvwist, pers. comm. DFO South Coast Stock Assessment).

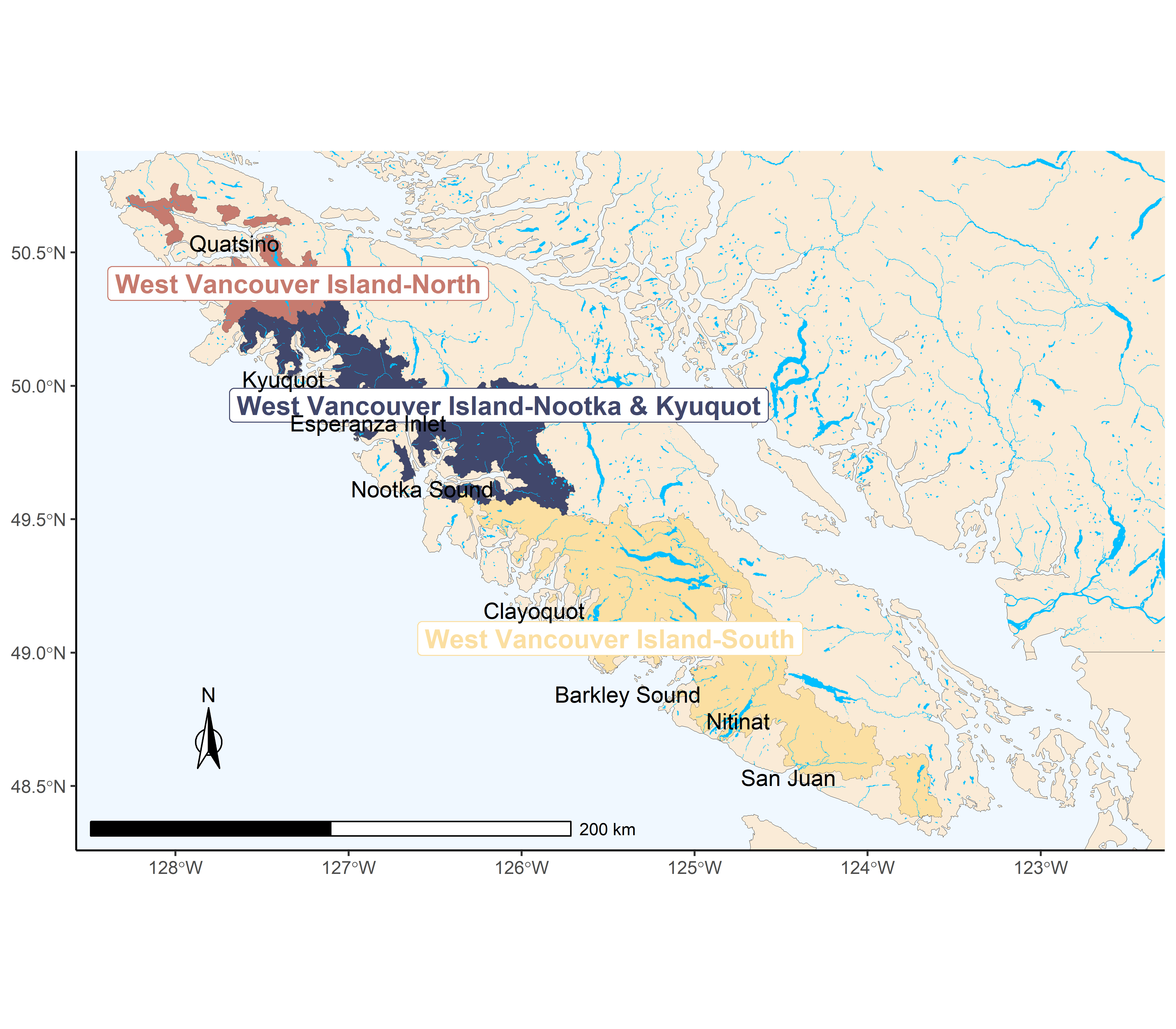


Table 4.1: Overview of WCVI Chinook Stock Management Unit. Italics represent indicators with average PNI values < 0.5. Note, the inlets, San Juan and Nitinat do not contain indicator stocks with PNI < 0.5 and are not included in these analyses. WCVI is West Coast of Vancouver Island.

|  |  |  |
| --- | --- | --- |
| 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 ([DFO 2012](#ref-dfo_assessment_2012)). ‘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 ([DFO 2012](#ref-dfo_assessment_2012)).

### 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-dfo_integrated_2016)). 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-brown_2020_2020) ([2020](#ref-brown_2020_2020)).

WCVI Chinook was identified as a stock of concern in the 2021 Integrated Fisheries Management Plan, IFMP, for South Coast Salmon, and a rebuilding plan is under development ([DFO 2021a](#ref-dfo_integrated_2021)). 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-dfo_integrated_2021)). 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-dfo_integrated_2021)).

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](#ref-parken_habitat-based_2006)). 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-liermann_using_2010) ([2010](#ref-liermann_using_2010))), 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-holtby_conservation_2007)). 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.](#ref-parken_habitat-based_2006) ([2006](#ref-parken_habitat-based_2006)) by identifying 3rd order watershed areas that contain spawning habitat and omitting areas above obstacles to fish passage from the [Provincial Obstacles to Fish Passage database](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-dfo_wcvi_2021) ([2021b](#ref-dfo_wcvi_2021))). 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.

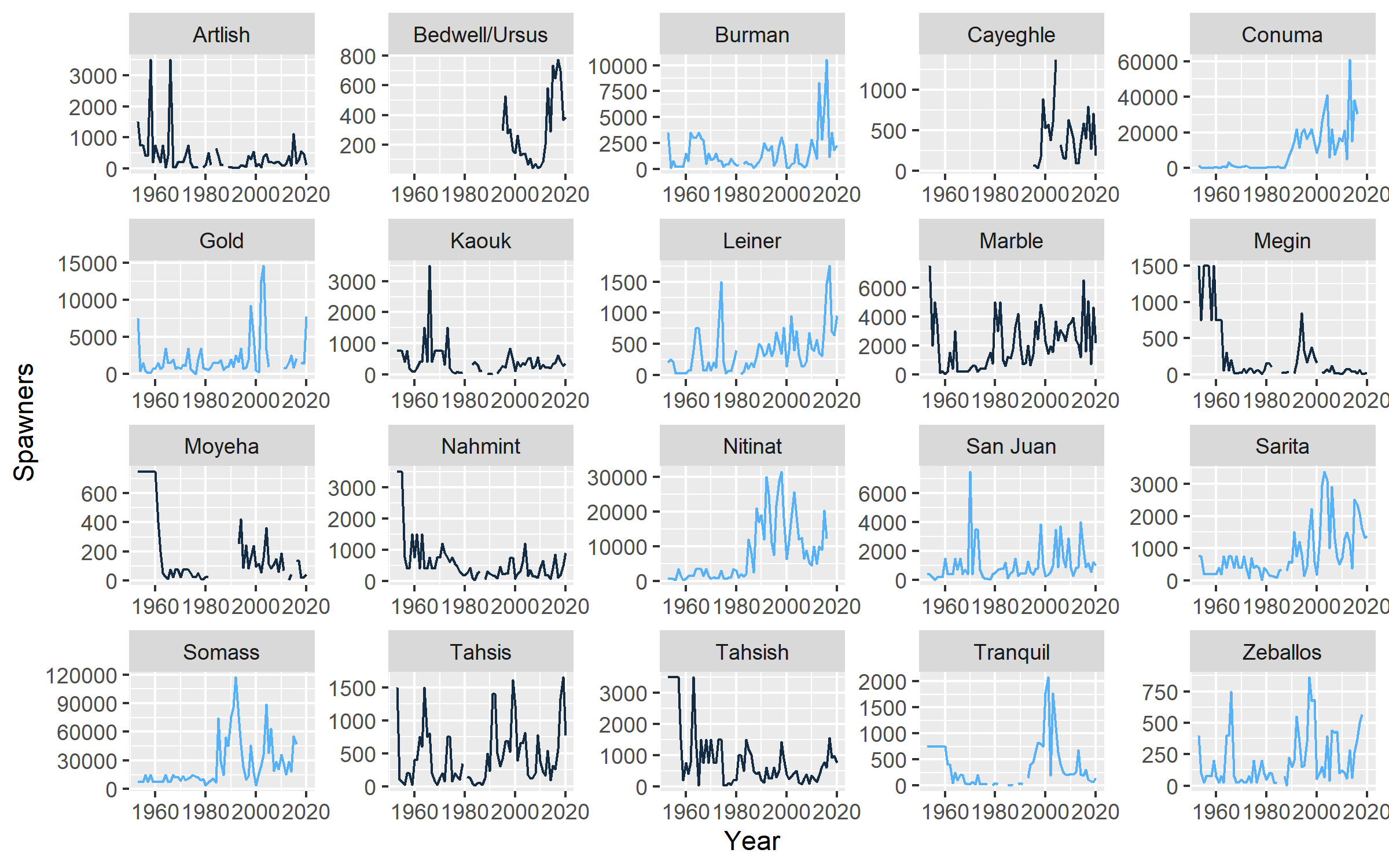


Figure 4.2: Time-series of spawner abundances by indicator stock. Dark blue time-series are indicator stocks with Proportionate Natural Index (PNI) values <= 0.5; light blue time-series are indicator stocks with PNI < 0.5, i.e., are highly enhanced.

### 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-withler_genetically_2018)). 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.](#ref-parken_habitat-based_2006) ([2006](#ref-parken_habitat-based_2006)) (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](#ref-parken_habitat-based_2006)), (>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 (3.6)) 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.](#ref-parken_habitat-based_2006) ([2006](#ref-parken_habitat-based_2006)), because we derived productivity independently from the life-stage specific models, whereas [Parken et al.](#ref-parken_habitat-based_2006) ([2006](#ref-parken_habitat-based_2006)) 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 |

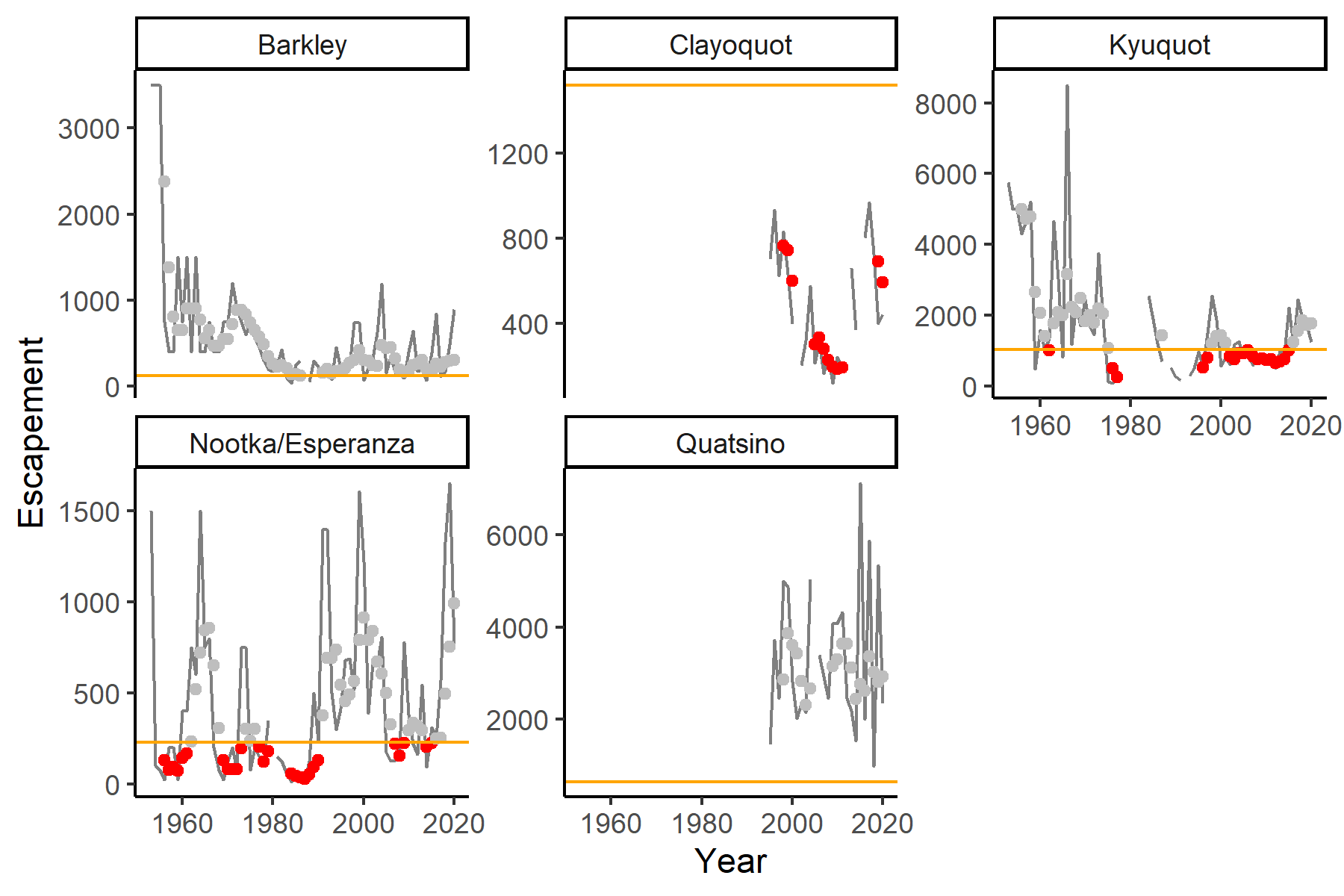


Figure 4.3: Time-series of spawner abundances by inlet, including only indicators stocks that are not highly enhanced. Horizontal yellow line is Sgen and dots are generational geometric average spawner abundances coloured by red (below Sgen) and grey (above Sgen).

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 B). 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) (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 4.4; 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.

Table 4.4: Parameters used for inlet-specific projections of WCVI Chinook population dynamics.

|  |  |  |
| --- | --- | --- |
| Paremeter | Value | Source |
| Ricker (mean) | WCVI-South = 1.14, WCVI-Nootka & Kyuoquot = 1.58, WCVI-North = 1.53 | Run reconstruction for WCVI Chinook (1985- 2019, D. Dobson & D. McHugh pers. comm.) |
| Ricker (SD) | 0.5 | Approximate 95% CI and bounds from life- stage specific model (W. Luedke per. comm.) |
| (Spawners at replacement, mean) | Barkley = 637, Clayoquot = 7879, Nootka/Esperanza = 1184, Kyuquot = 5273, Quatsino = 3384, | MLE estimate from watershed-area model |
| (SD) | Barkley = 0.40, Clayoquot = 0.30, Nootka/Esperanza = 0.37, Kyuquot = 0.31, Quatsino = 0.32, | Derived from standard error of MLE estimate from the watershed-area model |
| Ricker sigma | WCVI-South = 0.80, WCVI-Nootka & Kyuoquot = 0.69, WCVI- North = 0.68 | Run reconstruction for WCVI Chinook (1985- 2019, D. Dobson & D. McHugh pers. comm.) |
| Covariance in Ricker residuals among inlets | Equal to covariance in spawner time-series among inlets | Covariance in spawners among inlets from wild indicator stocks (D. Dobson & D. McHugh, pers. comm.) |
| Ave age proportions at maturity (age 2, 3, 4 and 5). Ages 5 and 6 are grouped. | WCVI-South = 0.02, 0.14, 0.45, 0.38; WCVI-Nootka & Kyuoquot = 0.01, 0.10, 0.48, 0.40; WCVI-North = 0.02, 0.15, 0.47, 0.36 | Ave ppns from run reconstruction (D. Dobson & D. McHugh pers. comm.) |
| Variability in age ppns (tau from multivariate logistic distribution) | WCVI-South = 0.7, WCVI-Nootka & Kyuoquot = 0.6, WCVI-North = 0.7 | Estimated from time-series of ppns of ages-at-maturity from the run reconstruction. Assumed variable over CUs and years. |
| Average exploitation rate | 0.30 | Average pre-terminal ERs 2010-2019 for Robertson Creek hatchery indicator (D. Dobson & D. McHugh pers. comm.). Varied in sensitivity analyses 0.05 - 0.45. |
| Interannual variability in exploitation rates (CV) | 0.17 | Estimated from pre-terminal ERs 2010-2019 for Robertson Creek hatchery indicator. Assumed to be beta distributed, constrained between 0-1. |
| Variability in exploitation rates among inlets (CV) | 0.085 | Assumed to be half of interannual variability, varied in a sensitivty analysis (0-0.17). Assumed to be beta distributed, constrained between 0-1. |
| Initial abundances | SREP (inlet- specific) | MLE from watershed-area model |
| Extirpation threshold | 2 | Mating constraint |

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.

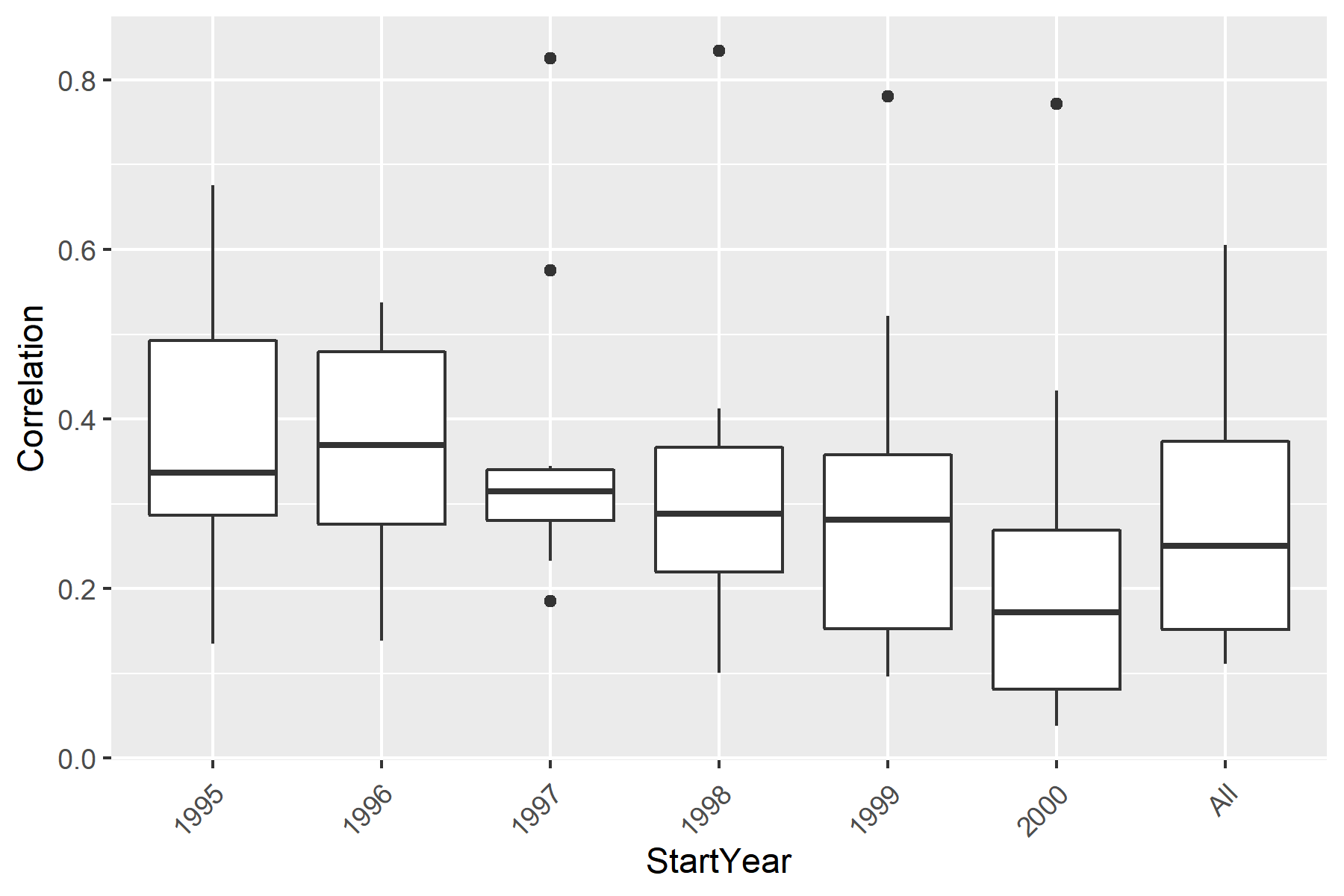


Figure 4.4: Running correlations in spawner abundances among inlets in 20-year time periods, with the start year of the 20-year period on the X-axis. Each boxplot shows the distribution of pairwise correlations among the 5 inlets (n=10 pairwise correlations).

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.

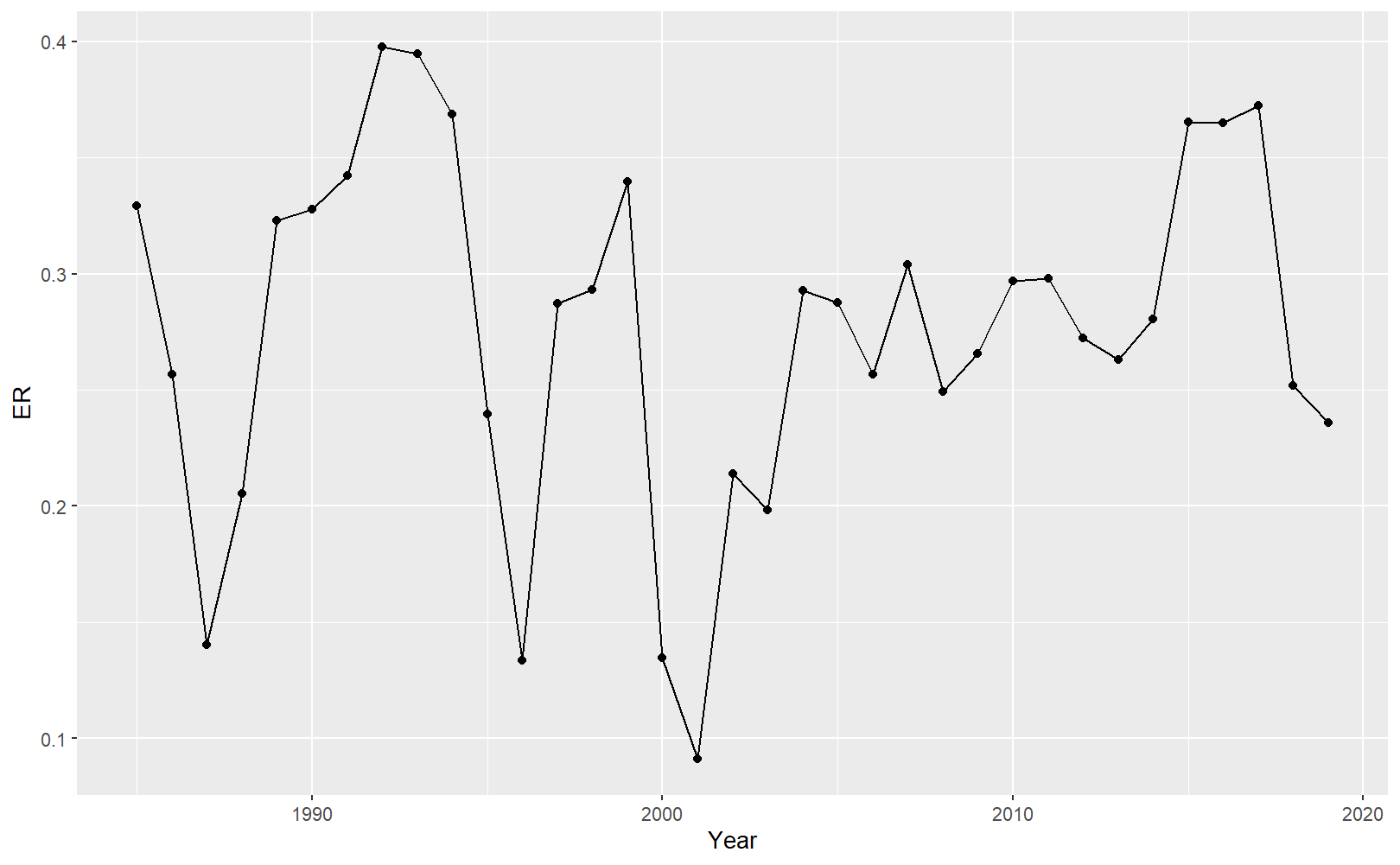
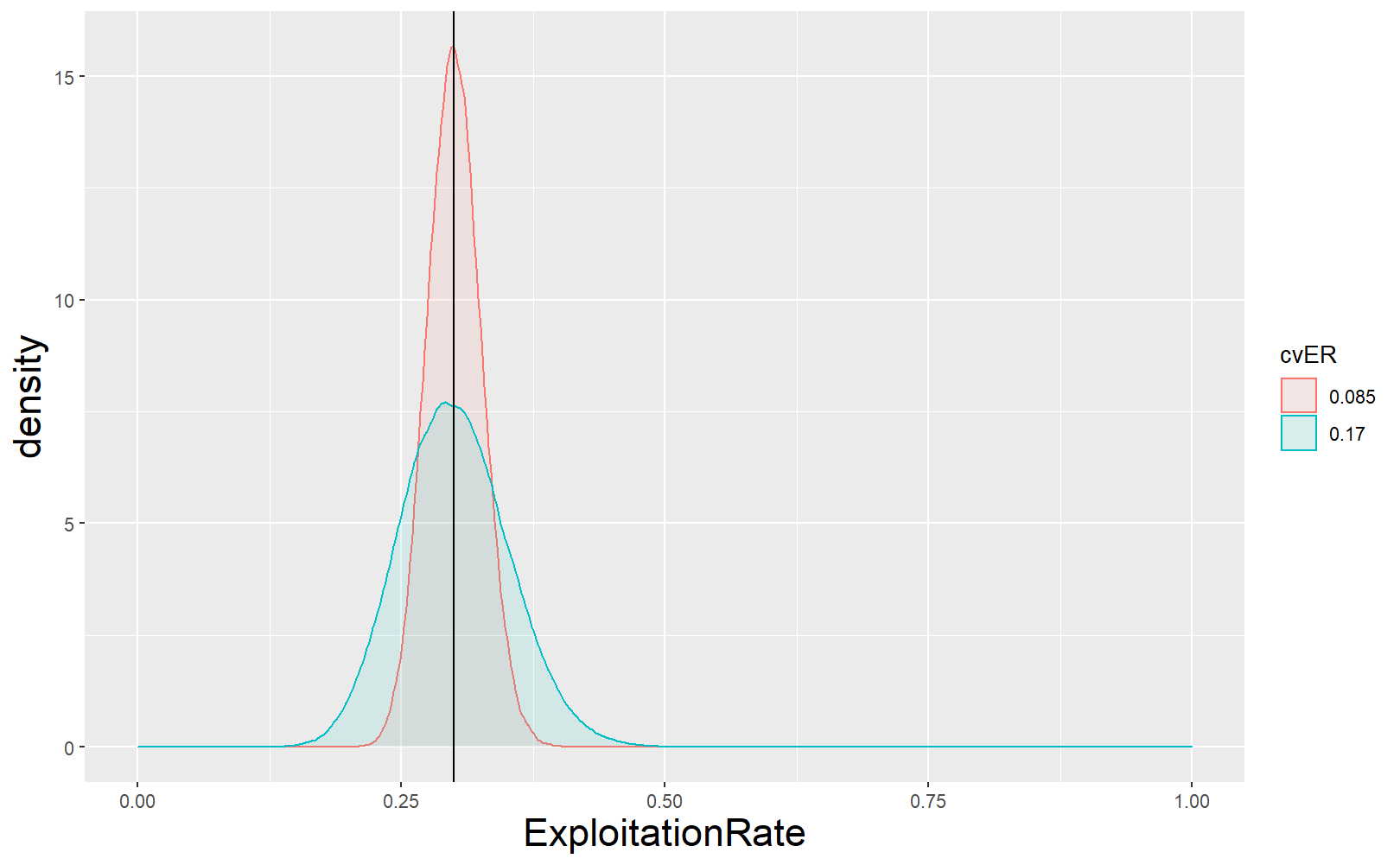


Figure 4.5: Pre-terminal exploitation rates for Robertson Creek CWT indicator.

*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 4.4). 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.

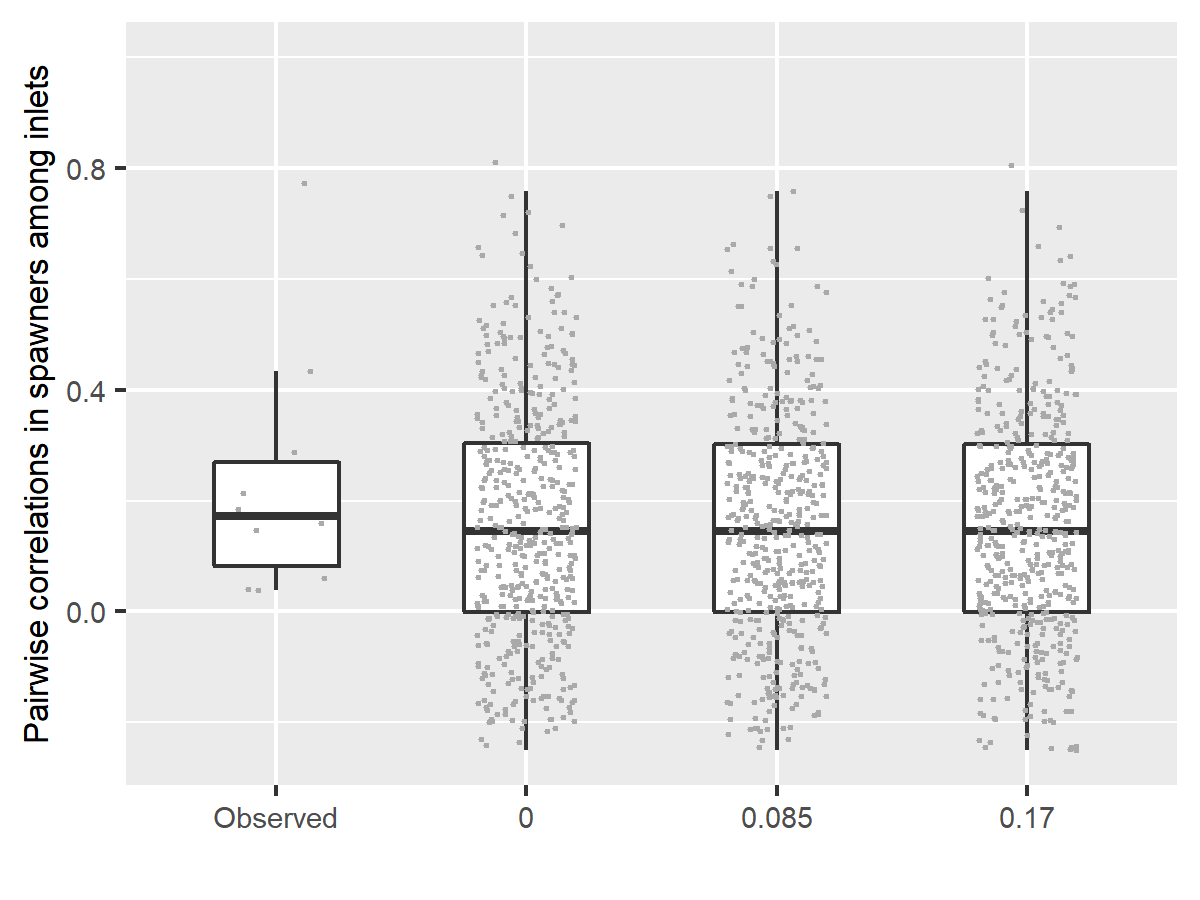


Figure 4.7: Distribution of correlations of spawner abundances among inlets for observed data over the most recent 20 years (n=10 pairwise correlations) and projected time-series, with a cv in exploitation rates among inlets = 0, 0.085 or 0.17 (0.17 is equal to the estimated interannual variablity in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

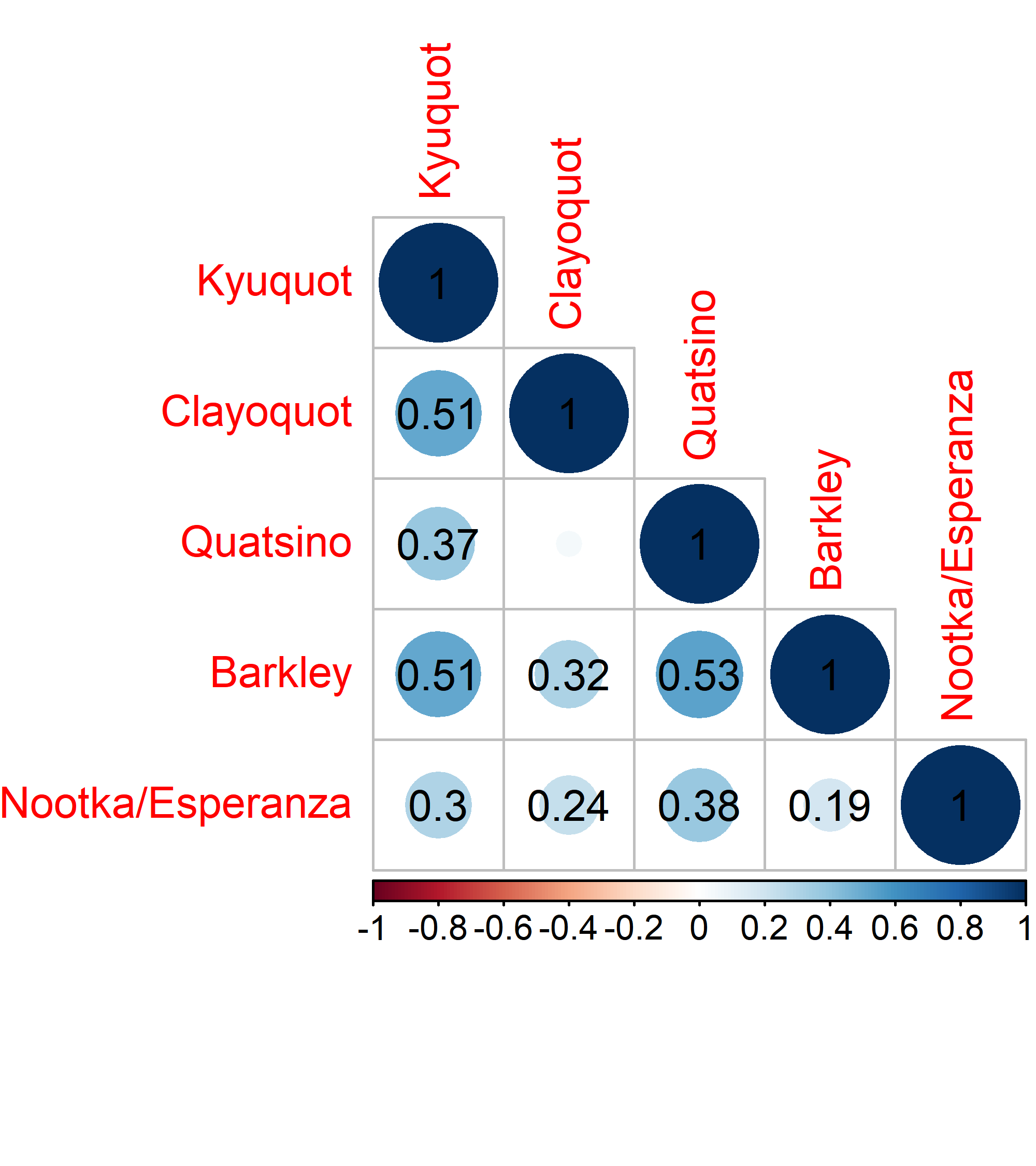


Figure 4.8: Bubble plot of correlations in spawner abundances among inlets over time, 1994-2020.

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.

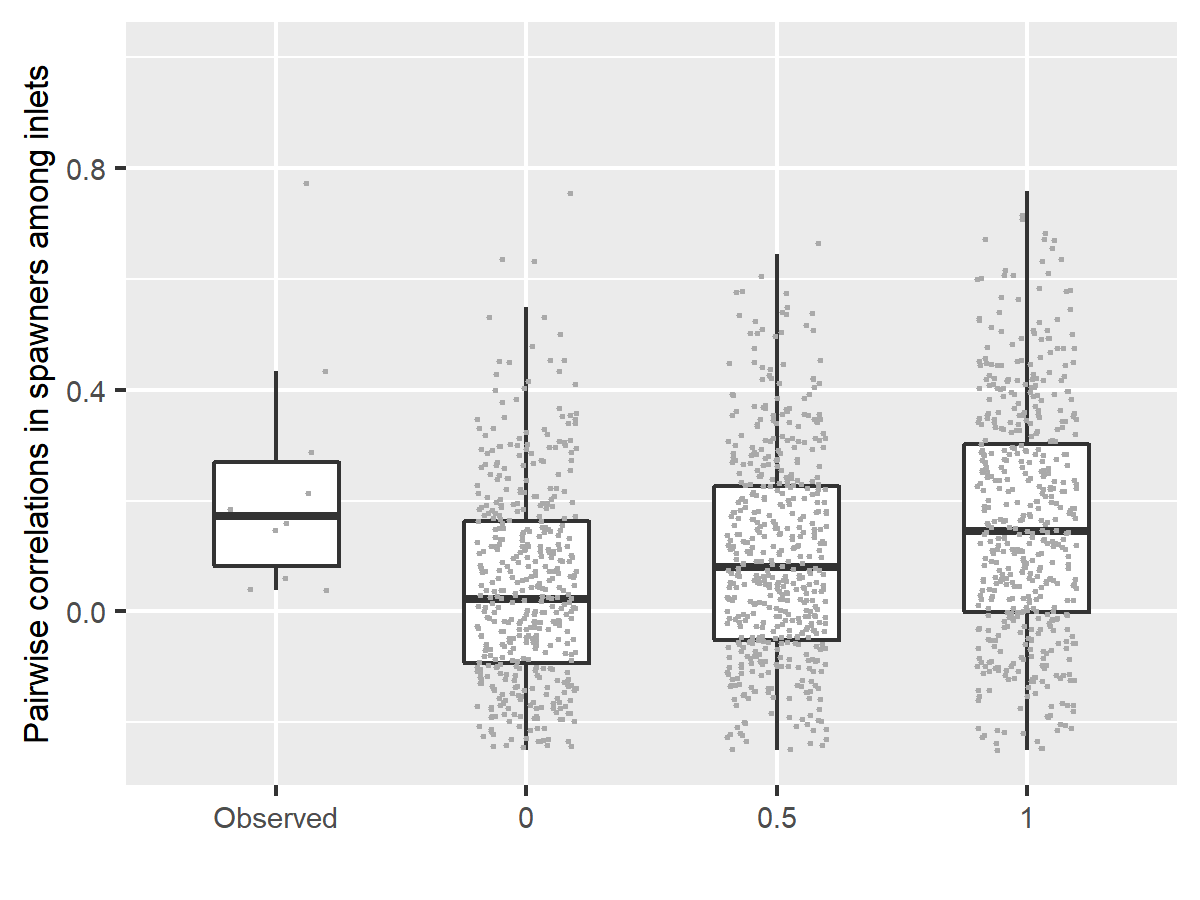
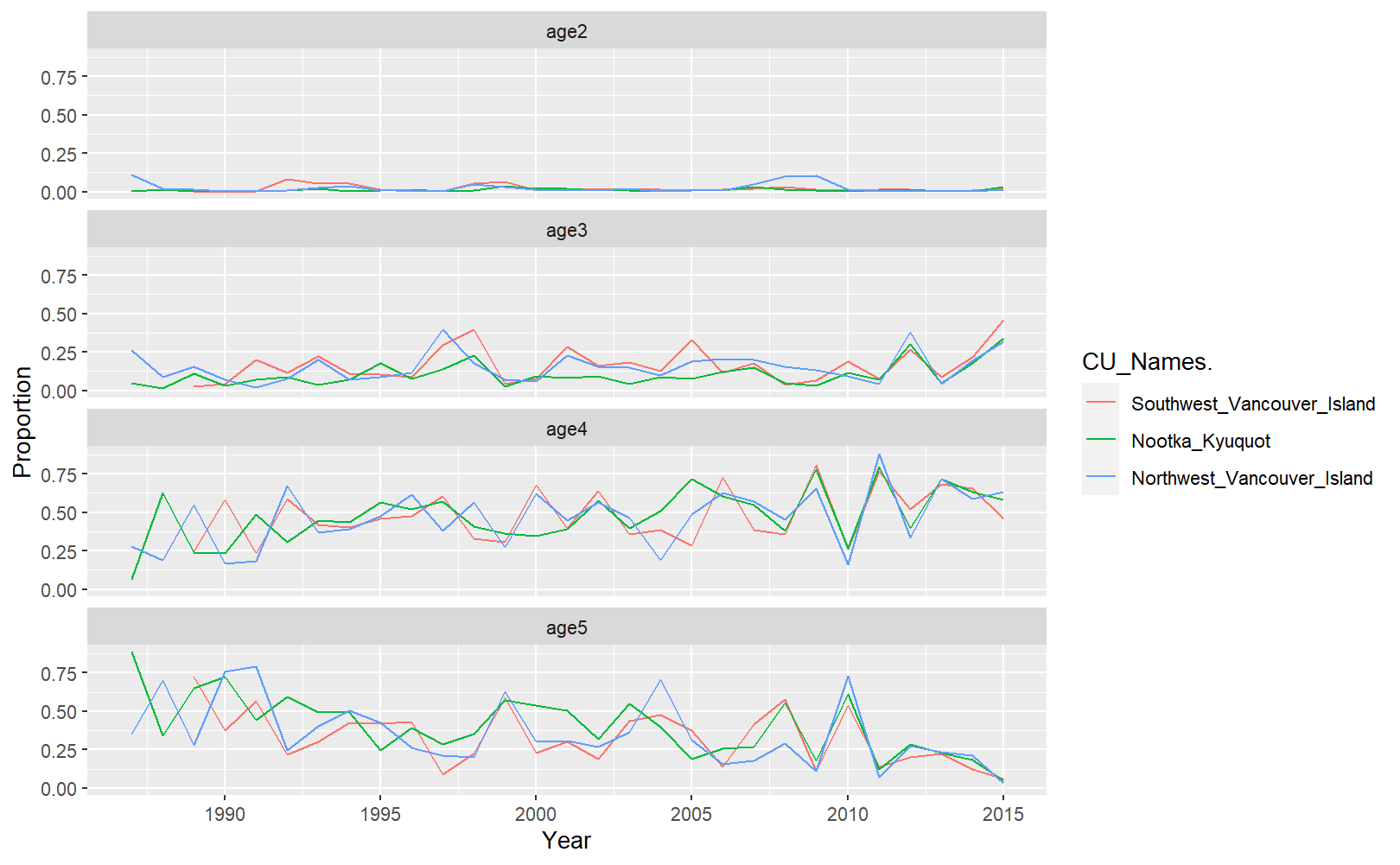


Figure 4.9: Distribution of correlations of spawner abundances among inlets for observed data over the most recent 20 years (n=10 pairwise correlations) and projected time-series, assuming a scalar on covariance in recruitment residuals from 1 (equal to observed spawner correlations), 0.5 and 0 (no correlation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

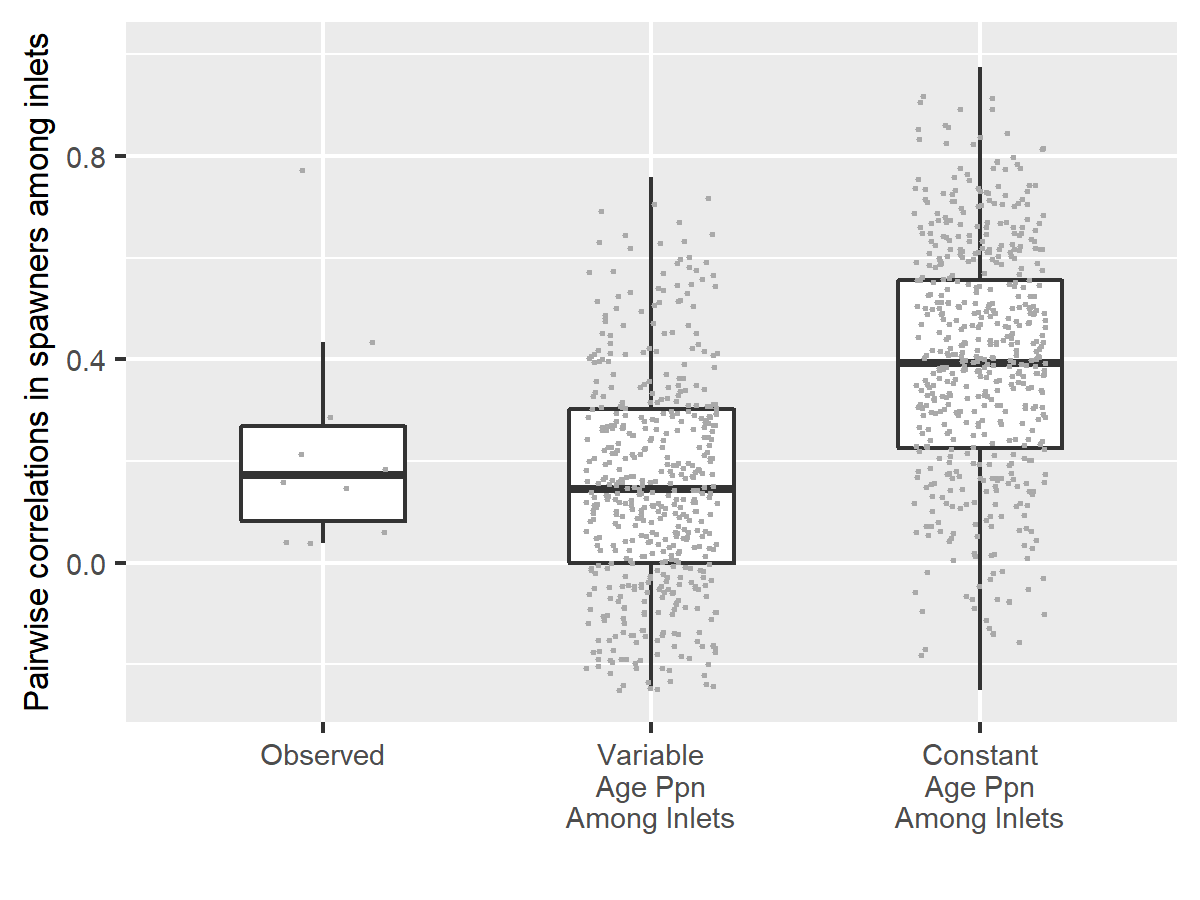


Figure 4.11: Distribution of correlations of spawner abundances among inlets for observed data over the most recent 20 years (n=10 pairwise correlations) and projected time-series under the assumptions of variable age proportions among CUs and constant proportions among CUs. We assumed a cv in exploitation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

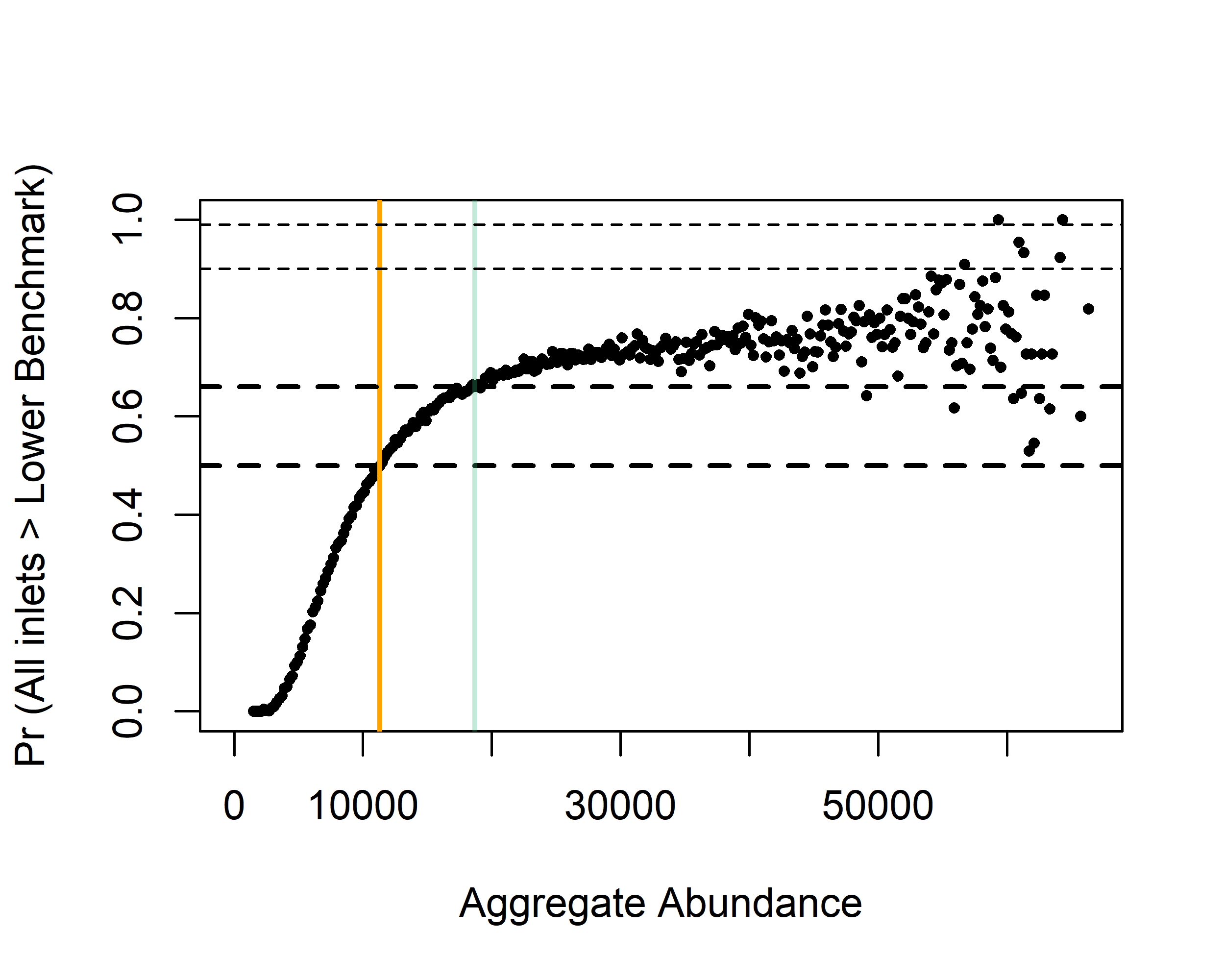


Figure 4.12: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials. Candidate LRPs at p=0.5 (yellow) and p=0.66 (pale green) are highlighted. Each dot is the proportion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

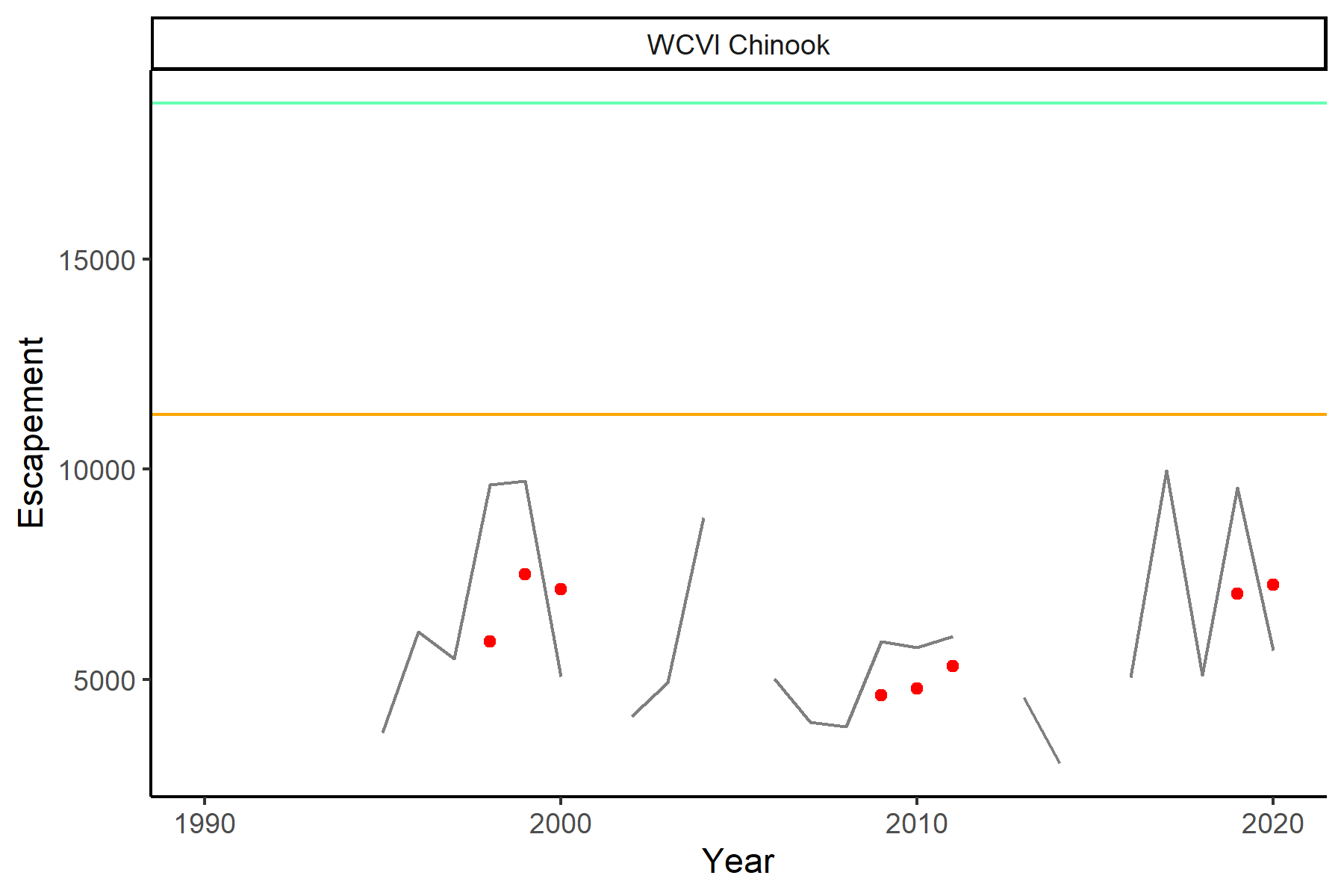


Figure 4.13: Time-series of aggregate escapement for WCVI Chinook (indicator stocks with PNI > 0.5), with projection-based LRPs associated with component inlets being > lower benchmarks at p=0.5 (yellow) and p=0.66 (pale green). Red points are the generational average escapement (geometric mean), red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

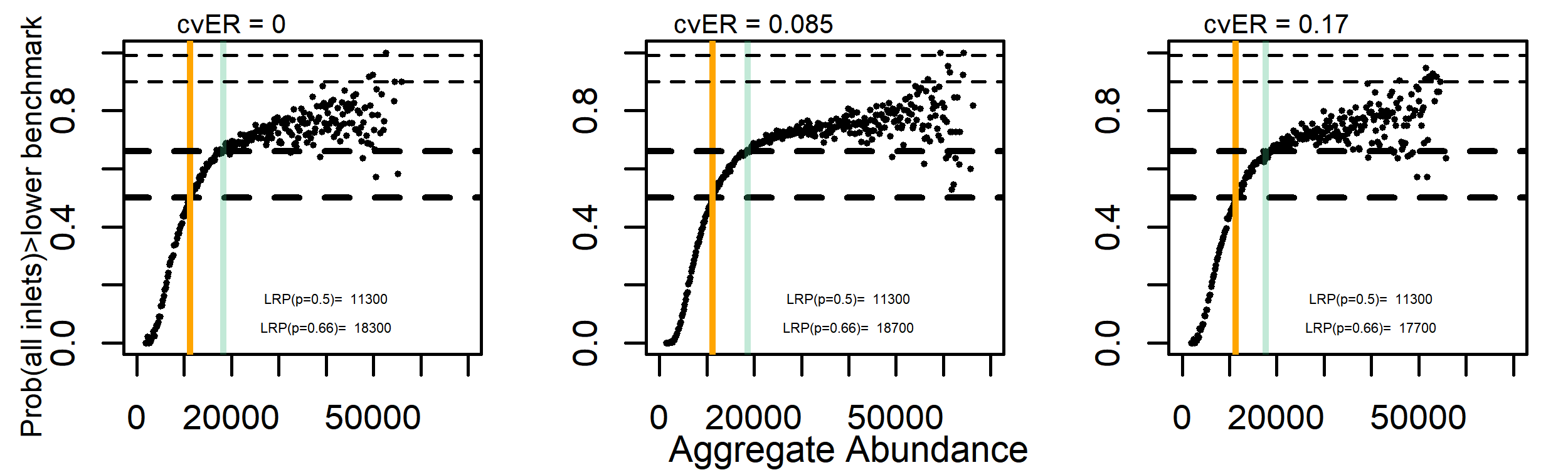


Figure 4.14: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials. The projections assumed variability in ERs among inlets with a cv=0, 0.085, and 0.17.

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.

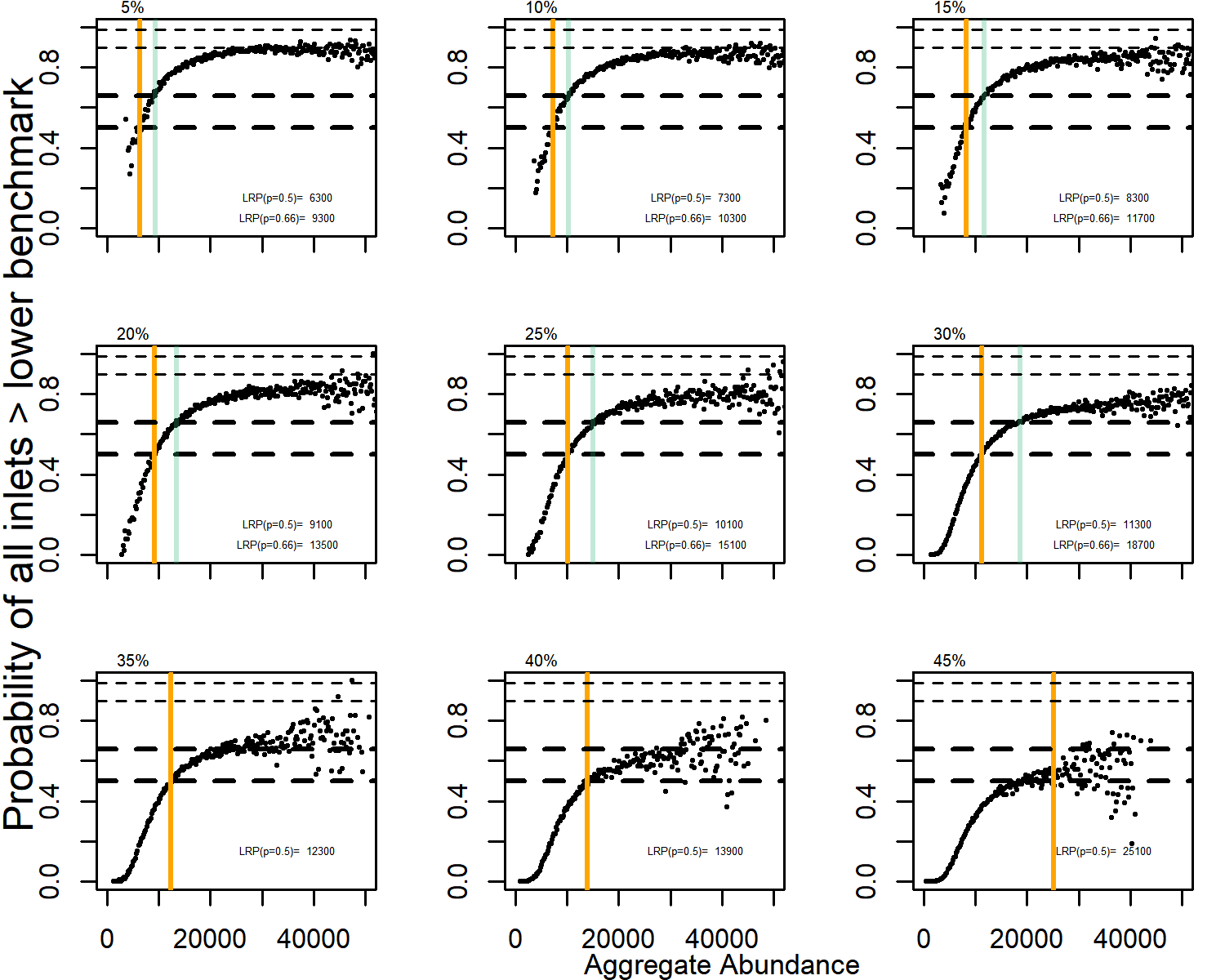


Figure 4.15: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials, under a range of average exploitation rates from 5-45%.

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-holt_cautions_2015)). 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.

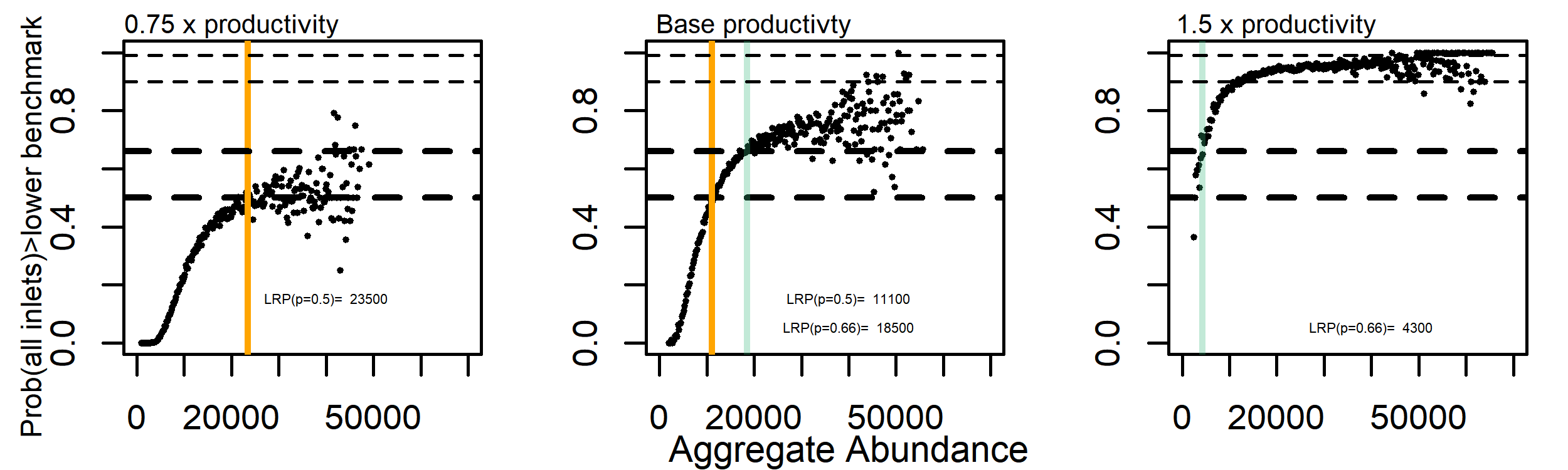


Figure 4.16: Projection-based LRPs estimated under assumptions of reduced producitivty (0.75x of current levels) and increased productivity (1.5x current levels). More MC trials are required for stabilization of LRPs at low productivity.

## 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 2016) (Figure 4.17). All methods indicate this SMU being below its LRP for years where data are available.

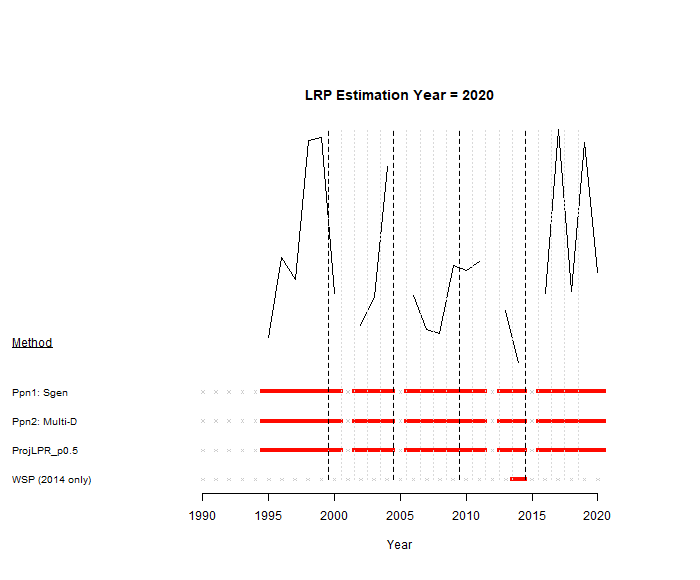


Figure 4.17: Historical evaluation of status using available methods for estimating LRPs. Red bars indicate status below LRP; grey x’s indicate status not available

## 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-holtby_conservation_2007) ([2007](#ref-holtby_conservation_2007))). This area includes deep fjords, glaciers, large rivers, and small coastal streams. Chum salmon CUs spawning in the Fraser River watershed are not included in this SMU. They have been categorized as a separate ‘Inside South Coast Chum - Fraser’ SMU. While these two SMUs have substantial overlap in ocean fisheries, they have been separated into two SMUs based on differences in terminal fishery impacts and freshwater habitats.

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 (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-debertin_marine_2017) ([2017](#ref-debertin_marine_2017))). Other unique characteristics of this SMU include high contrast in abundance among CUs and relatively low correlation in abundance among CUs over time. The SMU covers a large area with many diverse watersheds, flow regimes, and ocean entry locations.

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.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018))). In other cases, percentile benchmarks may be inappropriate due to low productivity, high harvest, and because they do not account for shifting baselines ([Holt et al.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018))).

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 .

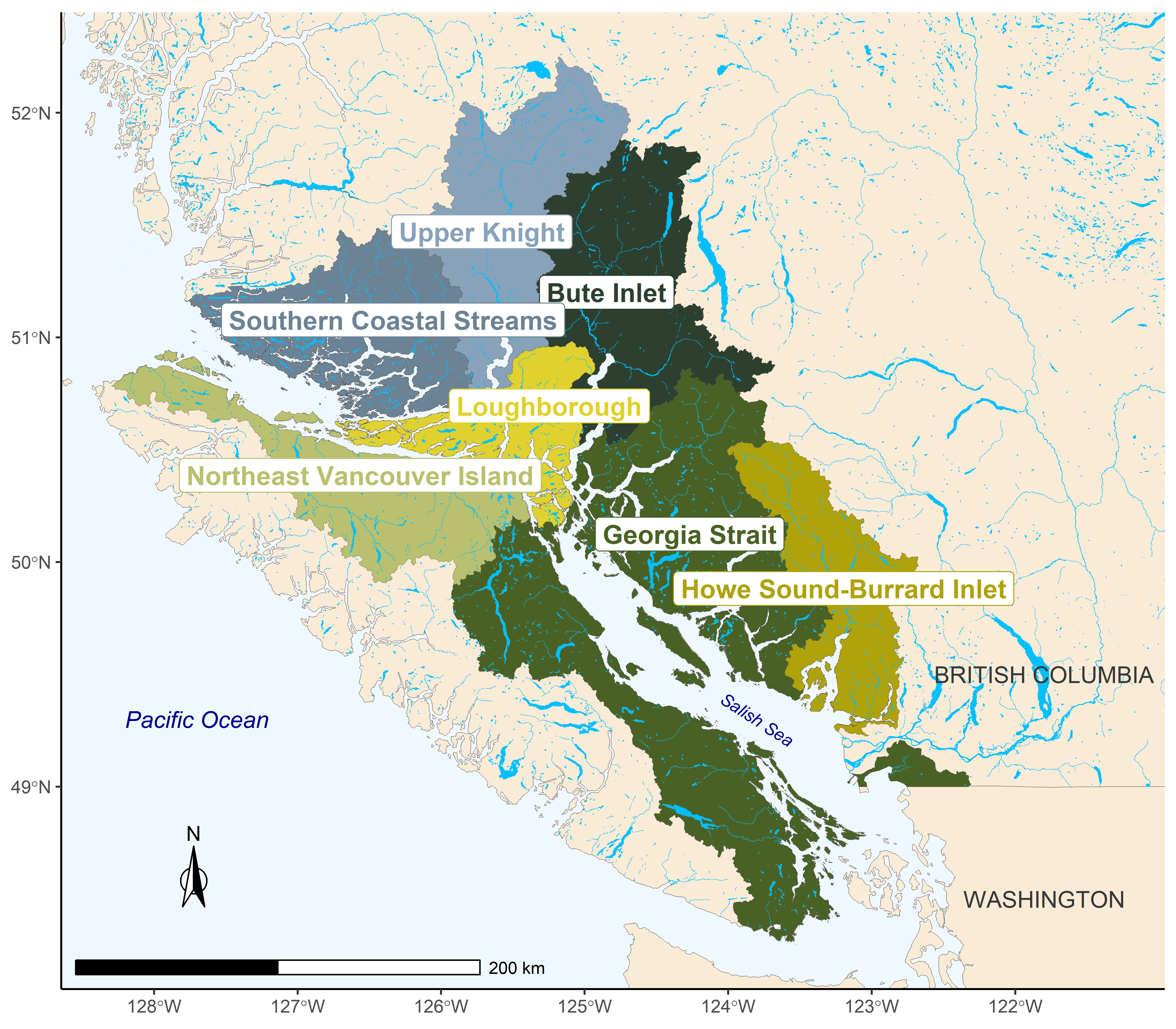


Figure 5.1: The seven Conservation Units that make up the Inside South Coast Chum Stock Management Unit (not including Lower Fraser and Fraser Canyon Conservation Units).

## 5.2 DATA

We used the same data used in [Holt et al.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)), but updated to 2018. [Van Will](#ref-van_will_inner_2014) ([2014](#ref-van_will_inner_2014)) provides more details on the data sources, infilling procedures and run reconstruction, which were reproduced for this study. We did not include the Lower Fraser or Fraser Canyon chum CUs. More details can be found in Appendix A.

## 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-pestal_algorithms_2021) ([2021](#ref-pestal_algorithms_2021)), 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-holt_indicators_2009) ([2009](#ref-holt_indicators_2009))). 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-debertin_marine_2017) ([2017](#ref-debertin_marine_2017)), [Litz et al.](#ref-litz_competition_2021) ([2021](#ref-litz_competition_2021))). 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.](#ref-clark_evaluation_2014) ([2014](#ref-clark_evaluation_2014)), [Holt et al.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018))). The suitability of percentile benchmarks was evaluated for ISC Chum by [Holt et al.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)), who tested how well percentile benchmarks matched benchmarks from stock-recruit parameters, using retrospective and simulation analyses. [Holt et al.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)) 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 .

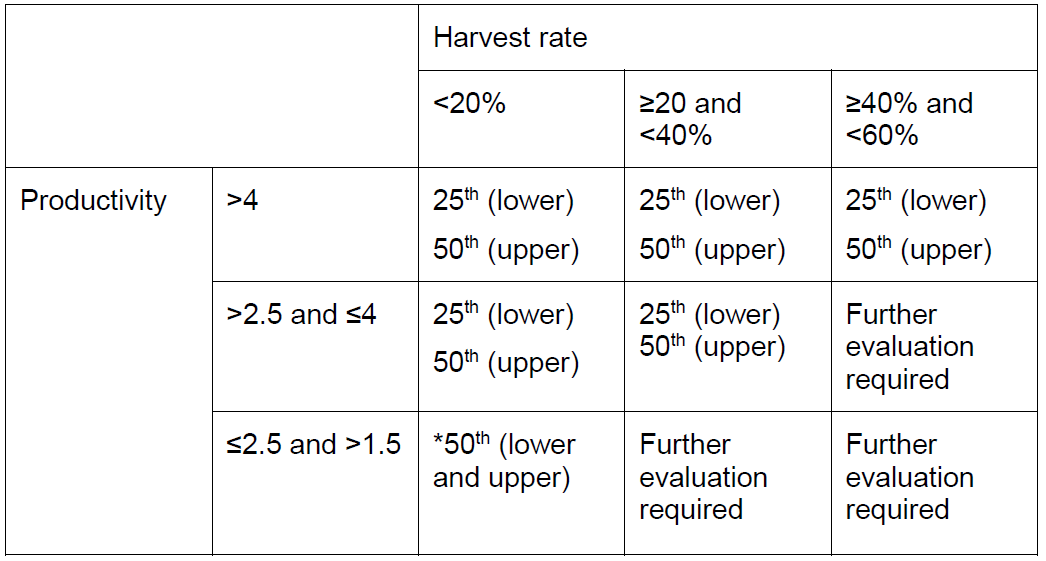


Figure 5.2: Selected percentile-based lower and upper benchmarks identified to be similar or higher in value than stock-recruitment based benchmarks under the WSP, along gradients in productivity (recruits/spawner—Ricker alpha to match below text?) and average harvest rates. \* denotes the low-productivity 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.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)) 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 perecntile 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 rapid status assessment to ISC Chum, we used the percentile benchmarks as recommended in [Holt et al.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)) 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 we 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.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)). This method used the raw annual escapement values to calculate the benhcmarks 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 benchmakrs for each year.

Table 5.1: Scenarios using different subsets of data (CU names abbreviated) and methods to assign LRP status. ‘Y’ indicaes 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.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)) 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.

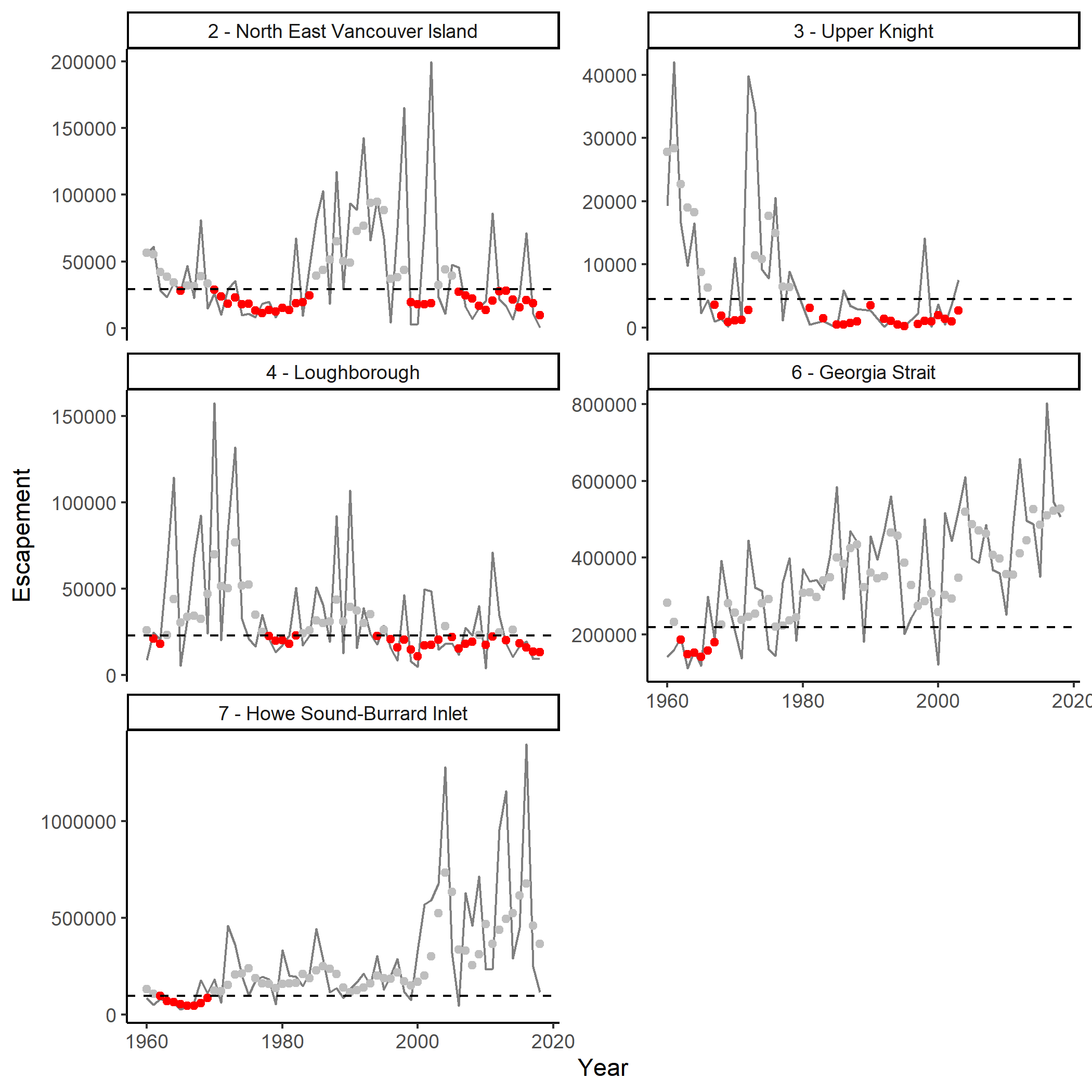


Figure 5.3: Spawner escapement (solid black line) with generational mean (4 year rolling geometric mean) of escapement in points.

**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.

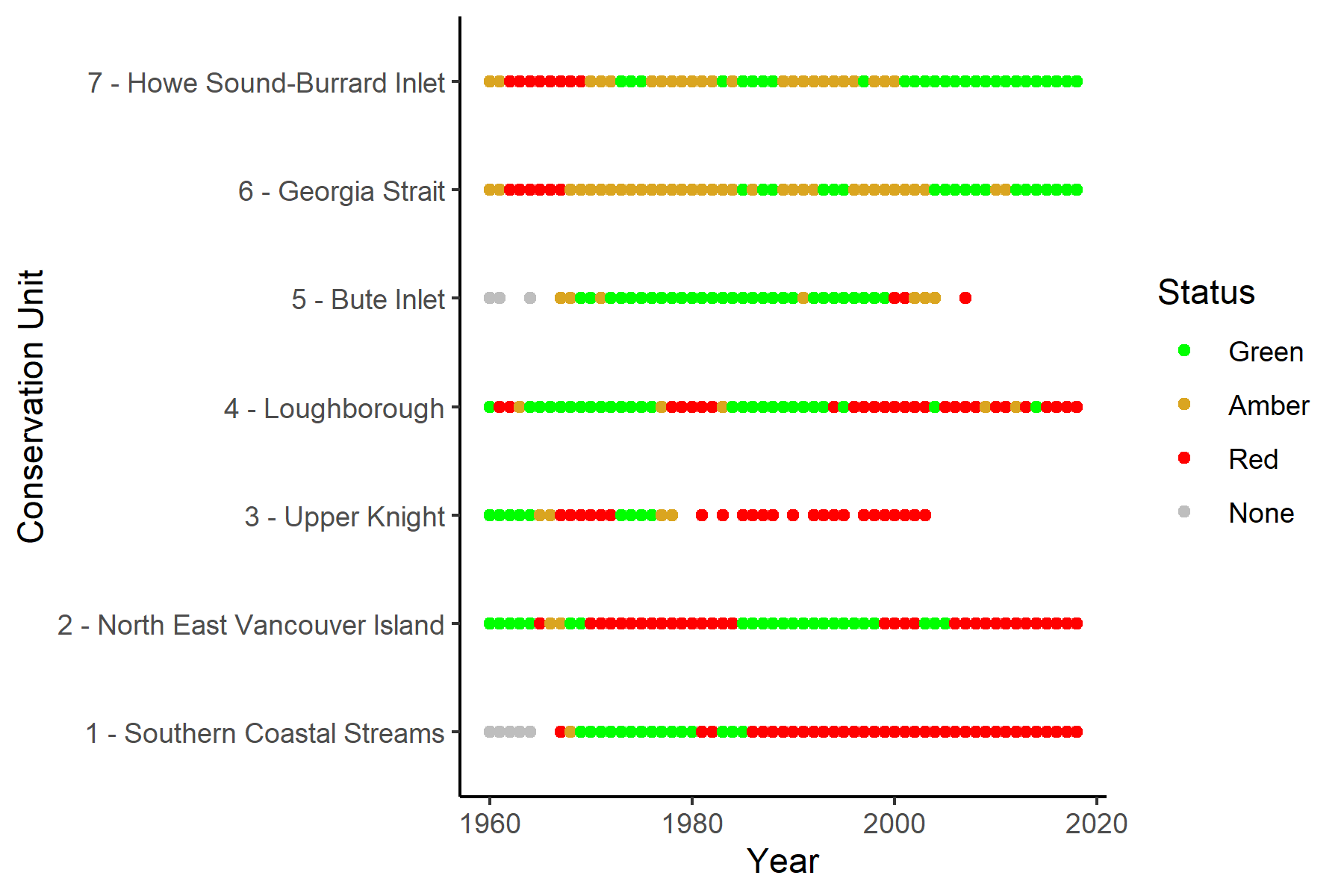


Figure 5.4: Status of CUs based on multi-dimensional status assessment (decision tree). Years with CU-level infilling were not included.

**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.

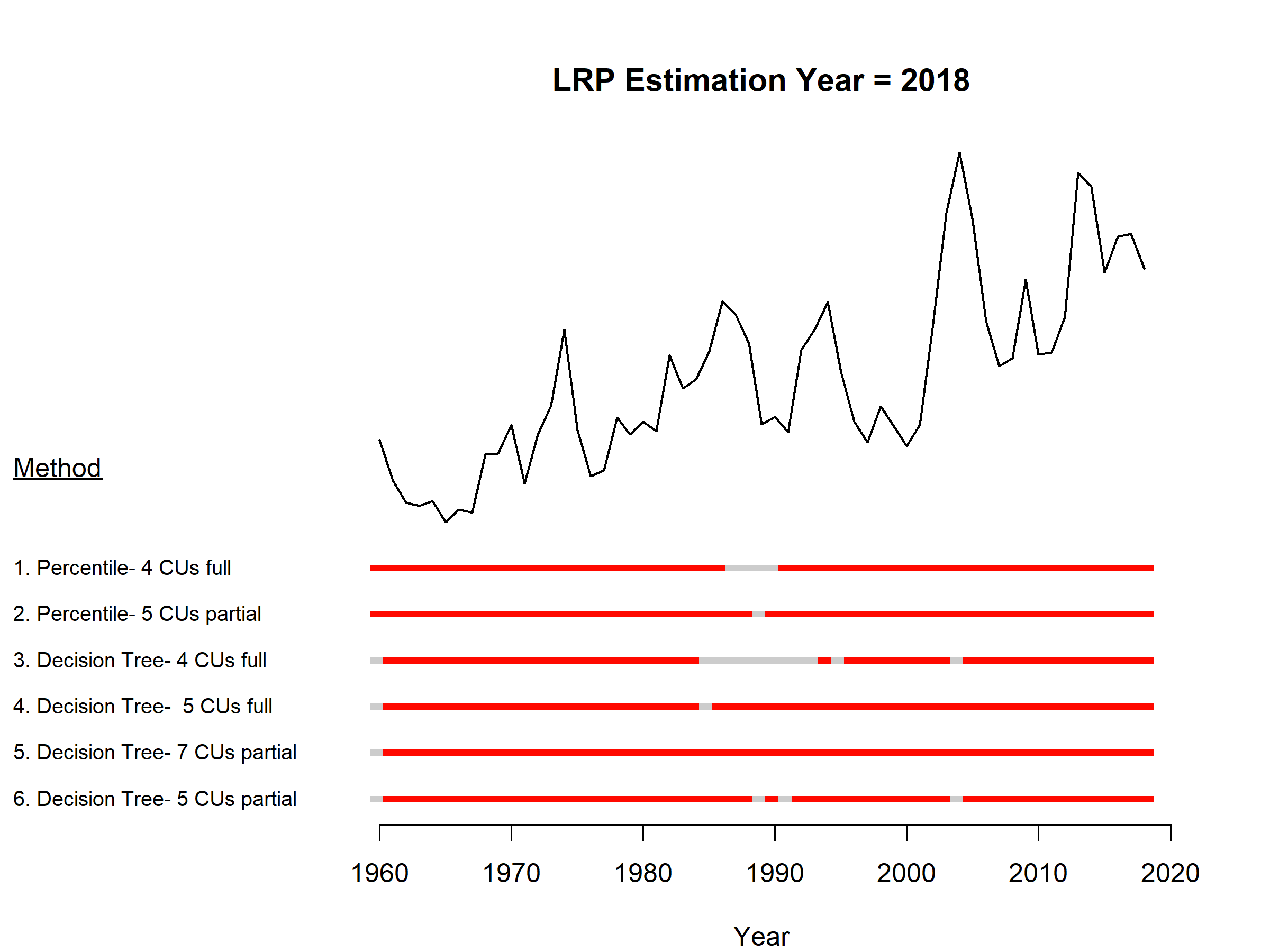


Figure 5.5: Comparison of LRP status (red = below LRP, gray = above LRP) for six scenarios. The black line shows aggregate abundance. Scenarios 1-3 and 6 do not include Bute Inlet or Southern Coastal Streams (no appropriate percentile benchmarks). ‘Full’ scenarios use only years with full time series (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-debertin_marine_2017) ([2017](#ref-debertin_marine_2017)), [Litz et al.](#ref-litz_competition_2021) ([2021](#ref-litz_competition_2021))). ~~Ocean conditions may also have an affect on ISC chum. The Pacific Decadal Oscillation (PDO) can have a positive or negative relationship with the productivity of wild Washington chum depending on the time period examined ([Litz et al.](#ref-litz_competition_2021) ([2021](#ref-litz_competition_2021))). The North Pacific Gyre Oscillation (NPGO) had a positive relationship with chum growth, mediated my PDO ([Debertin et al.](#ref-debertin_marine_2017) ([2017](#ref-debertin_marine_2017))).~~ 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-abudnance 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-hilborn_british_2012) ([2012](#ref-hilborn_british_2012))). 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-bue_escapement_2001) ([2001](#ref-bue_escapement_2001)), [Otis and Hasbrouck](#ref-otis_escapement_2004) ([2004](#ref-otis_escapement_2004))). 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.](#ref-clark_evaluation_2014) ([2014](#ref-clark_evaluation_2014))). These SEGs were calculated for each major river/system and are still done that way in Alaska ([McKinley et al.](#ref-mckinley_review_2020) ([2020](#ref-mckinley_review_2020))). 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-bue_escapement_2001) ([2001](#ref-bue_escapement_2001)) assessed this method on 11 populations of sockeye salmon and Chinook salmon from Upper Cook Inlet and Bristol Bay (in [Clark et al.](#ref-clark_evaluation_2014) ([2014](#ref-clark_evaluation_2014))). [Clark et al.](#ref-clark_evaluation_2014) ([2014](#ref-clark_evaluation_2014)) 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-hilborn_british_2012) ([2012](#ref-hilborn_british_2012)) 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-hilborn_british_2012) ([2012](#ref-hilborn_british_2012))), 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-hilborn_british_2012) ([2012](#ref-hilborn_british_2012)), [Holt et al.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)), 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.

~~Caveats with using muliti-dimensional approach~~

* ~~An essential part of the process is an expert review of the outputs from the algorithms (not done here). This approach should include a review by experts for any official use.~~
* ~~Learning tree was based on assessments for Interior Fraser coho, Fraser sockeye, and Southern BC Chinook. Not assessed for Chum. Further evaluation of how well the decision tree transfers to other species and regions should be done before using decision tree to assess status compared to LRP.~~

### 5.5.2 Suitabiliy 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-reid_two-eyed_2020) ([2020](#ref-reid_two-eyed_2020))
* Historical baseline before records from western science [Eckert et al.](#ref-eckert_diving_2018) ([2018](#ref-eckert_diving_2018)), [Lee et al.](#ref-lee_diverse_2019) ([2019](#ref-lee_diverse_2019)), [Ban et al.](#ref-ban_incorporate_2018) ([2018](#ref-ban_incorporate_2018))

Genetic tools and historical records

* Skeena sockeye [Price et al.](#ref-price_genetics_2019) ([2019](#ref-price_genetics_2019)), [Price et al.](#ref-price_portfolio_2021) ([2021](#ref-price_portfolio_2021))
* Skeena chum [Price et al.](#ref-price_abundance_2013) ([2013](#ref-price_abundance_2013))
* Cannery records [Meengs and Lackey](#ref-meengs_estimating_2005) ([2005](#ref-meengs_estimating_2005))

Archaeological records

* BC herring [McKechnie et al.](#ref-mckechnie_archaeological_2014) ([2014](#ref-mckechnie_archaeological_2014))

# 6 LESSONS LEARNED FROM CASE STUDY APPLICATIONS

To be completed.

* Synthesize main results and conclusions from case studies

Some ideas include:

* If data limitations arise in application of LRP to a stock, increased monitoring, data quality could be part of recovery plan/ trigger

# REFERENCES

# Appendix

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

### 7.0.1 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.

### 7.0.2 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.

### 7.0.3 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

#### 7.0.3.1 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.](#ref-holt_evaluating_2018) ([2018](#ref-holt_evaluating_2018)); 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.

##### 7.0.3.1.1 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).

##### 7.0.3.1.2 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.

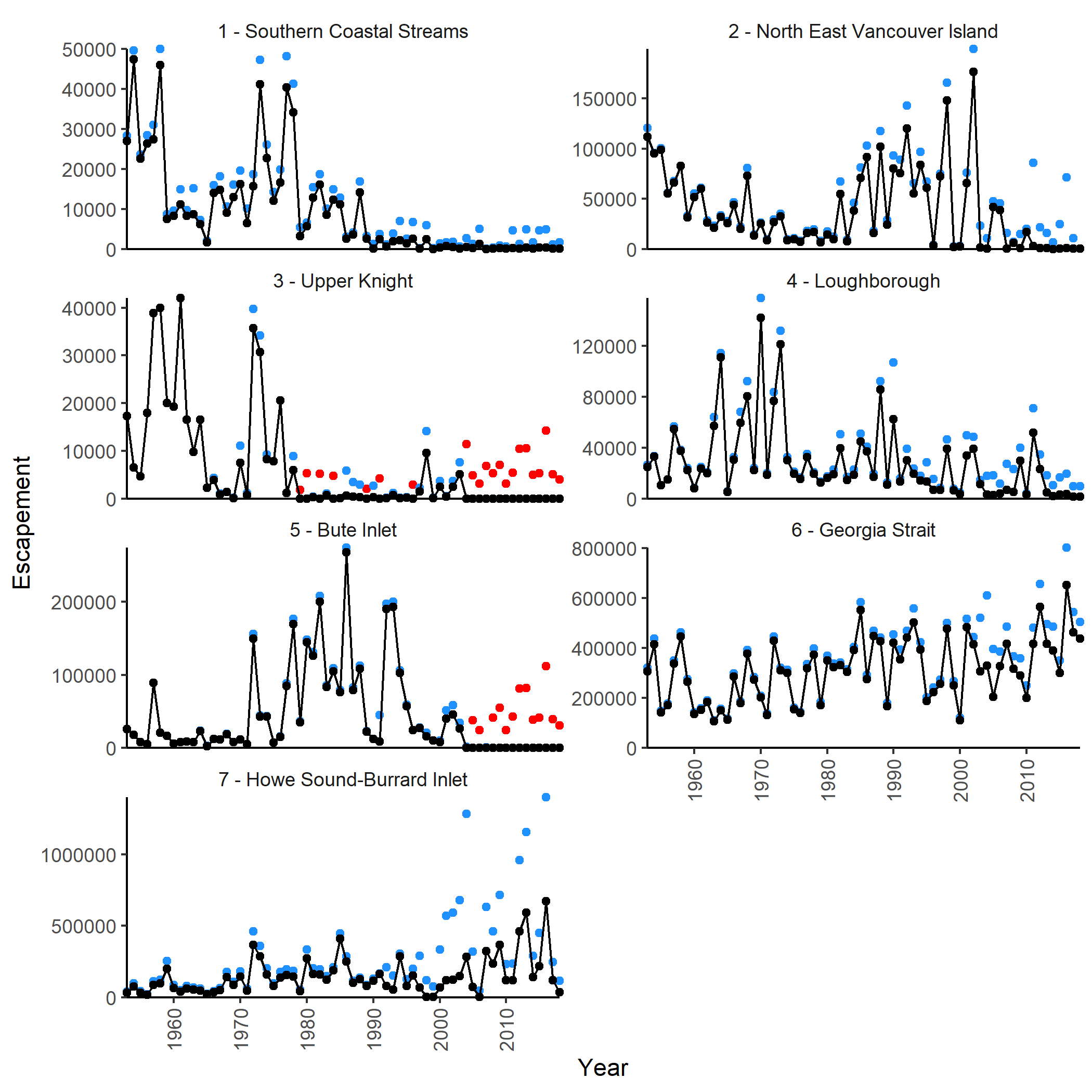


Figure 7.1: Chum salmon escapement for the seven Conservation Units. Black points indicate actual counts, blue points are infilled by stream, and red points are infilled by Conservation Unit.

#### 7.0.3.2 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 project [github page](https://github.com/Pacific-salmon-assess/samSim/tree/LRP). 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 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). This appendix describes the samSim model equations relevant to these study cases. 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 ?? parameters 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).

### 8.0.1 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.

#### 8.0.1.1 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.

#### 8.0.1.2 Recruitment Data is not available

When Recruitment data is not available, the ‘nPrime’ is set to 10 times the maximum age of recruits. Because the stock recruitment data is not available, the first step on this routine is to retrieve the stock recruitment parameters. The user has the option of providing either fixed values or a set of mcmc samples. If mcmc samples are provided, one set of parameters is used for each simulation trial.

The spawner recruitment parameters can be adjusted according to the user defined scenarios. 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 in this report. Recruitment is assumed to be correlated between the CU’s, the covariance matrix is calculated based on the variance-covariance matrix and the correlation matrix specified by the user.

Once 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 (Equation (8.1)). If the calculated number of spawners is lower than the user inputted extinction threshold, then the number of spawners is set o 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](#ref-schnute_influence_1995) ([1995](#ref-schnute_influence_1995))) (Equation (8.2). The age structure error can vary or be held constant among CUs. Calendar year recruitment is then calculated based on the brood year recruitments and the age structure of the returns (Equation (8.3).

The following step is to compute recruitment following the recruitment curve of choice. For the LRP version of samSim, three versions of the recruitment curve are available: A simple Ricker curve (equation (8.4) when ), Ricker curve with temporal autocorrelation in recruitment error (equation (8.4)), and Ricker curve with freshwater survival covariate (equation (8.6)). 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 (8.5)).

For the Ricker model with the survival covariate, the covariates for each calendar year are generated following a normal distribution with user defined mean and variance (Equation (8.8)). 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 (8.7)). 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 cap is , but the scalar can be modified by the user via the variable (Equation (8.9)). In addition, if the generated recruitment is lower than the user defined extinction threshold, then recruitment is set to zero.

#### 8.0.1.3 Compute management benchmarks

In the priming loop, the management benchmarks are only calculated in the last two generations, i.e. if . The management benchmarks are calculated according to three options: “stockRecruit,” “percentile” and “habitat.” All management benchmarks are denoted with the time index, , because samSim has the capability of estimating management 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.

If the “stockRecruit” option is used with the Ricker recruitment functions, then the lower benchmark is set to and the upper benchmark is set to 80% of . When the model with the survival covariate is used, the parameter is modified to incorporate the survival component (Equation (8.10)). 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](#ref-scheuerell_explicit_2016) ([2016](#ref-scheuerell_explicit_2016)) using the Lambert W function (Equation (8.11)). is estimated by solving Equation (8.12) numerically, as described by [Holt et al.](#ref-holt_indicators_2009) ([2009](#ref-holt_indicators_2009)).

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.

#### 8.0.1.4 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.

### 8.0.2 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 nYears, the latter being the number of projection years defined by the user.

#### 8.0.2.1 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 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.

#### 8.0.2.2 Project management benchmarks

Once is specified, the true management quantities and for the projection year are computed following Equations (8.11) and (8.12). 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.

#### 8.0.2.3 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-schnute_influence_1995) ([1995](#ref-schnute_influence_1995)). 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 (8.14)).

#### 8.0.2.4 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 (8.15) and (8.16)). 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.

#### 8.0.2.5 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 exploitation rates and calendar year recruits (Equation (8.22)). However, even though the harvest control rule specifies a fixed harvest control rule, the realized exploitation rates vary from year to year due to variability in the 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 ER values from beta distributions. Currently only the Canadian catches include the annual added variability.

The first layer of catch variability is implented at the MU level. This error is considered the same for all CUs within an MU. The Canadian exploitation rate value is drawn from a Beta distribution with mean and CV defined in the input files, these values are then transformed into shape parameters for the Beta distribution.

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 (8.20)-(8.21). The Catches are then computed by multiplying the CU specific and the calendar year recruits Equation (8.22).

The catch for Canada is further divided in two components, mixed stock fishery and single stock fisheries (Equations (8.23) and (8.24)).

The next step is to compute the aggregate exploitation rate and the remaining number of Spawners (Equations (8.25) and (8.26)).

#### 8.0.2.6 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 (8.27)-(8.28)), 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 (8.29)). Observed number of spawners is given by a log normal distribution truncated between the 0.0001 and 0.9999 quantiles (Equation (8.30)). The observed recruitment and observed exploitation rates are derived from the observed catches and observed spawnre numbers (Equations (??) and (??)).

Observed recruitment is set to the sum of observed spawners and catches

#### 8.0.2.7 Run stock assessment and calculate management quantities

This next phase of the projecton 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 ??. The LRP study cases, however, set the management benchmarks to the normative period, and for this reason the management benchmarks are kept constant and equal to the management benchmark at the last year of the priming period.

#### 8.0.2.8 Project population dynamics

The final step in the projection loop is to project the brood year recruitment for the current year. 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 ?? and Equations (8.8) and (8.7). Marine survival covariates are considered to be constant across CUs.

The following step is compute the age structure of the returns with variability, which follows the same procedure described in Section ??. The age structure follows a distriburion 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 Section?? and using Equation (8.4) for the simple ricker model, or Equation (8.6) 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 mentioned in the previous section (8.0.2.7. These are either stock-recruit or percentile benchmarks, as described in section 8.0.1.3 computed based on the true and observed spawner abundaces.

# 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.

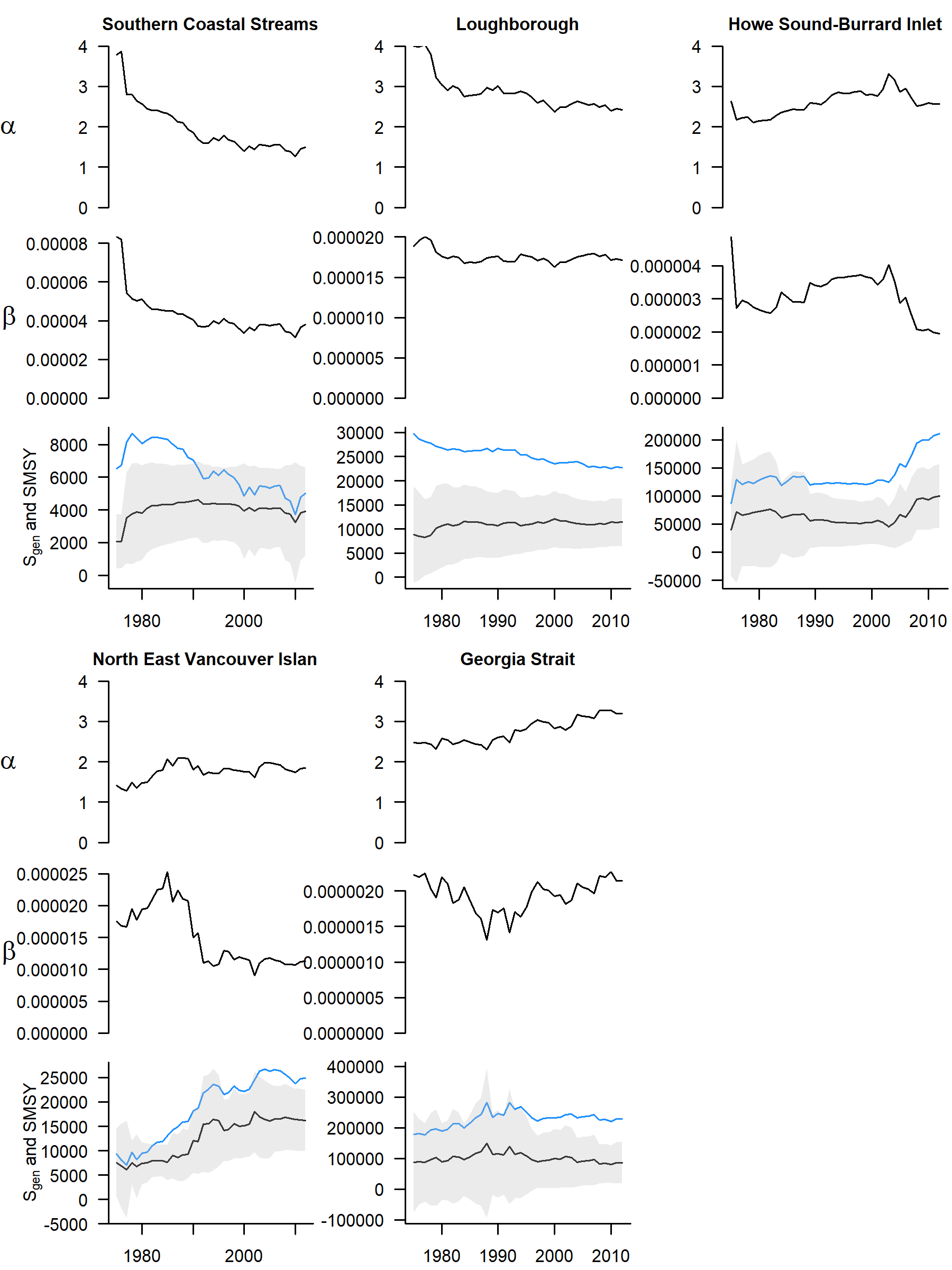


Figure 9.1: Retrospective estimates of , , (black line with gray confidence intervals) and (blue line) for five CUs in the Inside South Coast Chum SMU. Note y axis is identical across CUs for but varies for other parameters.

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 .

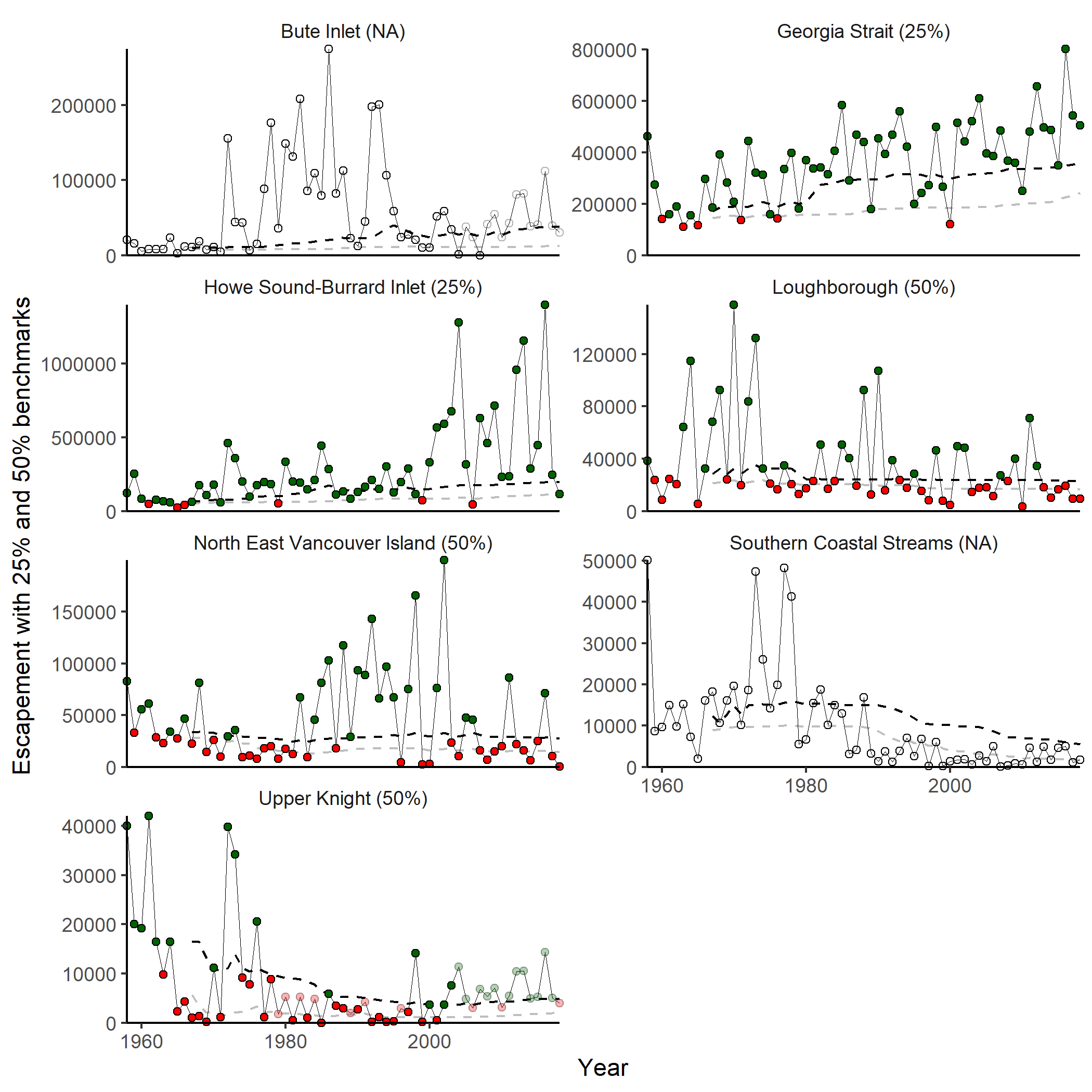


Figure 9.2: Escapement with 25th and 50th percentile benchmarks shown by gray and black dotted lines, respectively. Benchmarks are calculated using escapements up to the given year. Values following the CU names indicate the appropriate percentile benchmark. Green and red points indicate status above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

Ahmad, S. 2011. Diagnostic for residual outliers using deviance component in binary logistic regression. World Applied Sciences Journal 14(8): 1125–1130.

Arbeider, M., Ritchie, L., Braun, D., Jenewein, B., Rickards, K., Dionne, K., Holt, C., Labelle, M., Nicklin, P., Mozin, P., Grant, P., Parken, C., and Bailey, R. 2020. Interior Fraser Coho Salmon Recovery Potential Assessment. Canadian Science Advisory Secretariat Research Document 2020/025: xi + 222p.

Ban, N.C., Frid, A., Reid, M., Edgar, B., Shaw, D., and Siwallace, P. 2018. Incorporate Indigenous perspectives for impactful research and effective management. Nature Ecology & Evolution 2(11): 1680–1683.

Brown, G.S., Thiess, M.E., Wor, C., Holt, C.A., Patten, B., Bailey, R.E., Parken, C.K., Baillie, S.J., Candy, J.R., Willis, D.M., Hertz, E., Connors, B., and Pestal, G.P. 2020. 2020 Summary of Abundance Data for Chinook Salmon (*oncorhynchus* tshawytscha) in Southern British Columbia, Canada.

Bue, B.G., and Hasbrouck, J.J. 2001. Escapement goal review of salmon stocks of Upper Cook Inlet. Report to the {Board} of {Fisheries} {November} 2001, Alaska Department of Fish; Game, Anchorage.

Canada’s policy for conservation of wild Pacific salmon. 2005. Fisheries; Oceans Canada, Vancouver.

Clark, R.A., Eggers, D.M., Munro, A.R., Fleischman, S.J., Bue, B.G., and Hasbrouck, J.J. 2014. An Evaluation of the Percentile Approach for Establishing Sustainable Escapement Goals in Lieu of Stock Productivity Information. Alaska Department of Fish; Game.

COSEWIC. 2016. COSEWIC assessment and status report on the Coho Salmon (*Oncorhynchus kisutch*), Interior Fraser population, in Canada. Committee on the Status of Endangered Wildlife in Canada. Ottawa: xi + 50 p.

Debertin, A.J., Irvine, J.R., Holt, C.A., Oka, G., and Trudel, M. 2017. Marine growth patterns of southern British Columbia chum salmon explained by interactions between density-dependent competition and changing climate. Canadian Journal of Fisheries and Aquatic Sciences 74(7): 1077–1087.

Decker, A.S., Hawkshaw, M.A., Patten, B.A., Sawada, J., and Jantz, A.L. 2014. Assessment of the Interior Fraser Coho Salmon (*Oncorhynchus kisutch*) Management Unit Relative to the 2006 Conservation Strategy Recovery Objectives. Canadian Science Advisory Secretariat Research Document 2014/086: xi + 64 p.

DFO. 2012. Assessment of west coast of Vancouver Island Chinook and 2010 forecast. DFO Can. Sci. Advis. Sec. Sci. Advis. Rep. 2011/032: 17.

DFO. 2015. Wild salmon policy biological status assessment for conservation units of interior Fraser River Coho Salmon (*Oncorhynchus kisutch*). DFO Canadian Science Advisory Secretariat Science Advisory Report 2015/022: 12.

DFO. 2016. Integrated Biological Status of Southern British Columbia Chinook Salmon (*oncorhynchus* tshawytscha) under the Wild Salmon Policy.

DFO. 2018. The 2017 Fraser Sockeye Salmon (*Oncorhynchus nerka*) integrated biological status re-assessment under the Wild Salmon Policy. : 17.

DFO. 2021a. Integrated Fisheries Management Plan June 1, 2021 - May 31, 2022, Salmon Southern BC.

DFO. 2021b. WCVI Salmon Bulletin 2021, WCVI Chinook Terminal Forecast.

Eckert, L.E., Ban, N.C., Frid, A., and McGreer, M. 2018. Diving back in time: Extending historical baselines for yelloweye rockfish with Indigenous knowledge. Aquatic Conservation: Marine and Freshwater Ecosystems 28(1): 158–166.

Fox, J. 2016. Applied Regression Analysis and Generalized Linear Models. *In* Third. Sage Publications Inc.

Frame, D.J., Held, H., Kriegler, E., Mach, K.J., Matschoss, P.R., Plattner, G.-K., Zwiers, F.W., and Matschoss, P.R. 2010. Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties. : 7.

Fraser Coho Recovery Team), I. (Interior. 2006. Conservation strategy for Coho Salmon (Oncorhynchus kisutch), interior Fraser River populations. Fisheries and Oceans Canada, Ottawa, Ont. 132 p.

Grant, S.C.H., Holt, C.A., Pestal, G., Davis, B.M., and MacDonald, B.L. 2020. The 2017 Fraser Sockeye Salmon (Oncorhynchus nerka) Integrated Biological Status Re-Assessments Under the Wild Salmon Policy Using Standardized Metrics and Expert Judgment. : 218.

Hilborn, R., Schmidt, D., English, K., and Devitt, S. 2012. British Columbia Chum Salmon (*Oncorhynchus keta*) Fisheries: British Columbia Coastal and Adjacent Canadian Pacific EEZ Waters, Final Certification Report. Submitted to Canadian Pacific Sustainable Fisheries Society.

Holt, C.A., Cass, A., Holtby, B., and Riddell, B. 2009. Indicators of Status and Benchmarks for Conservation Units in Canada’s Wild Salmon Policy. : 82.

Holt, C.A., and Folkes, M.J.P. 2015. Cautions on using percentile-based benchmarks of status for data-limited populations of Pacific salmon under persistent trends in productivity and uncertain outcomes from harvest management. Fisheries Research 171: 188–200.

Holt, C., Davis, B., Dobson, D., Godbout, L., Luedke, W., and Tadey, J. 2018. Evaluating Benchmarks of Biological Status for Data-limited Conservation Units of Pacific Salmon, Focusing on Chum Salmon in Southern BC. : 87.

Holtby, L.B., and Ciruna, K.A. 2007. Conservation Units for Pacific Salmon under the Wild Salmon Policy. Research {Document}, Fisheries; Oceans Canada.

Korman, J., Sawada, J., and Bradford, M.J. 2019. Evaluation framework for assessing potential Pacific Salmon Commission reference points for population status and associated allowable exploitation rates for Strait of Georgia and Fraser River Coho Salmon Management Units. Canadian Science Advisory Secretariat Research Document 2019/001: ix + 81 p.

Kristensen, K., Nielsen, A., Berg, C.W., Skaug, H., and Bell, B.M. 2016. **TMB**: Automatic Differentiation and Laplace Approximation. Journal of Statistical Software 70(5): 1–21.

Lee, L.C., Thorley, J., Watson, J., Reid, M., and Salomon, A.K. 2019. Diverse knowledge systems reveal social–ecological dynamics that inform species conservation status. Conservation Letters 12(2).

Liermann, M.C., Sharma, R., and Parken, C.K. 2010. Using accessible watershed size to predict management parameters for Chinook salmon, (*oncorhynchus* tshawytscha), populations with little or no spawner-recruit data: A Bayesian hierarchical modelling approach. Fisheries Management and Ecology 17(1): 40–51.

Litz, M., Agha, M., Dufault, A., Claiborne, A., Losee, J., and Anderson, A. 2021. Competition with odd-year pink salmon in the ocean affects natural populations of chum salmon from Washington. Marine Ecology Progress Series 663: 179–195.

McKechnie, I., Lepofsky, D., Moss, M.L., Butler, V.L., Orchard, T.J., Coupland, G., Foster, F., Caldwell, M., and Lertzman, K. 2014. Archaeological data provide alternative hypotheses on Pacific herring ( *Clupea pallasii* ) distribution, abundance, and variability. Proceedings of the National Academy of Sciences 111(9): E807–E816.

McKinley, T.R., DeCovich, N., Erickson, J.W., Hamazaki, T., Begich, R., and Vincent, T. 2020. Review of salmon escapement goals in Upper Cook Inlet, Alaska, 2019. Alaska Department of Fish; Game, Anchorage.

Meengs, C.C., and Lackey, R.T. 2005. Estimating the Size of Historical Oregon Salmon Runs. Reviews in Fisheries Science 13(1): 51–66.

Otis, E.O., and Hasbrouck, J.J. 2004. Escapement goals for salmon stocks in Lower Cook Inlet, Alaska. Alaska Department of Fish; Game, Anchorage.

Parken, C.K., McNicol, R.E., and Irvine, J.R. 2006. Habitat-based methods to estimate escapement goals for data-limited Chinook salmon stocks in British Columbia, 2004.

Peduzzi, P., Concato, J., Kemper, E., Holford, T.R., and Feinstein, A.R. 1996. A simulation study of the number of events per variable in logistic regression analysis. Journal of Clinical Epidemiology 49(12): 1373–1379.

Pestal, G., MacDonald, B., Grant, S., and Holt, C. 2021. Algorithms for Rapid Status Approximation for Pacific Salmon Derived from Integrated Expert Assessments under Canada’s Wild Salmon Policy. Canaidan Technical Report of Fisheries and Aquatic Sciences.

Price, M.H.H., Connors, B.M., Candy, J.R., McIntosh, B., Beacham, T.D., Moore, J.W., and Reynolds, J.D. 2019. Genetics of century‐old fish scales reveal population patterns of decline. Conservation Letters 12(6).

Price, M.H.H., Gayeski, N., and Stanford, J.A. 2013. Abundance of Skeena River Chum Salmon during the Early Rise of Commercial Fishing. Transactions of the American Fisheries Society 142(4): 989–1004.

Price, M.H.H., Moore, J.W., Connors, B.M., Wilson, K.L., and Reynolds, J.D. 2021. Portfolio simplification arising from a century of change in salmon population diversity and artificial production. Journal of Applied Ecology: 1365–2664.13835.

R Core Team. 2021. R A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Reid, A.J., Eckert, L.E., Lane, J.-F., Young, N., Hinch, S.G., Darimont, C.T., Cooke, S.J., Ban, N.C., and Marshall, A. 2020. “Two-Eyed Seeing”: An Indigenous framework to transform fisheries research and management. Fish and Fisheries n/a(n/a).

Riddell, B.E., Luedke, W., Till, J., Taylor, S., and Tompkins, A. 2002. Review of 2001 Chinook Returns to the West Coast Vancouver Island, Forecast of the 2002 Return to the Stamp River / Robertson Creek Hatchery Indicator Stock, and Outlook for other WCVI Chinook Stocks. Can. Sci. Advis. Sec. Res. Doc. 2006/083: 44.

Scheuerell, M.D. 2016. An explicit solution for calculating optimum spawning stock size from Ricker’s stock recruitment model. PeerJ 4: e1623.

Schnute, J.T., and Richards, L.J. 1995. The influence of error on population estimates from catch-age models. Canadian Journal of Fisheries and Aquatic Sciences 52(10): 2063–2077.

Van Will, P. 2014. Inner South Coast Chum Stock Reconstructions (1953-2013).

Withler, R.E., Bradford, M.J., Willis, D.M., and Holt, C.A. 2018. Genetically Based Targets for Enhanced Contributions to Canadian Pacific Chinook Salmon Populations. Research {Document}, Fisheries; Oceans Canada.