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Application of a New Modelling Framework for the Assessment of Pacific Herring (*Clupea Pallasii*) Major Stocks and Implementation in the Management Strategy Evaluation Process

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Foreword

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ABSTRACT

This paper presents a new stock assessment and operating model framework for Pacific Herring (*Clupea pallasii*) that combines time-varying natural mortality, fishery reference points, and future harvest strategies. We develop and test a new Spatially Integrated Statistical Catch-at-Age Herring (SISCAH) model that incorporates, inter alia, a density dependent process for natural mortality, explicit representation of spawn-on-kelp fisheries, fisheries with discrete removal events over a short season, a single spawn index that blends dive and surface survey designs, and an age-composition likelihood function that accounts for correlation in residuals among age-classes. The primary purpose of the paper is to evaluate SISCAH as a stock assessment modelling framework for each of the five major stock assessment regions (SARs), while our secondary purpose is to evaluate SISCAH as an operating model for future management procedure testing. Overall, estimates of absolute biomass from the full SISCAH model (i.e., incorporating all new features) were qualitatively similar to the existing assessment framework, although the structural change to natural mortality processes, in particular, generated differences in recruitment and abundance over time, as well as biological reference points. When applied as a stock assessment model for each region, SISCAH meets goodness of fit criteria with low sensitivity to model priors and no strong retrospective patterns. In simulation self-tests based on two SARs, relative error distributions showed relatively small amounts of bias for most parameters.

The most impactful change in SISCAH was a component Allee effect under density dependent natural mortality (DDM) model that provides an ecologically plausible interpretation for patterns in Herring productivity and status in each SAR, such as slow recovery in Haida Gwaii or West Coast of Vancouver Island and persistent high productivity in Strait of Georgia. DDM also leads to plausible estimates of maximum sustainable yield (MSY)-based biological reference points, with higher optimal biomass and often lower maximum sustainable yield than previous approaches.

Finally, we demonstrate the operating model capability of SISCAH in generating patterns of recruitment, natural mortality, and biomass that are qualitatively similar to those estimated from the historical period. In general, persistent periods of low productivity interspersed with bursts of high productivity arise from the combination of compensatory recruitment and depensatory natural mortality. These properties provide more realistic situations in which to test performance of potential future harvest strategies for all Pacific Herring SARs.

1. INTRODUCTION

1.1. BACKGROUND

Fisheries stock assessments generally assume that natural mortality rates of exploited fish stocks, along with the biological reference points derived from them, are independent of both time and stock abundance. While the plausibility of such an assumption was never particularly high or broadly accepted within fisheries science, it persisted mainly because of a lack of strong evidence to the contrary. Pacific Herring (*Clupea pallasii*) in British Columbia (BC), along with many other important fish stocks, are exceptional cases in which the evidence for temporal changes in natural mortality is substantial and well-documented (Martell et al. 2012; Swain and Benoît 2015; Cook and Trijoulet 2016; Neuenhoff et al. 2019; Rossi et al. 2019; Swain et al. 2019). Indeed, estimated natural mortality rates of BC Pacific Herring in 3 of the 5 major stock assessment regions (SARs) have varied over a 3-fold range since 1951 (Martell et al. 2012; Benson et al. 2023). Such variation wreaks havoc on scientists' ability to provide harvest advice because the very definition of sustainable harvesting is continually shifting over time.

This paper develops a new stock assessment and modelling framework that can treat time-varying natural mortality of Pacific Herring as an intrinsic density-dependent process, as well as an extrinsic density-independent random walk in time. The resulting model structure represents an important step toward better understanding the production dynamics of Pacific Herring across all SARs, their underlying biological reference points, and implications for future harvest policy advice.

In fisheries stock assessment models, compensatory density-dependent processes regulating population abundance are usually represented via stock-recruitment models in which productivity, measured as recruits-per-spawner or recruits-per-spawning-biomass, increases as population density decreases (Beverton and Holt 1957; Ricker 1958). In other words, the decline in spawning abundance is compensated by an increase in juvenile survival, which helps to establish population resilience. Without compensatory production, there would be no surplus yield and, thereby, no fishing. Compensatory productivity implies relatively rapid population recovery from low spawning abundance when causes of decline, such as fishing, are removed. However, evidence from several collapsed fish stocks, including British Columbia's Pacific Herring, indicates the opposite effect, where net population productivity is lower at low abundance (i.e., depensatory) and recovery is either slower than expected, completely lacking, or actually getting worse after fishery closures (Hutchings 2015; Swain and Benoît 2015; Swain et al. 2019). In some of these depensatory cases, relatively stable recruitment rates (i.e., recruits-per-spawner) are consistent with meta-analyses indicating depensatory recruitment is either quite rare, or just difficult to detect (Liermann and Hilborn 2001; Keith and Hutchings 2012). On the other hand, post-recruitment natural mortality rates, which have historically been considered constant with respect to time and abundance, are sometimes elevated at low abundance, especially in the presence of predation by marine mammals (Swain and Benoît 2015; Cook and Trijoulet 2016; Neuenhoff et al. 2019; Rossi et al. 2019; Swain et al. 2019). This finding suggests that depensatory natural mortality may be an important yet seldom addressed risk in stock assessment and harvest strategy development for exploited species (Essington et al. 2015; Johnson et al. 2015; Swain and Benoît 2015; Neuenhoff et al. 2019).

Natural mortality in fishes is determined via ecological processes that depend, to varying degrees, on population density (Turchin 1999; Hixon and Jones 2005; Jacobsen and Essington 2018). For example, in the northeast Pacific Ocean, abundance and natural mortality rates of Pacific salmon (*Oncorhynchus* spp.) fluctuate considerably, with estimated predation mortality owing to marine mammals now dominating fishing mortality (Chasco et al. 2017). For some

Pacific Herring stocks in British Columbia, fishing mortality rates have also been consistently low (i.e., 0–0.2/yr) since the 1980s, while natural mortality rates have fluctuated from 0.3/yr to around 1.0/yr over the same period (DFO 2020a; Benson et al. 2023). Although the specific causes of variability and increasing trends in Pacific Herring natural mortality are unknown, there is ample speculation that growing populations of Humpback Whales (*Megaptera novaeangliae*), in addition to Harbour Seals (*Phoca vitulina*), Stellar sea lions (*Eumetopias jubatus*), and Pacific Hake (*Merluccius productus*) could be key contributors. Similar situations occur in eastern Canada, where increasing natural mortality rates of Cod (*Gadus morhua*) and Winter Skate (*Leucoraja ocellata*) are associated with rapidly growing abundance of Grey Seals (*Halichoerus grypus*) (Fu et al. 2001; Cadigan 2015; Swain and Benoît 2015; Swain et al. 2019). In some of these cases, stock assessment models assuming constant natural mortality and compensatory recruitment generated severely optimistic forecasts of population responses to lower fishery exploitation (Lane and Palsson 1996).

Fisheries stock assessment models, including those used for BC Pacific Herring over the past decade, that estimate temporal dynamics in natural mortality have mainly adopted descriptive density-independent models over explanatory density-dependent models. Density-independent approaches make no explicit assumptions about how the modelled species interacts with its surrounding ecosystem and, instead, simply attempt to describe how natural mortality changes over time, usually via time-varying natural mortality parameters estimated in temporal blocks or simple random walks (Martell et al. 2012; Nielsen and Berg 2014; Cadigan 2015; Johnson et al. 2015; Rossi et al. 2019; Benson et al. 2023). Their parsimony and statistical tractability make descriptive models easier to develop, implement, and defend—at least in the context of stock assessment modeling that is specifically focused on estimating historical biomass, productivity, and fishing mortality. In contrast, density-dependent models, in their simplest form, assume some non-linear relationship exists between prey abundance and their own natural mortality rate (Neuenhoff et al. 2019; Rossi et al. 2019; Swain et al. 2019). Although the explanatory approach has a solid theoretical and intuitive basis, it can be challenging to estimate latent, non-linear process models from sparse and noisy fisheries data. Interestingly, the quality and defensibility of natural mortality explanatory models is high in the context of developing sustainable harvest strategies for the future, which just happens to be a critical task for Pacific Herring science.

For example, suppose that natural mortality rates have been increasing over the most recent decade leading up to a stock assessment, as they had for Pacific Herring over the two decades leading up to the last stock assessment. We may have perfectly reasonable estimates of past natural mortality rates by year (M_t), but models used to evaluate future harvest strategies need to choose a priori scenarios describing how those rates could change in the future (Benson et al. 2023). Clearly, there is no guarantee that these scenarios will make ecological sense because “ M_t increasing”, “ M_t decreasing”, and “ M_t constant” have no real basis in ecological theory (Benson et al. 2023), especially for forage species, as well as no statistical basis for representing uncertainty. Thus, simulated performance of fishery harvest strategies will depend completely on the natural mortality scenario adopted or the weights placed on admitted alternatives. On the other hand, an explanatory density-dependent model, if properly parameterized, should reflect how natural mortality changes in response to fishing via its effect on abundance and the strength of density-dependence in mortality rates. The explanatory model may, therefore, represent a wider range of plausible ecological scenarios and fishery-induced risks, while also propagating statistical uncertainty in a tractable way.

In this paper, we develop a new statistical catch-at-age modelling framework for assessment and harvest strategy simulations for BC Pacific Herring that, among other things, is capable of implementing both density-independent and density-dependent natural mortality rates in the five

major Pacific Herring SARs. We examine estimation precision and identifiability of parameters for the density-dependent model via a simulation self-test as well as comparisons with density-independent models. Our results indicate that

1. density-dependent natural mortality models explain most of the historical variability in natural mortality estimated via density-independent models, resulting in comparable estimates of biomass, stock status, recruitment, and fishing mortality;
2. density-dependent natural mortality models produced temporally stable retrospective estimates of biological reference points; and
3. optimal harvest rate reference points for density-dependent natural mortality models can be lower than for density-independent models depending on the strength of density-dependence.

1.2. BRITISH COLUMBIA PACIFIC HERRING

Major Pacific Herring SARs are defined for Haida Gwaii (HG), Prince Rupert District (PRD), Central Coast (CC), Strait of Georgia (SOG), and West Coast of Vancouver Island (WCVI). The minor SARs are Area 27 (A27) and Area 2 West (A2W) (Figure 1). DFO Science, Pacific Region, conducts annual assessments of stock biomass and trends for the major SARs using a statistical catch age modelling approach last reviewed in 2017 (Cleary et al. 2019). The most recent stock updates were presented in September 2022 (DFO 2022a).

Management strategy evaluation (MSE), initiated in 2018, is used as a collaborative science and management process to identify harvest strategies capable of meeting diverse objectives within and among SARs. The first MSE cycle was completed in 2018 for the southern SOG and WCVI regions (DFO 2019; Benson et al. 2023) and 2019 for the northern HG, PRD, and CC regions (DFO 2020b). MSE updates also occurred for SOG and WCVI in 2020 (DFO 2021) and for 4 of the 5 major stock assessment regions (excluding HG) in 2022 (DFO 2023a). Due to the requirement for a Rebuilding Plan for Haida Gwaii herring, the latest MSE updates for HG herring are captured in the rebuilding plan (DFO et al 2025).

1.3. TRANSITION TO A NEW MODELLING FRAMEWORK FOR PACIFIC HERRING

Pacific Herring stock assessments are currently performed via the Integrated Statistical Catch Age Model (ISCAM) developed in Martell et al. (2012). This model formally estimated time-varying natural mortality rates via a time-dependent spline. Biological and management reference points, biomass forecasts, and operating model parameters for the MSE processes were based on the average natural mortality rates over the either the most recent 10-year period, or the historical average (Benson et al. 2023). Over the last decade, several modifications have been made to ISCAM; however, there are a number of improvements, in addition to the treatment of natural mortality, motivating the need for a new modelling framework.

Since 2018, Pacific Herring stock assessment reviewers and technical experts have requested improvements to the assessment model, including:

1. **Establishing a density-dependent process in which M varies in relation to biomass.** Modelling M as a density-dependent process dates back to Haist et al. (1993) and was most recently requested at the 2018 CSAS review (DFO 2022b).
2. **Specifically representing Pacific Herring spawn-on-kelp (SOK) fisheries.** SOK operations are licensed in 4 of the 5 major stock areas. Accounting for SOK egg removals and a mechanism that accounts for ponding mortality was recommended at the last CSAS

review (DFO 2022b). Historical data from these commercial fisheries (egg removals) and ponding mortality are not currently included in the annual assessment.

3. **Representing both the continuous and discrete nature of Pacific Herring fisheries.** ISCAM models fishing mortality (F) as a continuous process for all fisheries even though commercial herring fisheries often occur over short intervals during the spawning season. Modelling fishing mortality in both continuous and discrete fisheries, as appropriate, may better approximate the magnitude and impacts of fishing, especially when natural mortality changes substantially.
4. **Improving the method for estimating density-independent time-varying natural mortality.** ISCAM uses a spline function with 12 nodes evenly distributed across the historical time series, i.e., 1951–present. The resulting change in node positions (years) as the time-series increases in length affects the perceived historical M dynamics and increases sensitivity to sudden changes in the survey index. A simple random-walk approach would create more stable temporal dynamics in M that do not depend on time-series length.
5. Transitioning from ADMB to Template Model Builder software for performance improvements and long-term stability in the programming environment. ISCAM is built in ADMB, which is no longer supported by the developers. The new modelling framework is built in R-based Template Model Builder (TMB), which is increasingly used in fisheries assessments and simulation modelling (Kristensen et al. 2015).
6. **Update the observation model to reflect occasional surveys in which both surface and dive methods are deployed.** The herring spawn index is derived from both surface survey and dive survey observations. In ISCAM, these are modelled as two distinct survey “eras” with the surface survey occurring over 1951–1987 and dive surveys occurring over 1988–2022; however, in practice surface survey observations have occurred in most years since 1987 but they are treated as dive observations. The new modelling framework introduces an observation model that blends surface and dive survey observations via a lognormal likelihood function.
7. **Improve the likelihood function for age-composition data.** ISCAM uses uncorrelated age composition residuals, which, while not uncommon in fisheries assessment, could lead to optimistically low variance in simulated age-composition for future assessments (note: the Pacific Herring management procedure uses a model-based biomass estimator in MSE simulations). The new model revises the likelihood to capture correlated logistic-normal residuals where these might exist, thereby improving both parameter estimation (Francis 2014) and simulation of future age-composition data.

The above model revisions do not represent the complete listing of past requests because they leave out on-going research related to such processes as predator-prey dynamics, spatial connectivity, and implications of multiple scales of stock structure. Nevertheless, the new modelling framework is developed with these future goals and capabilities in mind.

The new modelling framework (described below) is a single stock implementation of the Spatially Integrated Statistical Catch Age (Herring) (SISCAH) model that was initially introduced for Pacific Herring as an operating model to support the rebuilding plan for Haida Gwaii herring (DFO et al 2025). The general modelling framework applied in SISCAH has also been reviewed via CSAS and adopted for management advice for the Atlantic Halibut fishery (Johnson et al. 2023) and for Greenland Halibut (Johnson and Cox 2023) as a potential future stock assessment framework.

We compare inferences between ISCAM and SISCAN for the sake of completeness in the transition between modelling frameworks as well as to better understand the impact of revisions 1–7 above. Specifically, we use a model transition analysis in which a “base” implementation of the new model is created to broadly match the structure of ISCAM to ensure starting estimates are comparable (Martell et al. 2012; Benson et al. 2023). Assumptions within the SISCAN base model are then modified to demonstrate the isolated effects of each proposed revision (Appendix B). Following the transition analysis, all proposed changes are combined into a single, new “full” SISCAN model that could be used in future Pacific Herring stock assessments and as well as for generating operating model hypotheses in the MSE work.

Following the transition analysis, we describe simulation self-tests, sensitivity analyses, and retrospective analyses that investigate the full SISCAN model performance and robustness to parameter assumptions and data. The full SISCAN model is then applied to each of the 5 major SARs. We summarise assessments across the 5 SARs here in the main document, with individual assessments provided in Appendix D. As part of these assessments, biological reference points are derived for each SAR using stochastic 200 year simulations, which indicate unstable equilibria at high harvest rates under a density dependent M formulation, and an asymmetric relationship between stochastic recruitment and natural mortality leading to lower equilibrium biomass than indicated under deterministic conditions.

Finally, we preview the use of SISCAN as an operating model by simulating three perfect information harvest strategies. This part of the paper is not meant to represent a complete MSE project with extensive stakeholder consultation, but rather to demonstrate some of the implications of the new model structure—especially density-dependent M —on biological reference points and expected performance of selected management procedures.

2. METHODS

2.1. STATISTICAL CATCH-AT-AGE MODELS

Modern integrated statistical catch-at-age models are widely used to estimate stock status and productivity for exploited finfish (Fournier and Archibald 1982; Hilborn and Walters 1992; Quinn and Deriso 1999; Maunder and Punt 2013). Such models explicitly estimate the number of fish in each age class from an initial recruitment age (usually either age 1 or 0), and track fish growth (length and/or weight) and sexual maturity through all subsequent age class until fish die either from natural or fishing mortality. In the intervening years, the biomass of each age class is derived from numbers-at-age using growth, and the mature fish make up the spawning stock biomass, which produces new recruits each year through a stock-recruitment relationship. Population dynamics in age-structured stock-assessment models are driven by a relatively small set of life-history parameters that determine natural mortality, maturity, growth, and stock-recruitment relationships; fishery and selectivity parameters that determine fishing effects on mortality and how this is spread over age-classes in the population; and finally, environmental parameters to represent unmodelled biophysical ecosystem processes that impact functional relationships (e.g., stock-recruitment) and parameters such as natural mortality, selectivity, etc.

To estimate the model parameters, the population dynamics component of the age-structured stock assessment models must be confronted with observational data (Fournier et al. 1990; Hilborn and Mangel 1997). The inclusion of multiple types of data make these models “integrated”, in the sense that they combine multiple types analyses that have previously have been applied in isolation (Maunder and Punt 2013), such as catch-curve and/or cohort analysis (Richards et al. 1997; Schnute and Haigh 2007), and biomass dynamics (Punt 2003). For Pacific Herring, data come from both fishery-independent surveys and fishery-dependent

monitoring providing information for estimation of time-trends in total population size and age structure. For example, age-composition data from fishery catches indicate the size of year-classes (or cohorts) in the catch, and the shape of those compositions results from a combination of recruitment, natural mortality, and age- or size-selectivity of the gear used to collect the data.

2.2. A NEW STATISTICAL CATCH-AT-AGE MODEL FOR BC PACIFIC HERRING

The OM used here is a sex-aggregated age-structured stock assessment model. SISCAH allows for a spatially-explicit component which is differed for future research. For the present application each SAR is considered a single, isolated stock.

The annual cycle in SISCAH runs from June 1 to May 31 with spawning generally occurring in the last quarter of each year. Where they exist, seine and gillnet fisheries target herring pre-spawning aggregations (roe herring) in February–April, while spawn-on-kelp fisheries remove fertilized eggs adhered to kelp between March 1 and May 1 in all areas except the Strait of Georgia which lacks commercial SOK fishing. A food-and-bait fishery targets herring during the overwintering period in the Strait of Georgia following their return from summer/fall feeding grounds off the west coast of Vancouver Island. Reduction fisheries occurred in all SARs during the 1950s and 1960s, targeting overwintering herring between September and January; however, this fishery was closed after stock collapses in all major herring SARs in the 1960s.

Data for modelling all five herring SARs over the period 1951–2022 include:

1. landed catch, catch-age composition and weight-at-age from the reduction fishery (all regions), food-and-bait fishery (SOG, PRD), and the seine roe, seine test, and gillnet fisheries (all regions);
2. closed- and open-pond spawn-on-kelp (SOK) landings for HG, PRD, CC, and WCVI; and
3. fishery- independent spawning biomass estimates derived via surface (generally pre-1987) or dive survey (post-1987) designs. For the operating model scenarios we simulate recruitment starting in 2020 to avoid reliance on the last couple of years of data, which has less information to inform estimates. Details of these data series are described and presented in Appendix A.

Table 1 provides SISCAH model notation, and Table 2 presents the mathematical specifications. Equation number prefixes are used to help organise processes into major components. For instance, model parameters are labeled P.X, equilibrium states EQ.X, non-equilibrium initial states NEQ.X, catch equations C.X, spawn-on-kelp harvesting K.X, and abundance dynamics are N.X. For proof of concept and due to computational time constraints equilibrium states are deterministic, in other words they ignore all process errors. However, equilibrium states for density-dependent natural mortality models are affected by an asymmetric interaction between the strength of density dependence and recruitment process errors. Thus, the equilibria for density-dependent natural mortality models in practice should be computed via simulation with process errors. Table 2 is not presented as a computable algorithm in which one starts at the top and proceeds to the bottom; therefore, some of the presentation below will jump around the table a bit. Model parameters (Table 2, P.1–P.4) are divided into four subsets consisting of leading parameters Θ^{lead} , nuisance catchability and variance parameters Θ^{cond} , fixed parameters Θ^{fixed} , and prior distribution hyperparameters Θ^{prior} for leading parameters. Finally, Table 3 provides the observation models (O.X), likelihoods for spawn indices (L.X) and age composition data (A.X), parameter prior distributions (Pr.X), and total model objective functions for each M model (F.X).

2.3. SISCAH STATE DYNAMICS

Unfished equilibrium characteristics are derived from unfished spawning biomass SB_0 , mortality depensation rate m_1 , and the asymptotic lower limit M_b parameters, as well as weight-at-age assumptions. From those, unfished mortality M_0 (EQ.1), equilibrium age structure via survivorship-at-age (EQ.2), spawning-stock biomass-per-recruit ϕ_0 (EQ.3), and unfished recruitment R_0 can be derived in order.

Age-class abundances are initialised in the year 1951 ($t = 1$) in a fished state for all SARs. Initial numbers-at-age $N_{a,1}$ are estimated via initialisation multipliers $\omega_{init,a}$ for each age-class $a \in \{1, \dots, 10\}$, scaling an unfished survivorship-at-age to non-equilibrium fished states (Table 2, (NEQ.1)), which is further scaled to initial numbers at age either by unfished recruitment R_0 (Haida Gwaii, CC, SOG, WCVI), or in PRD a freely estimated initial recruitment parameter R_{init} was used. Another approach to a fished initialisation of the population is adding an initial equilibrium fishing mortality F_{init} to the survivorship-at-age calculation (EQ.2), which we did not adopt for the final model but test in sensitivity analyses (Appendix D). Generally, adding F_{init} will decrease the proportion of initial recruitment (R_0 or R_{init}) added to the population as they have been removed via fishing. Ultimately, given the same data and likelihoods, the absolute number of fish in each age class in the first year should be relatively insensitive to the choice of initialisation method.

Instead, using F_{init} will affect the initial recruitment parameter, and anything that is dependent on it. So, when the population is initialised with R_0 , applying F_{init} will increase value of R_0 (as well as B_0) and affect deterministic stock-recruitment model estimates, which are calculated based on unfished equilibria. On the other hand, when the population is initialised with R_{init} , the value of R_{init} will increase, but this should have limited other effects on the population dynamics as R_{init} has no other role in the process model.

Recruitment on June 1 (N.1) is assumed to follow a Beverton-Holt stock-recruitment relationship parameterized via spawning biomass in the previous year (N.2), stock-recruit steepness h , unfished spawning stock biomass SB_0 , and stochastic annual recruitment deviations ω_t . Annual age-specific natural mortality rates $M_{a,t}$ are split into a constant age-1 mortality rate M_1 and a time-varying age-2+ natural mortality rate $M_{2+,t}$. The latter is formulated either as a random walk in time (density-independent model, DI; Appendix B) or as a density-dependent (DD) function of age-2+ biomass

$$M_{2+,t} = \left(M_b + e^{-m_1 \frac{B_{2+,t}}{B_{2+,0}}} \right) \cdot e^{\epsilon_t} \quad (1)$$

where M_b is the baseline or minimum natural mortality rate (0.4/yr in Figure 2), $m_1 > 0$ is the rate of depensation in natural mortality, $B_{2+,t}$ and $B_{2+,0}$ are the start-of-year total age-2+ biomass in year t and at unfished equilibrium, respectively, and ϵ_t is a stochastic process error applied each year (Haist et al. 1993). The above DD formulation for natural mortality is used for all SARs except for the Prince Rupert District region, where the data or our parameterization of the model did not support the DD model formulation well enough for convergence of model posteriors (see below). This may be understandable given that PRD mortality has been relatively low and flat compared to other SARs for most of the 1951–2022.

For density dependent natural mortality models, curvature of the natural mortality function as determined by the m_1 parameter (Figure 2) controls the difference between unfished equilibrium mortality M_0 and the lower limit M_b . Functions with a low m_1 value are shallower and the

resulting difference between M_b and M_0 allows natural mortality to drop lower than M_0 more often, as well as reducing the asymmetry generated by M_b as biomass needs to be much larger for M_b to limit downward variation in natural mortality. The ability for $M_{2+,t}$ to drop below M_0 is associated with a higher probability that biomass will remain above the unfished level SB_0 for longer after a string of high recruitments. Conversely, higher m_1 values are associated with steeper functions at very low biomass, but flatter over most of the rest of the biomass range; therefore, spawning biomasses above SB_0 are observed much less frequently and for shorter periods, as we show in the results.

There are two features of the density dependent M model that are important for interpreting results later in the paper. First, the M_b value provides an asymptotic lower limit on the natural mortality rate that will cause a positively skewed distribution of $M_{2+,t}$ in the presence of process variability in age-2+ biomass (caused mainly via recruitment variability). This leads to a sometimes-noticeable difference between equilibria generated via deterministic vs. stochastic simulation. For that reason, our performance metrics for harvest strategy projections are all based on stochastic simulation trials. Second, there is a statistical limitation in estimating higher m_1 values. As m_1 increases above 6, M_0 and M_b values converge, which renders m_1 almost impossible to identify since a wide range of high m_1 values explain the observations equally well.

The above density dependent mortality formulation is one possible approach to modelling density dependence in natural herring mortality. Other formulations include a model structure that allows both depensation and compensation (Logan et al. 2005), excludes an asymptotic lower limit (Logan et al. 2005; Haist and Schweigert 2009), or uses a linear response to depletion rather than a negative exponential (Logan et al. 2005). However, these were ruled out because examination of mortality and biomass estimates from the previous herring assessment showed no indication of compensatory density dependence in mortality, and in fact showed a negative exponential relationship for most areas. Additionally, when mortality is allowed to decline to zero (i.e., no asymptotic lower limit) the stable unfished equilibrium is removed from the model dynamics when process errors are applied (Haist and Schweigert 2009). SISCAH presently can also use a random walk to model mortality, as has been previously used for herring assessments. We use this in PRD given convergence issues for the DDM model for that area. Both random walk and DDM models are presented in Appendix B. Other formulations can be evaluated for possible addition to the suite of herring operating models in the future.

Commercial catch is represented in discrete removal events occurring at a fractional time of year δg (Table 2, C.1–C.6), where δg for each gear g represents the midpoint of each fishery's season. Fish are removed from the population in fishery temporal order implied by the δg values. Fishery-specific asymptotic selectivity-at-age is modelled as a logistic function of age (Table 2, C.1) with parameters s_g^{50} (age-at-50% selectivity) and s_g^{95} (age-at-95%). Selectivity-at-age for young fish aged less than some minimum age are set to 0 (Table 2, C.1). Numbers-at-age (and biomass-at-age) available to each fishery are computed by depleting the initial numbers for the year down to their expected number present at the midpoint of the fishing season via scaled natural mortality, i.e., $\delta g \cdot M_{a,t}$ and fishing mortality from preceding fisheries $(1 - s_{a,g'} \cdot U_{g',t})$ (C.2). The total numbers- and biomass-at-age alive at the time of fishery g are then scaled to vulnerable numbers via selectivity (C.3) and empirical weight-at-age $w_{a,t}$ (C.4). The total harvest rate $U_{g,t}$ for fleet g is then calculated as catch over vulnerable biomass (C.6), which is then looped back to the top for use in survival calculations (C.2) for any fisheries later in the year. Note that the harvest rates for generating population changes in response to fishing in this formulation can be difficult to interpret when there are substantial SOK fisheries (described below) since they represent the total biomass captured, and not the total biomass

mortality, where the latter depends on post-ponding survival. We note where these issues arise later in the paper.

2.4. SPAWN-ON-KELP FISHERY MODEL

Four of the five herring SARs include removals from some form of commercial spawn-on-kelp (SOK) fishery. Spawn-on-kelp fisheries harvest fertilised herring eggs deposited on kelp without harvesting the mature fish depositing the spawn. For closed-pond fisheries, mature fish from pre-spawning aggregations are captured via purse-seine, towed inshore, and then transferred to a closed net-pen (pond). Herring inside ponds are then encouraged to spawn on kelp blades (usually *Macrocystus integrifolia*) hung within the pond (Schweigert et al. 2018). The main difference for open-pond fisheries is that fish are not impounded, and instead kelp blades are laid out in or close to areas where herring are expected to spawn. Because there are some historical SOK harvests for which the type (open or closed-ponding) is unknown, we assume that all SOK harvest was from closed-pond operations with an assumed ponding-associated mortality. For our models we used the SAR 10 year average SOK harvest. Further SOK details are covered in Appendix A.

SOK fisheries require a model to convert between ponded herring numbers-at-age and landed SOK product (Table 2, K.1–K.6). The unitless conversion factor Ψ_t (K.1) between landed SOK product and ponded biomass (K.2) combines fecundity $F = 200$ eggs/gram of spawning biomass for an average female herring, the proportion of mature individuals in the pond $p_{m,t}$, the proportion of female individuals in the aggregate population $p_f = 0.5$, the proportion of effective spawners in the aggregate population $p_{eff} = 0.35$, and the average weight in grams of landed SOK product per unfertilised egg $\gamma = 2.7$ (Schweigert et al. 2018). The proportion mature $p_{m,t}$ is the only time dependent quantity since it depends on the annual spawning age structure.

Ponded fish are temporarily removed from the herring stock the same way as catch (C.2–C.5), and the harvest rate is calculated as ponded fish over vulnerable biomass $P_t/B_{g=4,t}$. Ponded fish-at-age are also calculated by spreading ponded biomass out in proportion to the biomass-at-age distribution (K.3), estimated by applying the SOK fishery selectivity. Selectivity for SOK fisheries is assumed to be the same as the seine roe fleet because there are no age composition observations and the ponded fish are collected via purse-seine. Surviving ponded fish are returned to the post-spawning biomass after applying a post-ponding mortality rate of $M_{cSOK} = 0.315$ (K.5) (Shields and Kingston 1982; Schweigert et al. 2018).

2.5. OBSERVATION MODELS AND LIKELIHOOD FUNCTIONS

Pacific Herring stock abundance and population composition are monitored via surface and dive survey spawn survey indices, as well as fishery-dependent catch-at-age composition data.

2.5.1. Spawn index observation model

Historically, the spawn survey has been considered two separate indices: a pre-1987 surface survey and a post-1987 dive survey (Appendix A). Closer scrutiny of those data sets reveals that the two designs have overlapped in several years, both around the 1987 split as well as more recently, with surface survey observations in PRD during 2020, and in HG, CC, and WCVI in other years. Note that the 2020 and 2021 surface observations with remote vehicles for Haida Gwaii are more akin to and are treated as dive observations (see Appendix A). If these values had been treated as surface surveys the spawning biomass would have likely been inflated. In SISCAH, the two spawn index survey designs are treated as components of a single blended relative biomass index (Figure A.4), with a yearly catchability scalar q'_t and survey residual

standard error τ'_t , derived via weighted averaging of surface and dive survey specific catchability parameters q_{sr}, q_{sd} and residual standard errors τ_{sr}, τ_{sd} (Table 3, L.2–L.3); note that the square of residual standard errors are combined as variances, as variances are additive and standard errors are not. The weights $\eta_t, 1 - \eta_t$ are the proportions of total observed spawn from the surface and dive surveys, respectively.

2.5.2. Age composition observation models

Proportion-at-age (i.e., age composition) observations are modelled via a logistic-normal likelihood function (Schnute and Haigh 2007; Francis 2014), with expected values calculated as proportions of the catch-at-age (Table 3, O.2). Age composition residuals are modelled using a correlated logistic-normal likelihood function, which provides a more realistic error structure for both parameter estimation (Francis 2014) and simulation of future age-composition data compared to more traditional multinomial likelihoods.

Annual age data samples are weighted relative to the average annual sample size for each fleet (A.4), and gear-specific lag-1 auto-correlation matrices are estimated for age composition residuals (A.1). We avoid zeroes in the age composition data via a tail-compression procedure that combines data from age classes with less than 2% of the samples with neighbouring age classes that were above that threshold, creating a variable number of age bins at each time step (A.5). Gear specific age sampling error standard deviations are estimated via their conditional maximum likelihood estimates (A.7).

2.6. MODEL PRIORS

This section details priors used for fitting SISCAH to data, with prior hyperparameters given in Table 4. Many of the priors came from previous ISCAM modelling output satisfying the need for prior predictive checks. The formation of priors that were not from previous output, mostly those surrounding natural mortality, are detailed below, and are derived in a manner that also satisfy the need for prior predictive checks.

2.6.1. Initial year-class strength, recruitments, and natural mortality

There are standard-normal priors on process errors for initial year-class strength, recruitments, and natural mortality (Table 3, Pr.1–Pr.3). These were based on values from previous ISCAM modelling output.

2.6.2. Selectivity priors

Selectivity priors were based on values from ISCAM modelling output and then adjusted via tuning to fit the data well enough for a closed loop simulation (Table 4).

2.6.3. Density dependent M

The density-dependent (DD) natural mortality model involves three parameters: m_1 , M_b and σ_M , which, if given poor starting values, can lead to non-convergence issues. Non-convergence is reduced by deriving a starting value for m_1 via post-fitting the DD natural mortality function (Equation 1) to estimates of biomass and mortality under a density-independent random walk model, as described in the transition analysis (Appendix B). For all areas, a fixed σ_M value is set at 0.3, allowing a high degree of variation from DD function. The M_b parameter is also fixed, with the assumed value found via a likelihood profiling approach over a grid of M_b values in increments of 0.01 (Appendix D). The final M_b value is that which produced the lowest negative log likelihood function value and a convergent SISCAH model (positive definite hessian, low

gradients). Finally, a normal prior is applied to the derived quantity $\log M_0 = \log (M_b + e^{-m_1})$ (Table 3, Pr.4), following the same prior mean as prior on initial Mt values for the mortality spline in ISCAM (Table 4), but with half the prior standard deviation, i.e., $\log M_0 \sim N(\log(0.45), 0.2)$.

The normal prior on $\log M_0$ is on a derived quantity, or a change-of-variables from the model parameter $\log m_1$, and therefore the prior density requires an adjustment by the determinant of the Jacobian matrix for the change-of-variables (Carpenter et al. 2017). Because the M_b parameter is fixed, the change-of-variables is a 1-1 scalar valued function $f(\log m_1) = \log M_0$, with

$$J(f(\log m_1)) = \frac{df}{d(\log m_1)} = \frac{-m_1 e^{-m_1}}{M_0}. \quad (2)$$

The log determinant (i.e., absolute value) of the Jacobian is then subtracted from the negative log prior density (Table 4).

2.6.4. Stock-recruit steepness

The stock-recruit steepness (h) prior in SISCAL is a *Beta*(20, 9.84) distribution, with a mean of 0.67 and a standard deviation of 0.08. This prior was chosen to have the same prior mean as the previous modelling approach using ISCAM (Table 4), however the prior was made more informative to improve model convergence under the DDM hypothesis.

The steepness prior also requires a Jacobian adjustment, as the model parameter is $\text{logit}(y)$ where $y = \frac{h-0.2}{0.78}$, which is applied so that h is bounded between 0.2 and 0.78. The Jacobian adjustment is again a scalar valued function $f(y) = 0.2 + \frac{0.78}{1+e^{-y}}$, with

$$J(f(y)) = \frac{df}{d\text{logit}(y)} = \frac{0.78}{(1 + e^{-\text{logit}(y)})^2}. \quad (3)$$

Again, the log determinant $\log |J(f)|$ is subtracted from the negative log prior density (Table 4).

2.6.5. Catchability

Surface survey catchability is estimated with a log-normal prior ($\mu_{q_s} = 1, \tau_{q_s} = 1$, Table 3, Pr.6), while the dive survey is assumed to be absolute with $q_d = 1$. While the dive survey assumption is different from the very informative ISCAM prior, it is qualitatively consistent with the previous approach (DFO 2020c). The assumption that the dive survey measures absolute spawning biomass (on average) is appropriate given the coverage of the survey, although there is some debate on the impact of egg survival and hatching rates on estimated total spawn.

Nevertheless, a fixed assumption (or informative prior) is needed for spawn survey catchability because the highly variable nature of herring abundance, combined with high observation uncertainty and recently low fishery removals, make it difficult to discern the size of populations from herring dive survey data alone.

2.6.6. Spawn index residual standard error

An inverse gamma prior is assumed for the surface and dive components of the spawn index residual variance (Table 3, Pr.7). The same vague inverse gamma distribution is used for both surface and dive survey designs, with shape parameter $\alpha_1 = 2$ and scale parameter $\alpha_2 = 0.27$, corresponding to a variance prior mode of 0.09 and prior standard deviation of about 0.23. Prior

standard deviations were found by simulating random draws from the distribution, as there is no closed form solution for the variance moment of an inverse gamma distribution with shape parameter $\alpha \leq 2$. These prior hyperparameters were chosen to reflect a moderate level of confidence in the spawn index data, with the prior mode corresponding to a roughly 30% CV in spawn index residuals.

As above, spawn index residual standard error components are transformed before the prior is applied, so a Jacobian adjustment is required. Here, for both designs the model parameter is $\log \tau_j$ ($j = s$ or $j = d$), and the prior is applied to $f(\log \tau_j) = \tau_j^2 = (e^{\log \tau_j})^2$. The Jacobian is then

$$J(f) = \frac{df}{d \log \tau_j} = 2\tau_j^2, \quad (4)$$

with $\log |J(f)|$ subtracted from the negative log prior density (Table 3).

2.6.7. Lag-1 autocorrelation in age composition residuals

A simple least-squares penalty is applied to the logit transformed auto-correlation factor ρ_g (Table 3, Pr.8)

2.6.8. Improper Jeffreys prior

Unfished biomass SB_0 and initial recruitment R_{init} have improper Jeffreys priors applied to penalise their magnitude (Table 3, Pr.10).

2.6.9. Fixed recruitment process error variance

Recruitment process error variance σ_R is fixed for each area at the values given in Table 4. These values are found via an iterative re-weighting scheme, optimised so that the standard deviation of the estimated recruitment process errors ω_t is equal to 1 (i.e., the recruitment process errors are standard normal).

2.7. OBJECTIVE FUNCTION AND OPTIMISATION

The SISCAN objective function is proportional to the negative log posterior density function (Table 3, F.1), and defined as the sum of the observation data negative log likelihood function values (L.6 and A.8), negative log prior densities for process errors (Pr.1–Pr.3), and priors on other parameters or derived quantities (P.4–P.10).

SISCAN is coded in Template Model Builder (TMB) and the model objective function is optimised via the `nlminb()` function in the R statistical package (Kristensen et al. 2015; R Core Team 2015). The maximum posterior density estimates (MPDEs) of model parameters are considered converged when the maximum gradient component of the model likelihood surface at the MPDEs has an absolute value less than 10^{-3} , and the Hessian matrix is positive definite.

Optimisation of SISCAN takes a phased approach, with parameter estimation phases given in Table 5. Stock-recruitment relationship parameters SB_0 and h are estimated in phase 8, before which an average recruitment parameter $\bar{R}$ is used to drive population dynamics in place of the stock-recruitment relationship. The $\bar{R}$ parameter is removed from the model in phase 9, with recruitment process errors ω_t re-estimated relative to the stock-recruitment relationship; in areas where R_{init} is not estimated, the same approach is used to replace R_{init} with R_0 and re-estimate ω_a^{init} relative to $R_0 \cdot S_a$.

A likelihood profile based approach is used to estimate a fixed value for the DDM model M_b parameter. DDM model parameters M_b and m_1 are correlated, and m_1 is also correlated with B_0 given the link between biomass depletion and natural mortality rates created by the DDM model. Additionally, M_b and m_1 are very uncertain, and there is little guidance on potential parameter values in the literature, so informative priors for M_b and m_1 are not available. Therefore, to reduce correlation in the model posteriors and the reliance on informative priors for DDM parameters, we select a fixed value for M_b using the following approach:

1. Set $M_0 \sim \log N(0.45, 0.2)$ similar to ISCAM, $\text{jeffWtB0} = 1$, $\sigma_M = 0.3$, $\sigma_R = 0.8$
2. Use a likelihood profile approach to choose M_b based on lowest total likelihood for a model with convergent MPDEs (positive definite Hessian matrix, no non-finite standard errors)

Once M_b is found, we apply an iterative re-weighting scheme to find σ_R values for each area so that the effective standard deviation for normalised process errors is 1.0, i.e., $\frac{\omega_{R,t}}{\sigma_R} N(0, 1)$.

Given fixed values for M_b and σ_R , the joint Bayesian posterior distribution for SISCAH model parameters is estimated. Bayes posteriors are sampled via a Hamiltonian Monte-Carlo sampler in the `{tmbstan}` R package (Monnahan and Kristensen 2018). Hamiltonian Monte-Carlo differs from Markov-Chain Monte-Carlo by minimising the auto-correlation between successive posterior samples, thereby producing a mixed model posterior sample with lower absolute sample sizes and little or no thinning (Monnahan et al. 2017). Parameter values are sampled from the posterior as 4 independent chains of 2000 samples, with initial values for each chain randomly chosen so that they are overdispersed relative to the MPDEs and point estimates of their uncertainty derived from the model Hessian. Bayes posteriors are considered fully mixed (i.e., converged) when potential scale reduction factors $\hat{R}$ are less than 1.01 for life-history and selectivity parameters or 1.02 for process errors and other random effects, and effective sample sizes for all estimated parameters are greater than 400 (i.e., 100 for each chain) (Betancourt and Girolami 2015; Vehtari et al. 2021).

We also determine a model posterior to be acceptable when there are fewer than 2% of all samples have divergent transitions, as long as we can confirm the posterior around the divergence is not overly pathological. Confirmation can come from other diagnostics, such as the results of simulation analyses, trace plots of posterior chains, and pairs plots of joint marginal posterior distributions. Divergent transitions occur where successive samples in a posterior chain diverge from a pre-calculated expected path through the posterior distribution defined by the Hamiltonian matrix (Monnahan and Kristensen 2018). Ideally, model posterior distributions have zero divergent transitions and there is some concern that divergent transitions inhibit the ability of the sampler to reach all areas of the posterior and reflect the underlying posterior density accurately, and some recommendations go so far as to recommend that 1 divergent transition is too many (Betancourt and Girolami 2015; Best and Punt 2020; Vehtari et al. 2021). On the other hand, sometimes it is difficult to avoid divergent transitions entirely, given a highly parameterized model that is fit to noisy data and has some level of dependence on informative priors. As such, there is high probability that chains will encounter areas of the posterior where the geometry of the surface defined through parameter space by the model objective function can have higher local curvature than in other areas, and it may be impractical to eliminate all divergent transitions (Carpenter et al. 2017). In general, the methods to reduce divergent transitions include (i) switching to non-centred distributions to avoid a ‘funnel’ in the joint posterior of variance and random effect parameters, (ii) adding Jacobian adjustments to priors for any change-of-variables that have been made, as described above, (iii) increasing the `adapt_delta` and `max_tree_depth` HMC tuning parameters to decrease step size and increase the number of jumps between samples to improve coherence between the projected path from

the Hamiltonian matrix and the path traced out by the discrete jumps taken by the sampler, and (iv) increasing the regularization of some parameters via informative priors. For SISCAH, we (i) use fixed variance parameters for recruitment and mortality process errors, and observation errors are not sampled directly, so there is no funnel effect to be concerned about for random effects but possibly for other parameter combinations depending on correlation, (ii) apply Jacobian adjustments for all changes- of-variables, and (iii) show the final values of tuning parameters for the HMC in Table 5. After steps (i)–(iii), it is still impossible to completely eliminate divergent transitions for the four DDM models, so we inspect the location of divergent transitions in joint-marginal posteriors for all parameters via pairs-plots (Appendix D), and accept posteriors if the prevalence of divergent transitions in the combined chains is lower than 2% of the total number of samples, and the divergent transitions did not exhibit clustering across the range of joint posteriors or show a funnel effect.

2.8. COMPARISONS WITH ISCAM

SISCAH and ISCAM assessment models are compared in two ways:

1. Final model fits of ISCAM and the full SISCAH model, as specified in Table 6 are presented and compared here in the main body of the paper.
2. A piece-wise transition analysis from ISCAM to SISCAH, detailed in Appendix B, compares the following features:
 - a. discrete fishery removals in a pulse event,
 - b. spawn-on-kelp fisheries (except SOG),
 - c. a blended survey index, and
 - d. density-dependent natural mortality (except PRD).

In both comparisons, we examine estimated natural mortality, recruitment, spawning biomass, and fishing mortality to judge similarities and differences between the two models. Models in the transition analysis are also compared quantitatively via selected life-history and observation model quantities.

2.9. SIMULATION SELF-TEST

We use simulation self-tests to better understand the statistical properties of SISCAH parameters. For example, the density-dependent model adds structural parameters that could result in bias and reduced precision of other estimated parameters, including those involved in biological reference points.

SISCAH is subjected to four simulated data scenarios for CC and SOG assessment models. For each SAR, the maximum posterior density estimates (MPDEs) of observation model parameters are used to simulate new biomass index and/or age composition data in the following data scenarios:

1. Only blended spawn **Index data simulated**
2. Only fishery Age data simulated
3. **All data simulated**, combining 1 and 2
4. **Random Priors**, combining 3 with randomly drawn prior means for m_1 and M_b (where estimated).

For each data scenario, 100 random seeds are used to draw new observation errors for the simulated data in Monte-Carlo trials. The simulated data are then used to refit SISCAH, re-estimating model parameters, biomass, recruitment, etc. Those quantities are compared to the ‘true’ values used to simulate the data, generating distributions of relative estimation errors

$$RE(\hat{\theta}_i) = \frac{\hat{\theta}_i - \theta}{\theta}, \quad (5)$$

where RE denotes the relative error, $\hat{\theta}_i$ was the SISCAH estimate of the quantity θ from Monte-Carlo trial i , and θ was the true value used to simulate the data. Bias in SISCAH estimates of θ was measured using the median relative error

$$MRE(\theta) = \text{median}_i RE(\hat{\theta}_i), \quad (6)$$

and precision was measured by directly via the standard deviation of the relative error distribution, and also by comparing the MRE to the median absolute relative error

$$MARE(\theta) = \text{median}_i |RE(\hat{\theta}_i)|. \quad (7)$$

2.10. BC PACIFIC HERRING STOCK ASSESSMENTS UNDER FULL SISCAH MODEL

Detailed stock assessments each SAR under the full SISCAH model are presented in Appendix D. Assessments include goodness of fit, interpretation of time-trends in model states, biological reference points, retrospective analyses, and sensitivity analyses.

2.10.1. Model goodness of fit

Stock assessments for each SAR are evaluated individually for goodness of fit, which we generally determine via observation model standard errors (lower is better), time-trends or auto-correlation in observation error residuals and process errors, and visual inspection of model estimates of biomass, recruitment, and natural mortality for evidence of model artefacts or unexpected behaviour. While ‘unexpected behaviour’ is somewhat vague, the experience of the authors fitting catch-at-age models to data for each BC herring SAR guides this component.

2.10.2. Biological reference points

Equilibrium yield-per-recruit reference points establish an equilibrium relationship between harvest rates, biomass-per-recruit, and average annual yield (i.e., a yield curve). Yield curves are computed via standard equations for single-species fisheries exploited by a single fleet or multiple fleets (Smith et al. 1993). This section describes the estimation of multi-sector MSY reference points for BC herring under the SISCAH model with density-dependent mortality. The density-independent approach, which is currently used in the ISCAM model, is described in Appendix E. The derivation for the simplest case (single-sector with constant M) is not given here, but interested readers can find derivations of the simplest case, and more complex cases, elsewhere (Quinn and Deriso 1999; Mangel et al. 2013; Moffitt et al. 2016).

The analytical approach used for density-independent M does not work for the density-dependent M model because of the positive feedback in mortality. Under the density-dependent M assumption, the natural mortality rate depends on the fishing mortality via the latter’s effect on age-2+ biomass. This implicit relationship between the input fishing mortality F and the equilibrium M is further complicated by the presence of an unstable equilibrium for higher values of the depensation rate parameter m_1 . Those higher m_1 values create a sudden increase

in M as F exceeds a certain threshold, which makes it difficult to trust numerical derivative-based approaches to solving for the implicit relationship (e.g., Newton-Rhapson).

Additionally, preliminary simulations show that deterministic equilibria are not completely appropriate for populations with density-dependent M formulation. Specifically, biomass will equilibrate lower when recruitment is stochastic under the density-dependent M (DDM) model, even in the absence of fishing. From the DDM model formulation, it is much easier for M to increase under stochastic recruitment than decrease because of the asymmetry in the $M \sim B$ relationship. Using unfished conditions as an example, when a population is unfished with no recruitment process error, natural mortality equilibrates to $M_0 = M_b + e^{-m_1}$. Added recruitment variability drives biomass variation, leading to variation in mortality around M_0 where decreases are bounded below by M_b and increases are bounded above by $1 + M_b$. The value of m_1 determines the centrality of M_0 between these two extremes, as well as the ‘ease’ of moving up and down the DDM curve. As a result, under stochastic recruitment the mean mortality rate equilibrates above M_0 , which results in lower long term average biomass than the deterministic estimates of SB_0 derived from SISCAH.

We use a stochastic simulation approach to estimate reference points in the presence of DDM and recruitment variability. The same parameterization $F_g = r_g f$ used for reference points under density independent M (Appendix E applies, and for each value of f , a distribution of model states (Table 2, A.1–A.4) and total yield $Y_t = \sum_{g=1}^3 C_{g,t} + K_t$ are calculated, where K_t is landed SOK product, over a 200-year simulation with recruitment and natural mortality process errors. A distribution of equilibria is calculated over 200 replicates conditioned on distinct random draws from the SISCAH posterior distribution. For each draw, the population is simulated forward in time with random recruitment and mortality process errors, simultaneously integrating over parameter uncertainty and environmental variability. Over all draws, the median biomass, mortality, catch, and recruitment are taken over the middle 100 years of the simulation under each F value, with yield derived from the Baranov catch equation assuming total mortality for each SAR is

$$Z_{a,t} = M_a(B_{a,t}) + \sum_g s_{a,g} F_g, \quad (8)$$

where $M_a(B_{a,t})$ is the mortality rate for age a based on the start of year age-2+ biomass $B_{a,t}$ (density-dependent for age-2+, and M_0 for age-1), $s_{a,g}$ is selectivity-at-age- a for fleet g , and F_g is the fleet-specific fishing mortality rate. Catch for the seine roe, gillnet, and food-and-bait fishery (SOG, PRD) only is in biomass units, while the catch for SOK fisheries is in ponded biomass equivalents (note the difference to yield). For areas with higher m_1 values, the unstable equilibrium described above manifests as a population crash point B_{crash} at some high harvest rate U_{crash} , which we define as the location on the yield curve where the rate of decline in yield is steepest (i.e., the minimum value of the first derivative of the yield curve with respect to U).

This definition does not mean it is the point at which the stock crashes, or the point at which a downward trend cannot be reversed, which could occur either before or after this point. It also is not the traditional definition of F_{crash} , which is

$$\phi(F_{crash}) = \frac{1}{a}, \quad (9)$$

where a is the slope of the stock-recruitment curve as SB approaches zero; this definition is used for estimating U_{crash} for SISCAH models that use the random walk M formulation. Although

this traditional definition is ‘biological’, in that it links crash points to the underlying stock-recruitment relationship, for DDM models we have examined it produces U_{crash} values that are far above the point where the equilibrium biomass is extirpated, as the definition is meant for models with compensatory dynamics. Therefore, the definition based on the shape of the yield curve is preferable. Although the definition based on the slope of the yield curve is not perfect, it does produce U_{crash} values that are either at or below the sudden declines in equilibrium yield and biomass. Moreover, because it is derived mathematically and not based on defined unproductive (or productive) periods, it can be implemented in feedback simulations more easily than empirical approaches.

2.10.3. Per-capita demographic rates

The density-dependent M formulation invites a reanalysis of the equilibrium dynamics of BC herring at low stock sizes. Previous work framed the BC herring limit reference points of 30% of unfished levels in the context of recent persistent periods of low-productivity/low-biomass and high mortality in some areas, attempting to find evidence of a threshold below which the stock becomes impaired (Kronlund et al. 2018; Forrest et al. 2023). Recent dynamics suggest there may be an Allee effect preventing fast recovery of herring in Haida Gwaii and WCVI, where there has been no fishing since 2005 but herring are recovering very slowly.

We demonstrate the population-level impact of an Allee effect in natural mortality by showing how estimated recruits-per-spawner, survival, and per-capita surplus production for all five BC herring SARs change with age-2+ biomass. The resulting equilibrium relationships suggest biomass levels below which productivity may be impaired as required in determining limit reference points.

2.10.4. Retrospective analyses

For each SAR, we use a retrospective analysis to determine how parameters estimated in SISCAN change as a year’s worth of data are removed one year at a time going back to 2013. Each of the results are considered a “peel”. Results from retrospective analyses are interpreted qualitatively by visual inspection of retrospective estimates of spawning biomass, year-class strength, and natural mortality, and quantitatively by comparing retrospective estimates of leading and derived quantities over all peels.

2.10.5. Sensitivity analyses

2.10.5.1. Stock-recruit steepness prior

For all SARs other than PRD, for which h is fixed, alternative steepness priors are used to adjust the prior standard deviation higher and lower, via increases and reductions in prior hyperparameters with the same proportions or adjusting the mean higher and lower via changing the relative size of the parameters.

We test $Beta(10, 19.84)$ and $Beta(26, 3.84)$ priors that corresponded to mean h values of 0.34 and 0.87, respectively, with a standard deviation of 0.08. We also test $Beta(20 * 5, 9.84 * 5)$ and $Beta(20/4, 9.84/4)$ priors that corresponded to prior standard deviations of 0.04 and 0.08, respectively, with a mean of 0.67.

For PRD, to check sensitivity to the steepness assumption we use four fixed values of h : 0.60, 0.65, 0.70, and 0.75.

2.10.5.2. Variance in interannual M deviations

The standard deviation around M process errors (σ_M) is fixed in SISCAN at values ranging from 0.05 (PRD) to 0.30 (HG). For each SAR, we test a “low” variance alternative assumption by halving the pre-specified σ_M values and a “high” variance alternative by doubling the pre-specified σ_M values.

2.10.5.3. Jeffreys prior

SISCAN applies a Jeffreys prior, with parameters either 0, 1, or 2, to SB_0 and R_{init} to penalise their magnitude. We test alternative values of the Jeffreys prior via ad hoc adjustments (e.g., if the Jeffreys prior is set to 1 then we test values of 0 or 2).

2.10.5.4. Selectivity

SISCAN applies log-normal priors to parameters for age-at-50% selectivity. We test the sensitivity of SISCAN to these priors by halving and doubling the prior mean while holding prior standard deviation fixed and by halving and doubling the prior standard deviation while holding the prior mean fixed.

2.10.5.5. Surface survey catchability

Surface survey catchability is estimated in SISCAN using a vague log-normal prior ($\mu_{q_s} = 0.5$, $\tau_{q_s} = 0.5$). We test the sensitivity of SISCAN to this prior by varying the μ_{q_s} to 0.25 and 0.75 while holding τ_{q_s} at 0.5, and by varying the τ_{q_s} to 0.25 and 0.75 while holding μ_{q_s} fixed.

2.10.5.6. Initial conditions

As outlined in the model description, all herring populations in all SARs are initialised in a fished state in 1951. Initial numbers at age are estimated as in (NEQ.1, Table 2), but there are several variations that we could have used. In total, there are eight variations comprising three choices between two options each. The three choices are

1. whether the base age-1 recruitment uses unfished recruitment R_0 or an initial recruitment R_{init} was used,
2. whether the initial mortality/survivorship S_a assumption includes fishing mortality F_{init} or just natural mortality, and
3. whether the stock relative age-structure was at equilibrium with respect to that mortality assumption or not, represented by estimated initial recruitment deviations. One combination can be ignored, which is an equilibrium age-structure with R_0 and $F_{init} = 0$, or an unfished initialisation, leaving seven options, that we discuss in Appendix D.

2.11. CLOSED-LOOP SIMULATIONS EVALUATING HERRING MPS

This section describes the closed-loop simulation approach used to evaluate perfect information management procedures for each of the five SARs. Our purpose here is not to complete a full management strategy evaluation, but instead to (i) demonstrate the simulation capability of SISCAN as an operating model and (ii) provide initial implications of simulating density-dependent natural mortality under harvest strategies that comply with the precautionary approach as implemented by DFO, including avoidance of biological limit reference point(s) (LRP) and performance evaluation against upper stock reference (USR) points.

DFO’s “Fishery Decision-Making Framework Incorporating the Precautionary Approach” policy (DFO 2009), hereafter called the PA Policy, describes requirements for incorporating the

precautionary approach for fish stocks in Canada. These requirements have been summarized into four elements (DFO 2023a):

- PA1: Establish limit and upper stock reference points that delineate critical, cautious, and health zones as well as a maximum fishing mortality rate (Marentette et al. 2021);
- PA2: A harvest strategy and harvest control rules (HCRs);
- PA3: Methods to incorporate uncertainty and the associated risks when developing reference points and implementing control rules based on those reference points; and
- PA4: Evaluation of the management system performance against objectives specified by the harvest strategy.

In this section, we test a management procedure based on “HS30-60” management procedures (Benson et al. 2023; DFO 2023a), distinguished by a ramped ‘hockey-stick’ harvest control rule (Figure 3) that takes forecast biomass depletion levels from a stock assessment model as an input, and produces a target harvest rate as an output. Performance criteria are calculated over three herring generations (i.e., 15 years) from the start of the projection period for all objectives, using thousands of simulations.

2.11.1. Operating model dynamics

The SISCAN closed-loop simulation framework is conditioned on the posterior distributions of parameters fitted to data for the 5 SARs as described above. For all SARs, the population dynamics and observation models for generating simulated data largely match those defined for the estimation model (Tables 2, 3), so we do not reproduce them in full. The only difference involves replacing the method for simulating stochastic recruitments and mortality in the historical period with the following bias-corrected stochastic projection versions:

$$R_t = \frac{4R_0B_{t-1}}{5B_0(1-h) + (5h-1)B_{t-1}} \cdot e^{\sigma_R^* \cdot \omega_t - 0.5(\sigma_R^*)^2}, \quad (10)$$

$$M_t = M_b \cdot e^{-m_1 \cdot \frac{B_t}{B_0} + \sigma_M^* \cdot \omega_t - 0.5(\sigma_M^*)^2}, \quad (11)$$

where σ_R^* and σ_M^* are the effective process error standard deviations for recruitment and mortality, found by applying the plug-in estimator for standard deviation of the estimated recruitment process errors. The above bias corrected recruitment dynamics are applied so that over a sufficiently large number of replicates and time steps, the median projected dynamics will match model equilibria (i.e., yield and biomass) when a constant removal rate is applied with perfect information (which we confirm by simulation as well).

2.11.2. HS30-60 harvest control rule

The HS30-60 harvest control rule (HCR) is defined by lower and upper control points set at 30% and 60%, respectively, of unfished spawning biomass, and a reference removal rate U_{Ref} (Figure 3). Mathematically, in year t the target harvest rate for the following year $t+1$ is determined by the HCR from a stock assessment as

$$U_{t+1} = \begin{cases} 0 & \hat{D}_{t+1} < 0.3 \\ U_{Ref} \cdot \frac{\hat{D}_{t+1} - 0.3}{0.6 - 0.3} & 0.3 < \hat{D}_{t+1} < 0.6 \\ U_{Ref} & 0.6 < \hat{D}_{t+1} \end{cases} \quad (12)$$

where U_{t+1} is the projected target harvest rate and $\hat{D}_{t+1}$ is the forecast biomass depletion level with respect to unfished biomass SB_0 derived from the reference point simulations. For the demonstration closed loop simulations in this paper, all assessments assume perfect information. Once the target harvest rate U_{t+1} is set via the harvest control rule, the total allowable catch (TAC) is set as

$$TAC_{t+1} = U_{t+1} \cdot \hat{SB}_{t+1}, \quad (13)$$

where $\hat{SB}_{t+1}$ is the SISCAN model forecast spawning stock biomass at spawn timing, in the absence of fishing.

The annual total allowable catch TAC_t is allocated into individual fisheries as

$$TAC_{f,t} = \rho_f TAC_t, \quad (14)$$

for $f = 1, \dots, 3$, where ρ_f is the average allocation to each fishery over the most recent 20 years with positive catch levels; years with zero fishing are skipped. Spawn-on-kelp allocations are in ponded biomass equivalents, and then converted to a catch limit for landed SOK product using the Ψ_t conversion factor i.e.,

$$TAC_{4,t} = \rho_f \cdot TAC_t \cdot \Psi_t. \quad (15)$$

The simulations of spawn-on-kelp fisheries and their TACs above are a generalized example for demonstration purposes and do not reflect the particular details of each individual SAR. For this paper, several assumptions were made to show the effect of moderate spawn fisheries that generally reflect current practices in regions where SOK fisheries have been viable. For example, we assume that all fisheries with any TAC allocated will take all allocated TACs in projections, and there is no priority between sectors. Future work should include consultation with SOK operators and area managers to update simulations with the real management system details that were excluded here.

We examine two or three reference removal rates U_{Ref} , depending on the SAR:

1. U_{MSY} : the optimal harvest rate according to simulation-based MSY reference points for each SAR,
2. $0.5U_{MSY}$: the harvest rate set to half of U_{MSY} , as recommended by the Lenfest Task Force (Pikitch et al. 2012), and
3. U_{USR} : the harvest rate associated with the upper stock reference (USR) at equilibrium (Table 7, estimated from simulation-based equilibrium biomass curves (Appendix C).

The provisional USR implemented in 2022 (DFO 2023a, 2023b) is above the SISCAN estimate of stochastic equilibrium unfished biomass SB_0 for Haida Gwaii and West Coast of Vancouver Island. Although biomass above unfished levels not uncommon in the presence of highly stochastic recruitment for forage fishes, it is impossible to derive a harvest rate that will drive the population to a level above unfished at equilibrium. Therefore, in the HG and WCVI regions where $USR > SB_0$, we set $U_{USR} = 0$.

2.11.3. Fishery objectives and performance metrics

2.11.3.1. Fishery management objectives

The objectives proposed for the BC herring fishery are based on input from First Nations, fishery managers, scientists, and industry (DFO 2020c, 2023a; Benson et al. 2023). These objectives may evolve through the iterative consultation process.

At present, only biomass objectives are stated for BC herring management decisions. This includes a conservation objective:

1. $P(SB > 0.3SB_0) \geq 0.75$: Maintain spawning stock biomass SB above the limit reference point of $LRP = 0.3SB_0$ in 75% of years measured over three herring generations, where SB_0 is the equilibrium unfished spawning biomass estimate from the operating model;

and a USR objective:

2. $P(SB > USR) \geq 0.5$: Maintain spawning stock biomass B above the upper stock reference (USR) in 50% of years measured over three herring generations, where the USR is defined as a proportion of mean biomass over a year range corresponding to a productive period, given in Table 7 (DFO 2023a).

Provisional USRs were added to the Herring Management Framework in 2022 (DFO 2023b).

Evaluating management procedures by simulation requires a quantitative performance indicator for each objective. Stock status indicators are all measured using the true operating model spawning stock biomass, and quantitative metrics are calculated over three herring generations (15 years), taken as the ‘reasonable’ time frame required by the DFO Precautionary Approach Framework (DFO 2006). Performance statistics corresponding to objectives 1 and 2, as well as other quantities of interest outlined below, are listed in Table 8. Performance statistics are calculated for each simulation replicate ($n = 100$) for a given combination of OM scenario and MP. The expected performance of a MP, given the data simulated by the OM, is summarized by the mean (or median) of each metric over all simulation replicates.

2.11.3.2. Additional performance metrics

In addition to biomass objectives, harvest outcomes are often of interest to managers and herring users. For example, the probability of exceeding the reference removal rate is a good measure of overfishing risk, and the probability of catches below a minimum feasible size for a fishery is a good measure of how economically viable an MP is, in the absence of economic yield calculations. The following additional metrics are defined in Table 8:

1. $P(B_t > B_{crash})$: Probability that biomass is above B_{crash} over the 15 year projection period.
2. Average Catch ($\bar{C}$): Average annual landings (excluding SOK).
3. Average Annual Variation (AAV_C): Average proportional interannual variation in commercial catch (excluding SOK).
4. Average Spawn on Kelp ($\bar{K}$): Average annual landings of SOK product.
5. Average Annual Variation (AAV_K): Average proportional interannual variation in SOK landings.
6. Probability of Unviable TAC (**pUnviable**): The average proportion of years and replicates where the catch is below the minimum observed level in the historical data.

2.11.4. Closed-loop feedback simulations

We use the following closed-loop simulation algorithm to apply the simulated candidate management procedure (Walters 1986; de la Mare 1998; Cooke 1999; Punt and Smith 1999; Sainsbury et al. 2000; Butterworth 2007):

1. For each SAR, initialize a pre-conditioned simulation model for the period 1951–2022 based on a random draw from the operating model posterior distribution;
2. Project the operating model population and fishery into the future one time-step at a time. At each step, apply the following:
 - a. Generate the catch and spawn survey data available for stock assessment;
 - b. Determine depletion level from a 1-year ahead forecast using perfect information;
 - c. Apply the HS 30-60 harvest control rule to generate a catch limit;
 - d. Update the operating model population given the catch limits for each fishery and new recruitment;
 - e. Repeat steps 2.a–2.d until the projection period ends.
3. Repeat steps 1. and 2. 99 more times;
4. Calculate quantitative performance statistics across all 100 replicates.

3. RESULTS

3.1. OVERVIEW

This section provides an aggregate view of the transition from ISCAM to SISCAH. Detailed transition results by SAR are in Appendix B. Simulation self-tests on the full SISCAH model are then presented for example SARs CC and SOG, followed by a summary of assessment results for each SAR. Detailed assessment results by SAR are in Appendix D. Finally, we summarize management procedures for each SAR.

3.2. TRANSITION ANALYSIS

The order of presentation of transition analyses first compares and contrasts ISCAM and the full SISCAH model within and across SARs, and then examines how structural changes within SISCAH compare to ISCAM for each SAR.

While similarities between the two models may be comforting for those familiar with ISCAM, differences between the two modelling frameworks are expected. For SISCAH, the model evaluation via simulation tests, retrospective analyses, and goodness of fit helps determine the overall suitability of the model, see Section 3.3 and Appendix D.

3.2.1. Comparisons between full SISCAH and ISCAM

Figure 4 presents spawning biomass, recruitment, and natural mortality for the full SISCAH model and ISCAM across all five SARs. The greatest differences occur in estimated natural mortality, which has a more jagged and less sinusoidal path. This occurs for both density independent mortality as used in PRD and density dependent mortality models, which occurs in all other SARs. The sinusoidal nature of M in ISCAM is created in part because of the spline model used to fit it. For DDM models the jaggedness is caused in part by the annual mortality process deviations with a larger standard deviation ($\sigma_M = 0.3$ for DDM models). There is also the

effect of the asymptotic lower limit in areas where m_1 is higher (CC and SOG), where M_0 approaches M_b , creating a hard lower limit on M_t over a wider range of biomass levels. That lower limit has the effect of constraining the deterministic component of M_t above M_b during times where ISCAM allowed M_t to decline further. Otherwise, the DDM model and ISCAM density-independent random walk model have a general agreement on average, with the general trend of the more variable SISCAH DDM model agreeing with the more smooth ISCAM RWM model.

It is unclear if the lower M_t values under the ISCAM model are spurious model artefacts or real mortality rates for BC herring. ISCAM uses a spline approach to estimate the log-Normal jumps for M_t given 12 freely estimated spline nodes. ISCAM's spline nodes have no auto-correlation and a larger standard deviation of 1.0, while the interpolated random walk jumps have a standard deviation of 0.1 (Martell et al. 2012). Most of the cases where ISCAM RWM estimates are much lower than the SISCAH DDM estimates are for mortality rates below 0.4, and as low as 0.2, which are very low mortality rates for herring. Additionally, the SISCAH density independent RWM model used for PRD has the same general trend and mean value as the ISCAM model, but a much lower amplitude in its variation. While ISCAM and SISCAH have a lot of differences that we test in stages (Appendix B), the approach to estimating the random walk for the M_t series only differs by the spline. On the other hand, the lower mortality rates in ISCAM are often estimated in the early parts of the time series, when there may have been fewer herring predators around given the high level of large marine mammal removals around that time.

SISCAH tends to estimate higher average spawning biomass during the surface survey years, while maintaining qualitatively similar time-series patterns to ISCAM. Biomass tends to converge for the dive survey years (post 1987) with some variation observed for HG and SOG SARs, attributed to dive versus surface survey designs in HG, and to more variation in mortality for SOG. The recruitment estimates from both models also have a similar pattern, generally tracking the same overall trend with more agreement when there is a higher proportion of dive survey design observations, and more divergence in earlier surface survey years.

The mortality and recruitment estimates also showed different end effects. The terminal year estimates from both models were often quite different, which largely stems from the difference in the underlying mortality process model, where terminal mortality is linked more closely to the start of year biomass. Then, if mortality is higher or lower, recruitment in the last couple of years needs to increase or decrease with mortality to arrive at similar biomass estimates.

Table B.1 compares estimated unfished spawning biomass, recruitment, natural mortality, stock steepness, and surface survey catchability for ISCAM and the intermediate SISCAH models. Most estimates are similar in magnitude for most SARs. Stock steepness h , and surface survey catchability q_s is lower under SISCAH across both DIM and DDM models. The difference in unfished spawning biomass SB_0 can be as high as 20% (PRD). Unfished recruitment is higher in all SARs except PRD under the full SISCAH model, but this is usually offset by a lower M_0 or change in stock-recruit steepness. To some extent, differences in unfished biomass and mortality are expected, because ISCAM uses a time-averaged natural mortality value over the entire model history to represent unfished conditions. In contrast, the deterministic estimates of unfished biomass and mortality in SISCAH are related to the density-dependent M model parameters M_b and m_1 . Moreover, with the M series for each SAR constrained by the intrinsic density-dependence, there are significant differences in annual natural mortality under SISCAH. Therefore, it is also expected that absolute recruitments are more variable even though spawning biomass is not.

3.2.2. Sensitivity to new model structures

In general, the six alternative structures used for SISCAN show relatively minor effects on estimates of unfished biomass, recruitment and natural mortality (Table B.1). Discrete fisheries, the blended index, and density-dependent natural mortality tended to raise the biomass, slightly, relative to the density-independent random walk (base) formulation.

Accounting for SOK removals has negligible effects on model estimates as expected, since these fisheries are generally small contributors to total mortality in the first place (Figures B.1, B.5, B.8, B.12, and B.16). The blended index also has relatively small impacts on model estimates, which is again expected since there are only a few instances where the blending is significant (Figures B.2, B.6, B.9, B.13, and B.17).

3.3. SIMULATION-ESTIMATION SELF-TESTS

The simulation-estimation experiment was parameterized using CC and SOG as typical cases. Here, we present estimates of bias and precision for life-history parameters (SB_0 , $2 + B_0$, R_0 , h , M_b , m_1 , M_0), selectivity parameters (s_1^{50} , s_2^{50} , s_3^{50}), and survey observation model parameters (q_s , τ_s , τ_d)

In general, simulated index data appears to affect the survey observation model quantities (q_s , τ_s , and τ_d) more, while simulated age data affects life-history parameters more.

3.3.1. Central Coast

As expected, the three simulated data scenarios introduced varying degrees of bias and precision of parameter estimates in the CC case. The random priors scenario often had the same or similar bias to the All Data Simulated scenario, but with additional uncertainty. Across all scenarios, the stock-recruit steepness h and selectivity s_g^{50} parameters had quite low sensitivity to the simulated data and priors (Figure 5), so we do not discuss them below.

The Index Data Simulated scenario had small effects on the median relative errors (MREs, i.e., bias) of unfished equilibrium biomass SB_0 and $2 + B_0$, recruitment R_0 , and mortality M_0 (less than 5%) (Figure 5, Table 9). Other parameters, including m_1 and all survey observation model parameters, had higher bias and more variability, but the magnitude of all MREs is within 12%, and all distributions overlapped with zero. The surface survey catchability component also has a bias of -0.09, which is not usual for a nuisance parameter fit to simulated data. Such behaviour is probably driven by the mean spawn index residual error of -0.13 (Figure D.38), which is related to the interdependency between dive and surface survey catchabilities caused by the blended spawn index. Additionally, this small bias in biomass is linked to the bias in m_1 , given that annual SISCAN estimates of M_t have very low bias (Figure 6).

The Age Data Simulated scenario has small effects on estimates of observation model parameters, and greater influence on life-history parameters. The largest bias is on the m_1 parameter with a median relative error of 21% (Table 9), indicating the sensitivity of that parameter to age composition data and the difficulty estimating it given identifiability issues, similar to difficulties estimating stock-recruit steepness without informative priors. Despite the high positive bias in m_1 , the equilibrium unfished mortality M_0 had a smaller bias of around -5%, thanks to the negative exponential relationship between M_1 and M_0 , as well as the asymptotic lower limit M_b . The other unfished equilibrium biomasses B_0 and $2 + B_0$ were also positively biased, at 9% and 12% respectively. Interestingly, the unfished recruitment R_0 estimate had very low sensitivity to simulated age data, with a bias of 1%, largely because R_0 is used to initialise the age-structure in 1951 so there are data sets directly informing the estimation of R_0 , while

unfished biomass levels are indirectly inferred from stock productivity over the model history. As such, given the stable R_0 value, the effect of simulated age data on m_1 and M_0 are reflected in SB_0 and $2 + B_0$.

The All Data Simulated scenario and Random Priors scenarios largely followed the pattern of the Age Data Simulated scenario for life history parameters, and the Index Data Simulated scenario for observation model quantities, but with more variability. The main notable exception is the unfished recruitment parameter R_0 , where the bias and precision behaves more like the Index Data Simulated case, which makes sense given the low bias from the simulated age data scenario.

Simulating random prior mean values for the density-dependent model m_1 parameter increases variance and sometimes affects bias in most life history parameters, but there is no real effect on selectivity, steepness, or survey parameters (Figure 5). As expected, the largest effect of random prior mean values is on the estimates of m_1 ; the resulting relative error distributions have a large range, but there is a small decrease in the bias (Table 9). This behaviour reflects the challenges with identifiability of m_1 , as identified in the Methods section. The degree of potential bias is not especially large and the effect on unfished mortality is proportionally much smaller, given the model specification. Further, process errors tend to compensate for the larger relative errors in mortality parameters, leaving most time-series estimates somewhat insensitive to the random priors (compare third and fourth column, Figure 6).

Overall, the level of bias and variation in life-history and survey parameters is not highly concerning. Most median relative errors are lower than 20% in magnitude and most distributions intersect zero, indicating that SISCAH model posteriors likely contain the correct value of most parameters for the CC population (Figure C.1). Additionally, biases in life-history parameters can have minor effects on population dynamics, as their effect is generally modulated by process error terms. Indeed, under the Index Data Simulated scenario, spawning biomass and recruitment tend to have a positive relative bias of around 0.1–0.2, consistent with the negative relative error in surface survey catchability (Figure 6); under the remaining scenarios there is still a small amount of bias, generally between -0.05 and -0.1. The reduction in bias can be attributed to changes in recruitment and mortality process errors, exemplified by higher variation in the natural mortality relative error envelopes, but low relative bias (Figure 6, third row). Process errors tend to have freedom to adjust to compensate for changes in the underlying life-history parameters, and this ability is further enabled by the additional variation in simulated age data here. Therefore, the resulting estimates of model states such as spawning biomass, recruitment, or demographic rates such as natural mortality, are somewhat insensitive to the bias in related model parameters (Figure 6).

The small negative bias in age-at-50% selectivity means that SISCAH includes more younger fish in the selected numbers for that fishery, translating into a positive bias in the vulnerable biomass for all three commercial fisheries (Figure 6). The overall effect of this bias in the history is minor, given that spawning biomass and mortality time series are not highly biased, but may indicate a negative bias in SISCAH model estimates of harvest rates for the historical period. It is currently unclear what the source of the bias is, as there are no priors applied to the selectivity parameters and there is very little variation in the estimation envelopes (Figure 5, Table 9).

3.3.2. Strait of Georgia

Simulation self-tests for SOG follow a similar pattern to the CC region, but with higher variation for some quantities (Figure 7). The Index Data Simulated scenario primarily affects surface

survey catchability and spawn index residual standard error components, and the Age Data Simulated scenario primarily affects life-history parameters.

As for CC, the simulated spawn index under the Index Data Simulated data generates some a negative bias of about 10% in the surface survey catchability component, which is probably linked to a negative mean spawn index residual error of -0.18 induced by the blended index (Figure D.57). As above, the bias in q_s also affects SB_0 , R_0 , m_1 , and M_0 , via the induced change in the DDM curve required to arrive at similar annual Mt estimates (Figure 8).

Under the Age Data Simulated scenario, there was a pronounced effect on m_1 , with a median relative error of around 0.6. In turn, the positive bias in m_1 created negative bias in M_0 , with an MRE of -0.07. As in CC, R_0 is used to initialise the SOG herring age-structure in 1951, so there is practically zero bias in R_0 based on simulated age data, suggesting that the spawn index in 1951 is more influential on unfished recruitment than the reduction fishery age composition data. Again, given the insensitivity of R_0 to simulated age data, the positive bias in m_1 and resulting negative bias in M_0 are reflected in positive bias for unfished biomass parameters SB_0 , $2 + B_0$, and negative bias in stock-recruit steepness h , or a larger and less productive stock.

Under the All Data Simulated scenario, where index and age composition data are simulated, the largest effect is again on the m_1 parameter. Negative bias in m_1 induced by simulated index data appears to offset the high positive bias when age data are simulated, arriving at a median relative error of 0.38 (Table 9, Figure 7). Bias from the two simulated data sets also seems to compound for q_s estimates, but not really for any other quantities (Figure 7).

The only parameter that is significantly affected by the Random Priors scenario is m_1 . Relative error distributions for all other quantities under the Random Priors scenario are basically identical to the All Data Simulated. As with CC, the random priors increase the variation in relative error distributions for m_1 and draw the bias a little lower than the All Data Simulated scenario.

Time-series of relative errors for SOG spawning biomass, depletion, and mortality show similar results as CC. The main differences are for the Age Data Simulated scenario, where the effects of the positive bias in SB_0 are observed in a negative bias in spawning biomass depletion estimates, especially after the surface survey years where catchability is primarily taken from the dive survey (Figure 8).

Selectivity model parameters also show a similar pattern to CC, where age-at-50% selectivity parameters have low bias and low variation in all scenarios. Median relative errors are at most 0.05 in magnitude, and the relative error distribution for gillnet does not overlap zero for Age Data Simulated and All Data Simulated (Figure 7). Again, this leads to an over-estimation of vulnerable biomass in the gillnet fisheries, which is caused by inclusion of a higher proportion of younger fish when fit to simulated age data.

3.4. SUMMARY OF STOCK ASSESSMENTS FOR FIVE MAJOR SARs

Overall, the stock assessments for all major SARs have acceptable goodness of fit and produce plausible estimates of model parameters and historical fishery dynamics. Posterior estimates of life-history and stock-status quantities indicate acceptable levels of uncertainty overall, with relative standard deviations in the 10%–20% range (Table 11; note that SB_0 uncertainty is reported as half of the interquartile range, for reasons described below).

The shape of the DDM model interacts with recruitment process deviations to increase average mortality rates, and decrease biomass, under stochastic (i.e., realistic) recruitment. Log-normal recruitment process deviations create a skewed distribution in age-2+ biomass, which translates

through the DDM model to generate a skewed distribution in mortality (Figure 9). Given the asymptotic lower limit M_b in the DDM $M \sim B$ relationship, there is an asymmetry in the function that adjusts the shape of the M distribution, so the long tail in biomass depletion above unfished translates into a higher density of natural mortality between M_b and M_0 , and the higher density in biomass depletion below 1.0 is stretched in the natural mortality distribution. The shape of the resulting distribution depends on the m_1 parameter and the σ_R value, but the result is a median mortality rate above M_0 , leading to lower average survival of recruits, in turn sustaining a lower average biomass even in the absence of fishing.

The interaction between recruitment variability and average mortality rates implies that simulation must be used to estimate unfished biomass and other fishery reference points. Given the variation driven by process errors, there is a need to integrate over a long time period to draw out ‘average’ behaviour. With longer time periods comes higher probability of very large or very small recruitment events, which means that biomass, yield, and other quantities can vary widely. Therefore, uncertainty in the value of unfished biomass and biological reference points derived via simulation is generally higher than would appear in most compensatory stock assessment models based on constant or density-independent natural mortality. Additionally, given the simultaneous integration over process errors and posterior distributions, there is too much noise to estimate model equilibria for each posterior draw, so a posterior standard deviation is not derivable. Instead, we estimate the 25th, 50th (median), and 75th percentile of unfished biomass and other reference points and report uncertainty as half of the inter-quartile range.

Given lower stochastic estimates of SB_0 derived via simulation, all five major herring SARs are estimated to be above their respective limit reference points (LRPs) in 2022 (Table 11). For example, in Haida Gwaii, stochastic SB_0 is now estimated around 7.6kt, putting 2022 biomass at around 141% of unfished levels. The remaining areas are similar, but the effect is not so pronounced. The remaining regions are estimated to be at 63%–70% of (stochastic) unfished biomass in 2022 (Table 11). To some degree, this is expected given that most stocks have been either lightly fished, or not fished at all, for several herring generations with limited signs of stock growth. Those persistent high mortality, low biomass regimes in some areas are being reflected in the model equilibria under the DDM formulation.

Biomass trends of all SARs largely reflect trends established by previous assessments because both ISCAM and SISCAH dynamics are primarily influenced by removals (or lack thereof) and spawn indices, where the latter are primarily assumed to represent absolute spawning biomass since 1987. Therefore, estimates of biomass are stable in the presence of several novel structural components in SISCAH. Overall, biomass is trending upwards, on average, over the last 10 years for all SARs.

The magnitude of estimated m_1 has a substantial impact on stock recovery from low abundance periods. In particular, higher values of m_1 allow mortality rates to return to unfished levels more rapidly following low abundance, and these stocks show faster recovery (e.g., SOG, CC). Conversely, lower values of m_1 , especially in HG and WCVI, result in slower recovery as mortality rates decline more slowly as biomass increases.

Estimates of MSY based reference points have several differences from previous assessments using ISCAM (Table 12). The density-dependent formulation for M explicitly includes a depensatory effect on the population at low stock sizes, which is the reduced productivity of a population at low abundance. Usually, when fisheries catch only mature herring with a 100% mortality rate, that depensation would shift the optimal yield and harvest rates lower. Here, the inclusion of spawn-on-kelp fisheries, with a relatively high post-ponding survival rate, produces higher optimum harvest rates but still relatively modest yields for some of the smaller SARs

(Figure 10). SARs with a higher proportion of SOK fishing can generally handle higher harvest rates because around 70% of the catch that is allocated to SOK fisheries survives harvest, and the total SOK yield is around 8% of the total ponded biomass in each year.

Equilibrium simulations show that for all stocks using the DDM model (i.e., excluding PRD), there is decline of biomass, yield, and recruitment to zero at harvest rates above a given point (Appendix D). These harvest rates, defined as U_{crash} , are associated with the steepest decline in equilibrium biomass and yield, and range from 9.7% for the CC region to 42.6% for the SOG region. Overall, U_{crash} values are around 50% or 100% higher than optimal harvest rates U_{MSY} , with the smaller differences occurring for higher U_{MSY} values. Furthermore, absolute values of both U_{MSY} and U_{crash} depend on how harvest rates are defined in the presence of SOK fisheries, as noted elsewhere in this paper.

Higher uncertainty in stochastic equilibrium values appears to correlate with lower m_1 parameters. As discussed in the Methods, there is a higher probability of exceeding unfished equilibrium biomass SB_0 for SARs with a lower m_1 value, as this leads to a higher probability that annual M_t values drop below the equilibrium M_0 . This is reflected in the per-capita surplus production, where areas with lower m_1 values, such as HG and WCVI have a higher rate of historical estimates of SB_t above the unfished level (compare range of estimated points vs. simulated lines, Figure 11), whereas CC has only a moderate amount, and SOG has one or two years where biomass is estimated above the stochastic equilibrium value of SB_0 .

The behaviour of equilibrium per-capita surplus production relative to spawning biomass levels is somewhat related to the m_1 parameter, but fairly consistent overall. For the most part, SARs with lower m_1 values have more gradual reductions in equilibrium biomass and yield, leading to more of a smooth tapering off in production after U_{crash} than an abrupt drop, while SARs with higher m_1 values have a steeper decline from higher yields. However, this is not as apparent in estimates of per-capita surplus production, where the maximum per-capita surplus production occurs towards very low spawning biomass, and an abrupt collapse in surplus production as harvest rates exceed U_{crash} (Figure 11). This behaviour appears consistent across all the SARs with DDM models, regardless of the m_1 value.

3.4.1. Retrospective analysis

Retrospective analyses suggest herring biomass and life history parameters have low sensitivity to additional years of data, with time series of spawning biomass, recruitment, and mortality appearing very stable over the 10 year retrospective peels. Occurrences of over- and under-estimation of biomass appear with equal frequency for HG, PRD, CC, and WCVI (Figures D.18, D.35, D.54, and D.92), whereas for SOG, there is greater tendency for SISCAN to under-estimate biomass for the last couple of years peels (Figure D.73). In general though, observed stability in the biomass and mortality time series is a result of process errors that adjust slightly over time to compensate for the variability in life-history quantities.

All SARs show some variability in unfished equilibrium quantities over the retrospective peels. Changes are observed in estimates of unfished biomass SB_0 and/or unfished recruitment R_0 for all stocks over the 10 years. Declines in unfished biomass over the retrospective analysis occur for HG, PRD and WCVI, ranging from 4% to 15%, whereas unfished biomass is fairly stable for CC, and increases by about 14% in the SOG region (details in Appendix D). The stability observed in unfished biomass for CC stems from changes in M_0 and R_0 to compensate for changes in the data.

Overall, the stability observed in the retrospective estimates indicates biological reference points and other management related quantities are likely to remain stable over time, potentially providing higher stability in management decisions as compared to the previous model. Specifically, ISCAM included time-dependency in unfished biomass and fishery reference points estimates, which was due to the time-averaged M used for stock-recruitment calculations (e.g., PRD retrospective, Table D.6). Stock specific retrospective analyses are presented in Appendix D.

3.4.2. Sensitivity analysis

SISCAH model estimates did show some more significant sensitivities to model priors, but these are within expected ranges for age-structured stock assessment models. The most influential sensitivity tests were the prior mean on M_0 , the variation in the M_t process deviations, and the stock-recruitment steepness prior mean. Additionally, as usual the steepness prior had a stronger effect on estimates of steepness and a weak effect on most other model parameters. The remaining sensitivities had little effect on most parameters (Tables D.3, D.7, D.11, D.15 D.19).

The parameters used to initialise herring populations in a fished state (i.e., F_{init} , R_{init} , ω_a^{init}) sometimes affect unfished equilibria, but do not have a large effect on current biomass. In general, applying an initial fishing mortality F_{init} increases unfished spawning biomass SB_0 , and sometimes unfished recruitment R_0 . If unfished biomass is adjusted with little effect on R_0 , it is because the initial fishing mortality effectively reallocates the initial total mortality from natural to fishing mortality, adjusting m_1 and M_0 . Therefore, a similar (or lower) R_0 arrives at a higher SB_0 given lower M_0 . On the other hand, sometimes the effect of F_{init} is greater on R_0 or R_{init} than on M_0 . In such situations, the total initial mortality is increased, pushing initial recruitment (i.e., R_0 or R_{init} , depending on the SAR) higher so model estimates of initial numbers-at-age remain similar; when R_0 is used to initialise the model, then F_{init} will also increase SB_0 .

3.5. DEMONSTRATION OF MANAGEMENT PROCEDURE EVALUATION

3.5.1. Operating model conditioning

Operating models are conditioned to random draws of the SISCAH model posteriors, and faithfully reproduce the historical dynamics of all herring SARs. Simulated dynamics in the projection period are also comparable to historical dynamics, as indicated by comparing the distributions of absolute recruitments between the historical and projection periods for each SAR (Figure 12).

3.5.2. Management procedure performance

The addition of SOK lowers the effective harvest rate from a given TAC. Under SOK fishing practices, a significant portion of the impounded fish are released alive, returning to the spawning stock in the following year. As such, higher rates of ‘whole-fish’ harvest are achievable with less overall fishing mortality felt by the stock. As discussed above when estimating reference points, the higher the allocation of TAC to SOK fisheries, the higher the optimal harvest rate that maximises fishery yield (Figure 10). Additionally, the effect of SOK allocation on optimal harvest rates is likely under-represented for this paper, as we treat all SOK catch as closed-pond fishing, with an assumed post-ponding mortality rate of 30%, and some of the catch in some SARs is confirmed to be from open-pond fishing. The assumption of all closed-pond SOK fishing acts as an upper bound on the total fishing mortality from SOK fishing, and is assumed since some of the catches could not be attributed to either open- or closed-

pond fishing. In future, catches that can be identified can be broken out into open- or closed-pond data series, improving the estimates of SOK fishery impacts on stock health.

For closed loop simulations, TAC allocation is set to the same allocation used to estimate fishery reference points. That is, fishery allocation is the observed proportion of landings in each sector over the most recent 20 years with fishing activity (Table 7).

3.5.2.1. Haida Gwaii

All MPs meet Objective 1, exceeding 30% of unfished biomass over 75% of the time under perfect information (all MPs have higher than 87% probability, Table 13, $P(SB > 0.3SB_0)$). The LRP objective is easily met given that the stochastic equilibrium SB_0 is 7.31kt for Haida Gwaii, and the current posterior median biomass is very close to this level (Table 11). In contrast, no MP meets the USR target objective (Table 13, $P(SB > USR)$), with the highest probability of exceeding the USR estimated to be 16.4% under the NoFish MP. The inability of achieving Objective 2 for Haida Gwaii is related to the scale of the USR, set to around 3 times unfished biomass (Figure 13, green line). Therefore, the only way that biomass can increase to that level is for a series of high recruitment events, as was the case for the period leading up to the time frame used to define the USR for Haida Gwaii.

Median average catch under the U_{MSY} MP is approximately 840t in the seine roe or gillnet fisheries and around 31 t (68,200 lbs) of spawn-on-kelp landings (Table 13, $\bar{C}$ and $\bar{K}$). On the other hand, there is considerable interannual catch variation at 31.5%, as well as a 14%–15% probability that annual landings are below the minimum observed in the history for the region (Table 13, AAV_C , AAV_K , and $pUnviable$). Given the low absolute catch levels, the catch variation is driven by small absolute differences in catch, which in turn is largely driven by recruitment process error. As described above, the interaction between stochastic recruitment and the DDM model generates a wide range of biomass levels in simulations, which in turn leads to large percentage variation in yields. Visually, high variability for HG herring translates into very wide simulation envelopes, and a very slow equilibration of biomass to the target harvest rates (Figure 13), despite harvest rates being at the reference removal rate with greater than 50% probability.

3.5.2.2. Prince Rupert District

Similar to the Haida Gwaii SAR, all MPs achieve Objective 1 in the PRD SAR, this time with practically 100% probability. Additionally, two MPs achieve Objective 2 (Table 13), namely the U_{USR} MP with 57% probability, and the NoFish MP with 81% probability. The U_{MSY} and $0.5U_{MSY}$ MPs do not meet the USR objective as their harvest rates are both higher than U_{USR} , implying lower equilibrium biomass levels. Indeed, the B_{MSY} estimate for PRD herring is very close to the harvest control rule's lower control point (and limit reference point) of $0.3SB_0$, which makes it impossible for the reference removal of U_{MSY} to be achieved since the median spawning biomass is primarily on the ramp of the harvest control rule (Figure 14).

Given the general size of the PRD stock ($SB_0 = 48$ kt) the median average catch is quite high. Mature fish yields from the gillnet/seine fisheries range from 2300 t (U_{USR}) to 5100 t (U_{MSY}), and SOK yields range from about 50 t (110,000 lbs) of SOK product to 107 t (235,400 lbs). Interannual catch variation (AAV_C and AAV_K) also varies with yield, ranging from about 10% under U_{USR} to 20% under U_{MSY} . Finally, there is almost zero chance of an unviable fishery, with only 1% probability of catches below the historical minimum under the U_{USR} harvest rate, and zero chance otherwise.

3.5.2.3. Central Coast

All Central Coast meet Objective 1, but any MP with positive rates of fishing have a difficult time meeting the USR objective (Table 13). Out of the MPs that allow fishing, U_{USR} comes closest to meeting Objective 2, with spawning biomass exceeding the USR around 33% of the time. The lower performance with respect to the USR is basically driven by the median biomass in 2022 being well below the USR, and the time it takes for the stock to equilibrate to the harvest rates (Figure 15).

Yields in the CC SAR are similar to PRD, with average landings of mature fish from seine/gillnet fisheries ranging from 2300 t to 4300 t, and spawn on kelp product ranging from 94 t (206,800 lbs) to 176 t (387,200 lbs). The probability of TACs below the historical minimum moderate compared to most other SARDS, at around 7% for U_{USR} and 0.5 U_{MSY} , and 9% for U_{MSY} .

3.5.2.4. Strait of Georgia

Objective performance for SOG herring is different to other areas, given the scale of the stock and the relative size of its USR. All MPs meet Objective 1 (Table 13), and since the USR is well below SB_0 , Objective 2 is practically met by both the U_{USR} and 0.5 U_{MSY} MPs (Table 13). Indeed, since $0.5U_{MSY} < U_{USR}$, the 0.5 U_{MSY} MP exceeds the 50% threshold for Objective 2 quite comfortably at around 58%. In all MPs, median biomass tends to equilibrate close to the equilibrium biomass associated with target harvest rates, missing B_{MSY} slightly due to the proximity of B_{MSY} to the lower control point of $0.3SB_0$ (Figure 16).

As expected from historical performance, there is very low probability of an unviable fishery at any harvest rate for SOG. Average catches range from 12 kt to 18 kt (Table 13), and the maximum probability of a closure is 6%, observed when targeting U_{MSY} (Table 13, pUnviable).

3.5.2.5. West Coast of Vancouver Island

Finally, the West Coast of Vancouver Island SAR has similar results to the Central Coast SAR. All MPs meet Objective 1, but due to the very high USR that is just below SB_0 there is a low chance of exceeding the USR. Indeed, the maximum probability of $SB > USR$ is 43.7% under No Fishing (Table 13, Objectives). For both the U_{MSY} and 0.5 U_{MSY} MPs, the effective harvest rate is often reduced from the reference removal rate, like in most areas where the biomass equilibrates near the $0.3SB_0$. (Figure 17).

In contrast to Central Coast, the three MPs with fishing produce lower catches, with yearly averages at around 1400 t for the 0.5 U_{MSY} MP, and 2500 t for the U_{MSY} MP, with a corresponding 11 t and 20 t, respectively, of SOK product. The probability of unviable catches for WCVI is highest across all SARDS, averaging around 15%–17% of years and time-steps (Table 13, pUnviable). The interannual variation in catch is not quite the highest for the WCVI region, ranging between 21% and 28%, but WCVI could be grouped with SPG and CC for equal second highest AAV.

4. DISCUSSION

This paper develops a new Spatially Integrated Statistical Catch-at-Age Herring (SISCAH) model as a substantial step forward in herring fishery assessment and management modelling, integrating the feedback from reviewers in previous rounds of MSE and stock assessment peer reviews (DFO 2020d, 2022b). Specifically, the feedback has resulted in seven major structural changes from the previous assessment model (ISCAM) that SISCAH now includes:

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1. A depensatory density-dependent natural mortality model that implicitly explains time-variation in natural mortality rates as a function of biomass (Haist et al. 1993), rather than as a descriptive random walk.
 2. Spawn-on-kelp fisheries in all areas except Strait of Georgia, to reflect the impact of removing spawn with reduced mortality on spawners.
 3. Fishery removals modelled as discrete pulse events at a given time of year reflecting the short season around herring spawning aggregations, rather than as continuous fishing mortality over the entire year.
 4. An embedded density-independent M model formulated as a simple random walk, for comparison with previous modelling approaches.
 5. Specification in Template Model Builder (Kristensen et al. 2015).
 6. A single blended spawn index combining dive and surface survey designs, which acknowledges that there are several years in the data set where spawn observations have been collected using both designs.
 7. An improved likelihood function for age composition data that includes lag-1 autocorrelation in age-composition residuals, reflecting that sampling errors may have a latent size- or age-based component.

Out of these changes, the single highest impact was from the inclusion of the density-dependent mortality model. As such, we focus the remainder of this discussion on describing and explaining the main effects on stock assessments and management procedure evaluation.

4.1. DENSITY DEPENDENT M IN STOCK ASSESSMENTS

Application of the full SISCAN model to five SARs has produced many valuable insights about the implications of using a depensatory DDM model and its effects on population parameter estimates. The five major herring SARs provide a natural experiment for studying the effects of the DDM model on estimates of BC herring life history parameters, historical biomass, and management related quantities. These five areas provide data sets from multiple stocks of the same species, each of which has a similar life history but very distinct exploitation patterns, as well as a long history of other assessment modelling approaches to draw on for comparison.

While there is some history of a non-linear DDM model being explored in the context of herring populations (Haist et al. 1993; Haist and Schweigert 2009), the current implementation in SISCAN is the first time we know of that the model specification suggested in Haist et al. (1993) has been applied for a fishery stock assessment. A linear DDM model has been explored for Ling Cod assessments in the Strait of Georgia (Logan et al. 2005), which could either be depensatory or compensatory depending on parameter values, but there are limited other examples that we could draw from.

We learned through this analysis that the DDM model we implemented has a sensitivity to recruitment process error variation. Specifically, under high recruitment process error variance, there is a tendency for mortality to equilibrate to constant fishing mortality slightly higher than the expected (deterministic) value of the DDM model, and biomass to equilibrate slightly lower. The effect is caused by an interaction between the asymmetry of the DDM model and the effect of uncertainty in recruitment (Figure 9). The distribution of depletion levels under log-normal recruitment variability is skewed, and when that distribution is transformed through the asymmetric DDM curve the resulting mortality distribution shifts the density. The way that density is shifted is dependent on the m_1 parameter value. Lower m_1 values spread density more evenly over the range, while higher m_1 values accumulate density closer to the asymptotic lower

limit M_b . In either case, the average mortality is higher, and therefore survival of each cohort is lowered, making biomass equilibrate at lower levels.

It may seem desirable to reparameterise or respecify the DDM model to reduce the sensitivity to recruitment process errors. For example, previous work has explored a similar non-linear model with zero as the asymptotic lower limit on mortality (Haist and Schweigert 2009). Under deterministic conditions there is no issue, but when simulating populations the presence of recruitment process error there could be situations where a string of positive recruitments drives biomass well above unfished levels, and as a result mortality drops close to zero (Haist and Schweigert 2009). As a result, the stable equilibrium at SB_0 does not exist under that formulation, and modelled biomass can therefore grow indefinitely. Alternatively, the linear model formulation with maximum and minimum values nominated over the biomass range could be adopted (Logan et al. 2005), but that also has similar issues. In the presence of recruitment process errors, biomass will occasionally go above unfished levels, requiring analysts to choose a behaviour for that new range. For the Logan et al. (2005) model, the options are to fix mortality at the rate associated with unfished biomass, or to allow the mortality to continue the linear trend with biomass. In the former case, the issues of an asymptotic limit are still present as mortality distributions will accumulate at the new limit. In the latter case, allowing the model to keep changing would require (in a depensatory model) a new limit at zero, which again removes the stable equilibrium at the unfished biomass level. Additionally, in either case the change in slope at the limit would create a cusp on the mortality model, which could introduce discontinuities in the first derivative of the objective function, creating problems for model fitting.

While there are some notable differences between ISCAM and the full SISCAN model, both models produce qualitatively similar absolute biomass trends and deterministic estimates of SB_0 . The initial step from ISCAM to the base SISCAN model in the transition analysis has the largest effect on model estimates, generally leading to drops in model estimates of the deterministic unfished biomass, and increases in unfished recruitment and mortality. Then, each feature of the full SISCAN model is examined, differences in equilibrium unfished biomass are reduced. Additionally, despite similar unfished biomass estimates, the full model often has higher unfished recruitment, which is offset by adjustments to the unfished mortality and/or changes in stock-recruit steepness. Similarities in absolute biomass and deterministic unfished equilibria is somewhat intuitive, given that spawning biomass dynamics are constrained by recent catches and spawn indices, the latter of which are largely assumed to be absolute estimates of spawning biomass. Additionally, differences in R_t and R_0 between models are expected when the DDM model introduces changes to natural mortality time-series, but the absolute spawning biomass remains quite similar.

Finally, we made a strong assumption about age-1 mortality, setting it to M_0 for simplicity. The assumption of unfished mortality for age-1 fish likely has an effect on the SISCAN's interpretation of data and estimates of model equilibria, as even though age-1 (and age-0) fish are very rarely encountered by fisheries and scientific surveys, age-1 recruitment estimates are the result of the stock-recruitment model and related quantities. If age-1 mortality was different, but numbers-at-age-2 estimates remained similar, there would be an adjustment to age-1 recruitment that would affect the R_0 , and through it, SB_0 and $B_{0,2+}$, with follow on effects for the DDM model parameters, and so on. Additionally, there is evidence of density dependence in the body condition of young-of-the-year in Pacific Herring (Reum et al. 2013; Boldt et al. 2019), which may imply density dependent mortality for those age groups given that worse body condition is associated with lower survival. In any case, there is limited evidence for what age-1 mortality may be for BC herring, and based on exploration of SISCAN via simulation/estimation and sensitivity analysis it would have limited effects on the absolute biomass levels, but future

work could explore alternative fixed age-1 mortality rates to understand its effect on reference points and unfished equilibria.

4.1.1. Biological reference points

Herring dynamics are typical of forage fishes, with boom and bust cycles driven by time-varying natural mortality rates (i.e., predation). Those cycles are driven by exogenous factors and confound age-structured stock assessment models, making it difficult to estimate the underlying intrinsic productivity of a stock, and therefore its unfished state (i.e., SB_0 and R_0) and equilibrium response to fishing (i.e., a yield curve). As a result, previous herring stock assessment models have estimated implausible MSY-based fishery reference points based on time-averaged natural mortality time-series, arriving at very high estimates of optimal harvest rates that produce unacceptable fishery performance in closed loop simulations (Martell et al. 2012; Kronlund et al. 2018).

In contrast, the full SISCAH model produces more plausible estimates of MSY-based biological reference points, many of which are different to those derived from ISCAM and more congruent with realized historical harvest rates. There are three main drivers of the change in fishery reference points. The first is intuitive and somewhat easy to predict, as it relates to the deterministic DDM model specification, driving estimates of MSY lower and estimates of B_{MSY} higher. This is as expected, given that the DDM model creates a compensatory feedback between fishing pressure, biomass, and natural mortality. As fishing pressure is increased, biomass drops, causing an increase in natural mortality and a compounding effect that accelerates the effects of fishing. As a result, the optimal fishing mortality rate under a density-dependent model is lower than under a density-independent model, such as a random walk, leading to a higher optimal biomass B_{MSY} and, often, lower optimal yield MSY.

The second driver of SISCAH fishery reference points is somewhat less predictable, as it stems from interactions of multiple non-linear stochastic processes. Specifically, as outlined above, asymmetry in the biomass and mortality relationship causes mortality, in the absence of fishing, to equilibrate at values above M_0 in the presence of recruitment process error. As a result, the entire equilibrium relationship between biomass and fishing pressure is shifted downwards, leading to lower SB_0 and SB_{MSY} values. This asymmetry is modulated by the m_1 parameter, with lower values producing higher asymmetry, so the effects are most noticeable for HG and WCVI. In contrast, higher m_1 values push the steep part of the M curve to the left, effectively reducing the biomass range over which depensation occurs, so it's harder to trigger high mortality events. This creates relatively constant M over a wider range of biomass under high m_1 cases that also make it easier for populations to recover from low abundance.

Given the sensitivity to recruitment process error, we estimate fishery reference points via simulation. Simulations simultaneously incorporate recruitment and mortality process errors and parameter uncertainty via posterior sampling, and produce estimates that are consistent with the higher equilibrium mortality and lower equilibrium biomass described above. However 400 year simulations with 100 replicates each are required to integrate over all that uncertainty and give models sufficient time to equilibrate. Such an approach increases the probability of a longer string of negative recruitment process errors, which can create a feedback effect where biomass drops and mortality rates increase towards their maximum of $1 + M_b$, even in the absence of fishing. When that occurs, the extreme mortality rate then effectively drives the stock to extirpation, and the low spawning biomass and resulting low survival rates make it virtually impossible for the stock to grow without an extremely large recruitment. As the number of time-steps increases, the probability of this occurring within a time-step grows. For Central Coast herring, the effect is somewhat mitigated by estimating a posterior distribution for σ_R , thereby

including correlation between m_1 and σ_R in simulations, but DDM models for the remaining SARs did not converge with σ_R estimated. As such, we avoid the extirpation risk in the tails by using median values for point estimates of unfished biomass and reference points, and the central 50% of distributions to represent uncertainty, avoiding the extirpation behaviour in the tails of the distribution.

The value of m_1 also has a significant effect on the equilibrium behaviour of populations at low abundance. For all SARs, as harvest rates were sustained near or above U_{crash} , stocks would exhibit unstable equilibrium behaviour, consistent with component Allee effects. When $U \geq U_{crash}$, surplus production would drop, manifesting as an inflection point in equilibrium yield and biomass. Depending on the SAR, this would either be a gradual tapering off (HG, WCVI), or a sudden collapse (PRD, CC, SOG), with the difference largely driven by the m_1 parameter, but also affected by other life history characteristics. For example, in HG, PRD, and CC there are apparently stable equilibria where the per-capita surplus production was negative, but stocks had not yet collapsed. In contrast, SOG and WCVI always have positive per-capita surplus production before periods of instability are evident.

The third main driver of SISCAH MSY reference points is the allocation of TACs among fisheries. In particular, it is clear from preliminary simulations that allocating ponded fish as TAC to SOK fisheries results in higher optimal harvest rates, since most of those ponded fish are returned alive to the spawning population (Figure 10). Thus, the absolute values of optimal harvest rates U_{MSY} and the inflection point U_{crash} are scaled to the allocation of catch limits among fisheries. An alternative allocating dead ponded fish would bring U_{MSY} and U_{crash} lower, but complicate catch limit calculations for SOK fisheries.

One combined effect of the changes in equilibrium relationships is that stocks look healthier and more exploitable because of lower unfished biomass and higher harvest rates when SOK fisheries are larger (e.g., Haida Gwaii). These estimates could give rise to a misconception that fishery openings will be more common and catches larger in the future, but that is only half the story. A closer look at the simulation results shows that, although the stock is healthier and there are more openings, the average catch over the projection period is very low, and the probability of unviable fisheries (catch limits below the historic minimum) is elevated as well. A better interpretation is that the equilibria are better scaled to recent stock dynamics, instead of the historical average level used by density independent models, which has not been observed in some SARs for more than 2 decades.

4.2. DENSITY DEPENDENT M IN CLOSED LOOP SIMULATIONS

The simulations in this paper represent a significant, pragmatic step forward in management procedure evaluation for BC herring. Time varying natural mortality has been a component of Pacific Herring stock assessment models since the mid 1990s, and has been the key driver of projection scenarios in the herring MSE (Cox et al. 2019; Benson et al. 2023). However previous MSE cycles took the approach of testing MPs against projection scenarios representing optimism and pessimism in M via random walks with “ M increasing”, “ M decreasing”, and an additional “ M constant” scenario. The random walk approaches are largely dependent on an analyst’s choice about where mortality ends up, and how quickly it gets there. Additionally, projected random walks didn’t appear to match the historical estimates of dynamics. Over the years, herring MSE analysts have considered ways to modify parameterisation of M in the projections to include depensation, with limited success.

The new SISCAH DDM model’s mechanistic explanation of density dependence in natural mortality produces more realistic operating model dynamics for testing candidate management

procedures (Haist et al. 1993; Haist and Schweigert 2009). Future dynamics in projections appear to match the historical dynamics well, retaining the time-variation of the history while eliminating analyst choice.

The results of closed loop simulations show that most MPs do very well with respect to the limit reference point objective. This is partially because the stochastic equilibrium value of SB_0 is lower than the deterministic SB_0 , making it much easier to exceed 30% of SB_0 .

4.3. EVALUATING HERRING MANAGEMENT PROCEDURES

The current approach to setting catch limits for herring SARs requires a lot of analysis to stay consistent with the PA policy. Each SAR has been through at least two MSE cycles, during which PA-policy-fulfilling management procedures were identified for all SARs except for Haida Gwaii (DFO 2020a; Benson et al. 2023); however, formal management procedures have not been adopted in a manner consistent with how they were evaluated. Harvest control rules are tested through simulation for 15 year time periods. As practiced the choice of target harvest rates and harvest control rules often change yearly based on expert judgement of the herring systems and/or unspecified objectives. As a result, DFO analysts have had to re-test the new management procedures frequently, even annually, a process that sometimes requires iteratively adjusting the HCR and harvest rates of the MP until the conservation performance is met (DFO 2023a). While such an approach may appear more conservative on the surface, there is a high likelihood that it unnecessarily reallocates analytical resources for limited gain in conservation performance. More than that this method also ignores longer term objectives, such as minimizing average annual variability. While adjustments to the harvest rate may occur, and reductions in harvest rate would in fact tend to lead to better performance against conservation objectives, the yearly changes in harvest control rules make it difficult to stay within PA4 above. Yearly changes create a de-facto management procedure that has not been simulation tested, so performance against objectives has not been evaluated. Additionally, annual changes to choice of management procedure create variation in OM estimates and performance metrics that are more based on noise from a single additional year observational data, rather than medium- or long-term trends that are well established when model updates are separated by 3 or more years.

4.4. RECOMMENDATIONS AND NEXT STEPS

4.4.1. Further SISCAH model development

1. An additional spatial component to herring stock assessments, to take advantage of the latent spatial structure in SISCAH, exploring one or more of the following:
 - a. A hierarchical model containing several SARs (Johnson and Cox 2018), where shrinkage priors are used share information among stocks to help SISCAH estimate highly uncertain parameters (e.g., $m1$, Mb , h).
 - b. A coast-scale spatial model incorporating movement among two or more SARs, exploring long standing hypotheses linking the three northern regions and two southern regions.
 - c. A SAR-scale spatial model incorporating movement among smaller management regions (e.g., PFMA) within each region, which is supported to some degree by historical tagging data.
2. Reparameterisation of the DDM model:
 - a. to reduce correlation between $m1$ and SB_0 ,

-
- b. to investigate a possible correction factor to bring deterministic and stochastic equilibria into line.
 3. Ensure that documentation and analyses allow reproducibility of results. The novelty of the DDM model introduces complexity to the analysis that some analysts may be unfamiliar with, and the size of this paper implies that a lot has gone into the development of the new modelling framework, and that there may be difficulty in reproducing this work outside of the list of authors.
 4. Define prior predictive checks to understand the influence of model priors relative to the data.
 5. Consider other sources of underestimated bias, including treating the dive survey as a presence-only survey.

4.4.2. Further MP development and timelines for routine MSE updates

The original herring HCR combining a 20% constant harvest rate with a constant escapement target of $0.25B_0$ was applied to SOG beginning in 1986, and subsequently to the other 4 SARs (though not simulation-tested for those areas). The rule was derived via simulation based on SOG stock dynamics and supported harvest rates up to 30% harvest rate for that area (Hall et al. 1988; Haist et al. 1993; Zheng et al. 1993). However, contrary to the predictions of the analyses done in the late 1980s, some herring SARs fell below the escapement target (aka cutoff level) relatively frequently, and despite reducing harvest rates, 3 of the 5 SARs fell into low productivity/ low biomass states beginning in the early 2000 and remained unproductive for long periods (Kronlund et al. 2018; Forrest et al. 2023).

Herring stock assessment science and the management actions dependent on those assessments continue to evolve incrementally. Since the development of the original management plan for BC herring, scientists' and managers' understanding of factors affecting herring productivity has evolved. Additional evidence has been gathered indicating environmental and ecological changes that have impacted size at age and natural mortality rates, as well as significant differences among herring SARs. As a result, those changes and differences were not considered in the original simulation-evaluation work, and it is unsurprising that when applied to other SARs the original herring MP did not perform as expected.

It is clear from all previous iterations of the herring management system that time-varying M is one of the most important influences on herring dynamics. Previous steps have accounted for time-varying M in assessment and MP evaluations (Cox et al. 2019; Benson et al. 2023), but as this paper shows, MPs must also account for the source of that time-variation, such as with the DDM model, or there will continue to be model mis-specifications that generate divergence between expected performance of simulated MPs and the true performance of the MP when applied to the real system. Model misspecification may also lead to divergence between science advice and real life experience on the water.

The Pacific Herring MSE process should aim to establish repeatable management procedures for each SAR that have a high chance of meeting overall fishery objectives. Indeed, where they have been adopted, simulation-tested MPs provide stability in the management system. Operating models like SISCAH are needed to simulate a range of ecological hypotheses influencing herring stock dynamics such as predation, food availability, growth, movement, stock structure, etc. Testing MPs against such scenarios could provide a better sense of reliability and, hopefully, repeated application of chosen MPs over several years before revisions are considered. This stands in contrast to the current approach where MSE-like simulations are performed every year in addition to full-blown stock assessments for each SAR.

Since its inception, herring MSE updates have occurred every 1–2 years. This frequency provides insufficient time for the consultative component of MSE and for analysts to develop the model structure needed to explore new ecological hypotheses and MPs. Suitability of biological reference points (e.g., LRP), biomass objectives (e.g., USR), and performance metrics used for monitoring short- and longer-term objectives should be considered and evaluated alongside operating model development, and updated or reviewed when appropriate. Going forward, the authors recommend adopting a minimum 3-year timeline for MSE updates, with choice of operating models defined via peer-review and MP choices via some form of management review (i.e., establishing objectives and evaluating MP performance), and for the frequency of MSE updates to be decided in conjunction with Fisheries Management. Annual stock assessments could be embedded within the MPs and could be used to examine realized MP performance against the original expected performance in MSE simulations (e.g., exceptional circumstances). Substantial deviations from the original expectations could be grounds for earlier revisions to the assessments, operating models, and MPs.

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6. TABLES

Table 1. Notation used in the SISCAH operating model.

Symbol	Value	Description
T	72	Total number of time steps 1951–2019
A	10	Plus group age-class
t	1, 2, ..., T	Time step
a	1, 2, ..., A	Age-class index
a_g^{min}	2, 2, 3, 2	Minimum age class selected by fishery g
g	1, 2, 3, 4	Gear index for (1) Reduction, (2) Seine Roe, and (3) Gillnet fisheries, and (4) the open/closed pond SOK fishery.
SB_0	-	Unfished spawning stock biomass
h	-	Beverton-Holt stock-recruitment steepness
R_0	-	Unfished equilibrium recruitment
R_{init}	-	Initial recruitment parameter
S_a	-	Unfished equilibrium survivorship-at-age
ϕ_0	-	Unfished equilibrium spawning biomass per recruit
N_a^{eq}	-	Unfished equilibrium age structure
β_1, β_2	-	Beta prior parameters for stock-recruit steepness
ω_t	-	Annual recruitment process error log-deviations
ω_{init}	-	Recruitment deviations for each age-class in the first year
σ_R	-	Standard error of ω_t recruitment deviations
q_s	-	Surface survey design catchability coefficient
τ_s	-	Surface survey design spawn index residual standard error
q_d	-	Dive survey design catchability coefficient
τ_d	-	Dive survey design spawn index residual standard error
q'_t	-	Annual combined survey catchability
η_t	-	Proportion of annual spawn survey index that was observed by the surface survey design
mat_a	0, 0.25, 0.9, 1, 1,...	Vector of proportion mature at ages $a = 1, \dots, 10$
m_1	-	Depensation rate in density dependent M
M_b	-	Asymptotic lower limit (base) of density dependent mortality
M_0	-	Unfished natural mortality rate derived from density dependent mortality model
ϵ_t	-	Annual log-normal process deviations in natural mortality rate
σ_M	-	Standard error in annual natural mortality log-normal deviations
$M_{a,t}$	-	Natural mortality rate for age a herring at time t

Symbol	Value	Description
$w_{a,t}$	-	Annual average weight-at-age observations
$w_{a,g,t}$	-	Annual average weight-at-age observations from gear $g = 1,2,3$
s_g^{50}	-	Age-at-50% selectivity for gear $g = 1,2,3$
s_g^{95}	-	Age-at-95% selectivity for gear $g = 1,2,3$
$s_{a,g,t}$	-	Selectivity-at-age a for gear g in year t
δg	$\delta g \in [0, 1]$	Fractional time-step at which catch from gear type $g = 1, \dots, 4$ is removed from the population
$N_{a,t+\delta g}$	-	Total numbers-at-age a in year t at fractional time-step δg
$N_{a,g,t+\delta g}$	-	Total numbers-at-age a vulnerable to gear g in year t at fractional time-step δg
δ_{spawn}	1	Fractional time-step for herring spawning
SB_t	-	Spawning biomass at the end-of-year spawning event in year t
R_t	-	Age-1 recruitment at the beginning of year t
B_t	-	Total biomass at the beginning of year t
$B_{g,t+\delta g}$	-	Vulnerable biomass for gear g at time t (possibly fractional time-step)
$U_{g,t}$	-	Harvest rate by gear g in year t
K_t	-	Total landed weight of Spawn-on-Kelp product at time t
P_t	-	Biomass of fish impounded for Spawn-on-Kelp fishery at time t
$P_{a,t}$	-	Biomass-at-age of impounded fish for the Spawn-on-Kelp fishery at time t
$P'_{a,t}$	-	Numbers-at-age of surviving fish released from Spawn-on-Kelp ponds at time t
Ψ_t	-	Conversion factor from impounded fish to landed SOK
F	200	Average fecundity of mature, female herring (eggs per gram of spawning biomass)
$p_{m,t}$	-	Proportion of impounded fish that are mature at time t
$p_{f,t}$	.5	Proportion of impounded fish that are female at time t
$p_{eff,t}$	.35	Proportion of impounded fish at time t that will spawn
γ	0.0024	Conversion factor from eggs to SOK product
I_t	-	Observed blended spawn index at time t
$\hat{I}_t$	-	Expected blended spawn index at time t for dive and surface survey designs
τ'_t	-	Design-weighted standard deviation of blended spawn index log-residuals
μ_{q_s}	-	Log-normal prior mean for q_s
τ_{q_s}	-	Log-normal prior standard deviation for q_s
$u_{a,g,t}$	-	Observed age-composition data for age a by gear $g = 1,2,3$ at time t

Symbol	Value	Description
$\hat{u}_{a,g,t}$	–	Expected age-composition data for age a by gear $g = 1,2,3$ at time t
$B_{g,t}$	–	Total number of age classes with age observations above 2% of the total sample size in year t
τ_g^{age}	–	Conditional MLE of age composition sampling error
μ_{M_0}	–	Prior mean on unfished natural mortality
σ_{M_0}	–	Prior standard deviation for unfished natural mortality
a_1, a_2	2, 0.27	Shape and scale parameters for inverse gamma prior on τ_s and τ_g
z_t	–	Yearly z-score for blended spawn index observations
ρ_g	–	Correlation-at-lag-1 coefficient for age composition residuals
C	–	Lag-1 correlation matrix for age composition residuals
K	–	Dimension transformation matrix for age composition logistic normal likelihood
V_g	–	Transformed correlation matrix for age composition logistic normal likelihood
$W_{g,t}$	–	Yearly sample-sized based weighting for age-composition residuals in gear $g = 1, 2, 3$
$l_{g,t}$	–	Centred logistic normal age-composition log-residuals for gear $g = 1, 2, 3$ at time step t
W_{SB_0}	–	Jeffreys prior weighting on unfished biomass (and R_{init} for PRD)

Table 2. Process model equations for the SISCAH OM.

Model Parameters

No.	Equation
(P.1)	$\Theta^{lead} = (B_0, R_{init}, \{\omega_t\}_{t \in 1:T}, M_b, m_1, \{\epsilon_t\}_{t \in 1:T}, \{s_g^{(50)} s_g^{(step)}, \rho_g\}_{g \in 1:3}, \{\tau_g, q_g\}_{g \in \{s,d\}})$
(P.2)	$\Theta^{cond} = (\{\tau_g^{age}\}_{g \in 1:3})$
(P.3)	$\Theta^{fixed} = (\{\text{mat}_a\}_{a \in 1:10}, h, \sigma_R, \sigma_M)$
(P.4)	$\Theta^{priors} = (\mu_{M_b}, \sigma_{M_b}, \mu_{m_1}, \sigma_{m_1}, \{\mu_{s_g^{50}}, \mu_{s_g^{step}}, \sigma_{sel_g}\}_{g \in 1:3})$

Unfished Equilibrium States

No.	Equation
(EQ.1)	$M_0 = M_b + e^{-m_1}$
(EQ.2)	$S_a = \begin{cases} e^{-(a-1)M_0} & a < A \\ \frac{e^{-(a-1)M_0}}{1-e^{-M_0}} & a = A \end{cases}$

No.	Equation
(EQ.3)	$\phi_0 = e^{-\delta_{spawn} M_0} \cdot \sum_a S_a \cdot \bar{w}_a \cdot \text{mat}_a$
(EQ.4)	$R_0 = SB_0 / \phi_0$
Non-equilibrium Initial States	
No.	Equation
(NEQ.1)	$N_{a,1} = R_{init} \cdot S_a \cdot e^{\omega_a^{init}}$
Spawning Biomass, Recruitment, and Numbers-at-age	
No.	Equation
(N.1)	$R_{t+1} = \frac{4R_0 SB_t}{SB_0(1-h) + (5h-1)SB_t} \cdot e^{\sigma_R \cdot \omega_t}$
(N.2)	$SB_t = \sum_a e^{-\delta_{spawn} M_{a,t}} \cdot N_{a,t} \prod_g (1 - s_{a,g} U_{g,t}) \cdot w_{a,t} \cdot \text{mat}_a$
(N.3)	$N_{a,t+1} = \left\{ \begin{array}{ll} R_{t+1} & a = 1, \\ e^{-M_{a-1,t}} N_{a-1,t} \prod_g (1 - s_{a-1,g} U_{g,t}) + P'_{a-1,t} & 1 < a < A \end{array} \right\}$
Catch from Discrete Fisheries	
No.	Equation
(C.1)	$s_{a,g} = \begin{cases} 0 & a < a_g^{min} \\ \left(1 + e^{-\log 19 \frac{a-s_g^{50}}{s_g^{95}-s_g^{50}}} \right)^{-1} & a \geq a_g^{min} \end{cases}$
(C.2)	$N_{a,t+\delta_g} = N_{a,t} \cdot e^{-\delta_g M_{a,t}} \cdot \prod_{g' < g} (1 - s_{a,g'} U_{g',t})$
(C.3)	$N_{a,g,t} = s_{a,g} \cdot N_{a,g,t+\delta_g}$
(C.4)	$B_{a,g,t} = N_{a,g,t} \cdot w_{a,g,t}$
(C.5)	$B_{g,t} = \sum_a B_{a,g,t}$
(C.6)	$U_{g,t} = \begin{cases} C_{g,t}/B_{g,t} & g = 1, \dots, 3 \\ P_t/B_{g,t} & g = 4 \end{cases}$

Spawn-on-kelp

No.	Equation
(K.1)	$\Psi_t = \mathbf{F} \cdot p_{m,t} \cdot p_{f,t} \cdot p_{eff,t} \cdot \gamma$
(K.2)	$P_t = \hat{K}_t / \Psi_t$
(K.3)	$P_{a,t} = P_t \cdot \frac{B_{a,g,t}}{\sum_{a'} B_{a',g,t}}$
(K.4)	$P'_{a,t} = \frac{P_{a,t} \cdot e^{-M_{SOK}}}{w_{a,g=4,t}}$

Table 3. Data likelihoods, model prior densities, and the final objective function for the SISCAH OM. $I(X)$ is the indicator function that takes value 1 when the statement X is true, and 0 otherwise. Priors are described in distribution notation rather than explicitly as density functions.

Observation Models

No.	Equation
(O.1)	$\hat{I}_t = q'_t \cdot SB_t$
(O.2)	$\hat{u}_{a,g,t} = \frac{N_{a,g,t}}{\sum_{a'} N_{a',g,t}}$

Spawn index data likelihood

No.	Equation
(L.1)	$z_t = \frac{\log I_t - \log \hat{I}_t}{\tau'_t}$
(L.2)	$q'_t = \eta_t q_s + (1 - \eta_t) q_d$
(L.3)	$\tau'_t = (\eta_t \tau_s^2 + (1 - \eta_t) \tau_d^2)^{1/2}$
(L.4)	$l_1 = \frac{1}{2} \sum_{t=1}^T \mathcal{I}(I_t > 0) \cdot (2 \log \tau'_t + z_t^2)$

Age composition data likelihood

No.	Equation
(A.1)	$\mathbf{C}_g = [\rho_g^{j-i}]_{i,j}$

No.	Equation
(A.2)	$\mathbf{K} = [I_{A-1} 1]$
(A.3)	$V_g = \mathbf{K} \cdot \mathbf{C}_g \cdot \mathbf{K}^T$
(A.4)	$W_{g,t} = \frac{\text{mean}_t(n_{g,t}^{Age})}{n_{g,t}^{Age}}$
(A.5)	$B_{g,t} = \sum_{a=1}^A \mathcal{I}(u_{a,g,t} > 0.02)$
(A.6)	$\vec{l}_{g,t} = \langle \log(u_{a,g,t}/u_{\mathbf{B}_{g,t},g,t}) - \log(\hat{u}_{a,g,t}/\hat{u}_{\mathbf{B}_{g,t},g,t}) \rangle_a$
(A.7)	$\hat{\tau}_g^{age} = \left(\frac{\sum_t \frac{1}{W_{g,t}^2} (\vec{l}_{g,t})^T \cdot V_g^{-1} \cdot \vec{l}_{g,t}}{\sum_t B_{g,t}} \right)^{0.5}$
(A.8)	$l_2 = \sum_g \left(\sum_{a,t} \log u_{a,g,t} + \log \hat{\tau}_g^{age} \sum_t (B_{g,t} - 1) + \frac{1}{2} \sum_t \log V_g + \sum_t (B_{g,t} - 1) \log W_{g,t} \right)$

Process error prior density functions

No.	Equation
(Pr.1)	$p_1 : \omega_t \sim N(0, 1)$
(Pr.2)	$p_2 : \omega_a^{init} \sim N(0, 1)$
(Pr.3)	$p_3 : \epsilon_t \sim N(0, 1)$

Leading parameter priors

No.	Equation
(Pr.4)	$p_4 : M_0 \sim \log N(0.45, .4)$

Priors on other parameters

No.	Equation
(Pr.5)	$p_4 : h \sim \beta N(20, 9.84)$
(Pr.6)	$p_5 : q_s \sim \log N(1, 1)$
(Pr.7)	$p_6 : \tau_g^2 \sim IG(2, 0.27)$

Objective function (negative posterior density)

No. Equation

$$(Pr.8) \quad p_7 = \sum_{g=1}^3 \rho_g^2$$

$$(F.1) \quad f = l_1 + l_2 + p_1 + p_2 + p_3 + p_4 + p_5 + p_6 + p_7 + W_{SB_0} \cdot \log SB_0$$

Table 4. SAR-specific hyper-parameter values for selected SISCAN model priors (defined in Tables 1 and 2) for Haida Gwaii (HG), Prince Rupert District (PRD), Central Coast (CC), Strait of Georgia (SOG), West Coast of Vancouver Island (WCVI), and the priors used in ISCAM for all SARs.

Parameter	HG	PRD	CC	SOG	WCVI	ISCAM
β_1	20.000	20.00	20.00	20.000	20.000	10.00
β_2	9.840	9.84	9.84	9.840	9.840	4.92
σ_R	0.786	0.80	0.54	0.458	0.554	—
μ_{M0}	0.450	0.45	0.45	0.450	0.450	0.45
σ_{M0}	0.200	0.40	0.20	0.200	0.200	0.40
σ_M	0.300	0.10	0.30	0.300	0.300	0.10
μ_{qs}	1.000	1.00	1.00	1.000	1.000	1.00
τ_{qs}	1.000	1.00	1.00	1.000	1.000	1.00
δ_{spawn}	0.870	0.83	0.83	0.790	0.790	1.00
WSB_0	1.000	1.00	1.00	1.000	1.000	0.00

Table 5. Estimation phases for each estimated model parameter, and HMC tuning parameter values, across the five stock assessment regions.

Parameter	HG	PRD	CC	SOG	WCVI
SB_0	8.00	8.00	8.000	8.00	8.000
R_{init}	1.00	1.00	1.000	1.00	1.000
$\underline{R}$	1.00	1.00	1.000	1.00	1.000
q_s	1.00	1.00	1.000	1.00	1.000
ω_a^{init}	2.00	1.00	1.000	1.00	1.000
h	8.00	8.00	8.000	8.00	8.000
$M_{a,1}$	—	3.00	—	—	—
m_1	3.00	—	8.000	3.00	3.000
S_g^{50}	7.00	7.00	7.000	7.00	7.000
ω_t	6.00	6.00	6.000	6.00	6.000
ϵ_t	5.00	5.00	5.000	5.00	5.000
τ_s, τ_d	2.00	2.00	2.000	2.00	2.000
ρ_g	4.00	4.00	4.000	4.00	4.000
adapt_delta	0.99	0.99	0.999	0.99	0.999
max_treeDepth	15.00	15.00	15.000	15.00	15.000
Total iterations	2,000.00	2,000.00	2,000.000	2,000.00	2,000.000

Table 6. Differences in major model components between the current herring OM (ISCAM) and the SISCAH OM.

ModelCpt	ISCAM	SISCAH
Stock Structure	Aggregated	Aggregated
Fishing Mortality	Continuous	Discrete fishing events
Age classes	2, ..., 10	1, ..., 10
Natural Mortality	Time-varying, cubic spline	Time-varying, Density Dependent or Independent
Fished Initialisation	Recruitment deviations for all age classes, and initial recruitment R_{init}	Recruitment deviations for all age classes applied to R_0 for all areas except Prince Rupert, which estimates R_{init}
Stock-Recruitment	Average recruitment $\bar{R}$ model in early estimation phases, with post-fit Beverton-Holt Stock-Recruit model in a later phase	Unfished biomass B_0 estimated freely as leading parameter; prior mean of steepness at 0.67.
Survey Catchability	Vague prior on surface survey and informative prior on dive survey	Vague log-Normal prior for surface survey q and ($q = 1$) assumption for dive survey
Survey Obs Error SD	Errors-in-Variables conditional maximum likelihood estimate, with weighting to distribute between surveys	Somewhat informative inverse gamma prior on both surface and dive survey design components of observation error SD
Rec Proc Error SD	Errors-in-Variables conditional MLE	Fixed based on model tuning
Age compositions	All age composition data included	Minimum 200 annual samples
Age-comp likelihoods	Logistic-normal with tail compression, equal annual weight; freely estimated standard deviation	Logistic-normal with tail compression and estimated lag-1 auto-regressive correlation matrix weighted by sample size relative to average annual sample size; conditional MLE of standard deviation
Spawn-on-Kelp Fishery	Absent	Removals from landed spawn-on-kelp product, vulnerable age-structure, proportion mature, estimates of the ratio of ponded fish to landed spawn-on-kelp, and post-ponding mortality rate

Table 7. Upper stock reference (USR) and fishery TAC proportions used for estimating reference points and allocating TAC in the projections. USR for each region is defined as a proportion (Proportion) of the average biomass in a productive period (Year Range). Fishery TAC allocation is calculated from the data as the average proportion of landings observed in each sector fishery over the most recent 20 years with fishing activity.

Region	USR definition		Fishery TAC allocation			
	Year Range	Proportion	Reduction/FB	Seine	Gillnet	SOK
HG	1975–1985	0.75	0.00	0.63	0.09	0.27
PRD	1983–1992	1	0.02	0.29	0.48	0.20
CC	1990–1999	1	0.00	0.60	0.07	0.33
SOG	1988–2007	0.8	0.24	0.37	0.39	–
WCVI	1990–1999	1	0.00	0.76	0.15	0.09

Table 8. Performance statistics calculated for BC herring closed loop simulations for each SAR. Biomass $B_{t,i}$ represents spawning stock biomass in year t and simulation replicate i , and reference points with a subscript i (e.g., $B_{0,i}$) represent the particular reference point value for the OM posterior draw that replicate is conditioned upon. The indicator function $\mathbf{1}(X \text{ is TRUE}) = 1$ or $\mathbf{1}(X \text{ is FALSE}) = 0$.

Performance Metric	Description	Definition
Objective 1 $P(SB > 0.3SB_0)$	Proportion of simulation trial years where spawning biomass exceeds the limit reference point of $0.3B_0$ over a 3 generation (15 year) period.	$P(SB > 0.3SB_0) = \frac{\sum_{i=1}^{100} \sum_{t=2023}^{2037} \mathbf{1}(SB_{t,i} > 0.3SB_{0,i})}{15 \cdot 100}$
Objective 2 $P(SB > USR)$	Proportion of simulation trial years where spawning biomass is above the upper stock reference over a 3 generation (15 year) period.	$P(SB \geq USR) = \frac{\sum_{i=1}^{100} \sum_{t=2023}^{2037} \mathbf{1}(SB_{t,i} \geq USR)}{15 \cdot 100}$
$P(SB > SB_{crash})$	Proportion of simulation trial years where spawning biomass exceeds the coast-scale spatial model incorporating associated with U_{crash} over a 3 generation (15 year) period.	$P(SB > 0.3SB_{crash}) = \frac{\sum_{i=1}^{100} \sum_{t=2023}^{2037} \mathbf{1}(SB_{t,i} > B_{crash})}{15 \cdot 100}$
Median Mean Catch $\bar{C}$	Median across replicates of mean landed annual catch over 15 year projections.	$\bar{C} = \text{median}_i \sum_{t=2023}^{2037} \left(\frac{1}{15} C_{t,i} \right)$
Catch Variability AAV_C	Median across replicates of average absolute annual change (variability) in landed catch.	$AAV_C = \text{median}_i \sum_{t=2023}^{2037} \left(\frac{ C_{t,i} - C_{t-1,i} }{\sum_{t=2023}^{2037} C_{t,i}} \right)$
Median mean SOK $\bar{K}$	Median across replicates of mean landed annual catch over 15 year projections.	$\bar{K} = \text{median}_i \sum_{t=2023}^{2037} \left(\frac{1}{15} K_{t,i} \right)$
SOK Variability AAV_K	Median across replicates of average absolute annual change (variability) in landed catch.	$AAV_K = \text{median}_i \sum_{t=2023}^{2037} \left(\frac{ K_{t,i} - K_{t-1,i} }{\sum_{t=2023}^{2037} C_{t,i}} \right)$
pUnviable	Proportion of simulation trial years where catch is below the historical minimum recorded level $C_{min} = \min_{t=1951:2022} C_t$ over a 3 generation (15 year) period.	$p_{Closed} = \frac{\sum_{i=1}^{100} \sum_{t=2023}^{2037} \mathbf{1}(C_{t,i} < C_{min})}{15 \cdot 100}$

Table 9. Median relative errors (MRE) and median absolute relative errors (MARE) for SISCAH model quantities under the SISCAH model simulation self-test when conditioned on Central Coast (CC) and Strait of Georgia (SOG) stock assessments. Columns show MREs and MAREs under the Index Data Simulated (simIdx), Age Data Simulated (simAge), All Data Simulated (simAll), and Random Priors (randPriors) scenarios.

CC									
Variable	simIdx		simAge		simAll		randPriors		
	MRE	MARE	MRE	MARE	MRE	MARE	MRE	MARE	
SB_0	-0.04	0.06	0.12	0.12	0.13	0.13	0.14	0.14	
$2+B_0$	-0.02	0.04	0.09	0.09	0.11	0.11	0.11	0.12	
R_0	0.04	0.04	0.01	0.03	0.03	0.04	0.03	0.04	
h	0.00	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	
M_b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
m_1	-0.11	0.13	0.21	0.21	0.20	0.20	0.18	0.18	
M_0	0.04	0.04	-0.05	0.05	-0.04	0.05	-0.04	0.04	
s_1^{50}	0.01	0.01	-0.01	0.02	-0.01	0.02	-0.01	0.02	
s_2^{50}	0.00	0.00	-0.01	0.01	-0.01	0.01	-0.01	0.01	
s_3^{50}	0.00	0.00	-0.01	0.01	-0.01	0.01	-0.01	0.01	
q_s	-0.09	0.09	-0.04	0.04	-0.14	0.14	-0.14	0.14	
τ_s	-0.12	0.14	-0.02	0.02	-0.10	0.11	-0.10	0.11	
τ_d	-0.06	0.10	0.02	0.03	-0.04	0.09	-0.04	0.09	
SOG									
Variable	simIdx		simAge		simAll		randPriors		
	MRE	MARE	MRE	MARE	MRE	MARE	MRE	MARE	
SB_0	-0.05	0.05	0.21	0.21	0.21	0.21	0.20	0.20	
$2+B_0$	0.00	0.02	0.13	0.13	0.15	0.15	0.14	0.14	
R_0	0.08	0.08	-0.01	0.02	0.06	0.06	0.06	0.06	
h	0.00	0.01	-0.07	0.07	-0.03	0.03	-0.03	0.03	
M_b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
m_1	-0.16	0.16	0.60	0.60	0.38	0.38	0.33	0.33	
M_0	0.05	0.05	-0.07	0.07	-0.06	0.06	-0.05	0.05	
s_1^{50}	0.00	0.00	-0.02	0.02	-0.01	0.01	-0.01	0.01	
s_2^{50}	0.00	0.00	-0.01	0.01	-0.01	0.01	0.00	0.01	
s_3^{50}	0.00	0.00	-0.02	0.02	-0.02	0.02	-0.01	0.01	
q_s	-0.10	0.11	-0.12	0.12	-0.22	0.22	-0.22	0.22	
τ_s	-0.11	0.13	-0.04	0.06	-0.11	0.13	-0.11	0.13	
τ_d	-0.03	0.08	-0.14	0.14	-0.04	0.10	-0.04	0.09	

Table 10. SISCAH model standard errors for observational data in all major stock assessment regions, and lag-1 autocorrelation factors for the age composition LN1 likelihood function. Values are shown for age composition sampling errors and correlation factors in the Reduction (and Food and Bait in SOG) fishery (τ_1^{age}, ρ_1), Seine-rope fishery (τ_2^{age}, ρ_2), and Gillnet-rope fishery (τ_3^{age}, ρ_3), as well as spawn index residual standard errors for the surface survey design (τ_s) and dive survey design (τ_d).

SAR	τ_1^{age}	ρ_1	τ_2^{age}	ρ_2	τ_3^{age}	ρ_3	τ_s	τ_d
HG	0.428	0.000	0.438	0.269	0.645	0.298	0.485	0.515
PRD	0.695	0.752	0.436	0.213	0.394	0.254	0.475	0.292
CC	0.468	0.094	0.357	0.211	0.430	0.261	0.395	0.284
SOG	0.654	0.769	0.312	0.483	0.538	0.743	0.342	0.309
WCVI	0.495	0.525	0.432	0.686	0.609	0.614	0.410	0.271

Table 11. Bayes posterior median (standard error) of SISCAH model leading parameters and some derived management quantities for Haida Gwaii (HG), Prince Rupert District (PRD), Central Coast (CC), Strait of Georgia (SOG), and West Coast of Vancouver Island (WCVI). SB_0 = Unfished spawning biomass (parentheses show half of the inter-quartile range from simulated reference points), R_0 = unfished equilibrium recruitment, R_{init} = initial recruitment, m_1 = despensation rate in density dependent mortality, M_b = lower limit of density dependent mortality, M_0 = unfished natural mortality derived from density dependent mortality model, h = stock-recruitment steepness, q_s = catchability coefficient for the surface survey design, SB_{2022} = spawning biomass for 2022, SB_{2022}/SB_0 = ratio of spawning biomass to unfished spawning biomass (parentheses show half of inter-quartile range).

SAR	SB_0	R_0	R_{init}	m_1	M_b	M_0	h	q_s	B_{2022}	B_{2022}/B_0
HG	7.31 (12.13)	350.31 (66.56)	350.31 (66.56)	1.39 (0.27)	0.33 (0.00)	0.58 (0.06)	0.69 (0.08)	0.30 (0.04)	10.76 (4.44)	1.47 (5.40)
PRD	52.13 (4.78)	399.28 (69.52)	345.20 (102.75)	3.00 (0.00)	0.32 (0.02)	0.37 (0.02)	0.63 (0.09)	0.48 (0.06)	32.77 (6.59)	0.63 (0.03)
CC	64.92 (15.40)	620.44 (68.01)	620.44 (68.01)	4.39 (0.91)	0.39 (0.00)	0.41 (0.02)	0.73 (0.06)	0.21 (0.02)	30.31 (7.40)	0.47 (0.04)
SOG	114.23 (29.86)	2477.62 (255.25)	2477.62 (255.25)	4.49 (1.33)	0.58 (0.00)	0.59 (0.02)	0.70 (0.07)	0.68 (0.07)	73.31 (15.78)	0.64 (0.08)
WCVI	41.81 (26.23)	848.60 (115.74)	643.65 (252.00)	2.07 (0.65)	0.42 (0.00)	0.55 (0.07)	0.70 (0.07)	0.57 (0.07)	26.68 (6.76)	0.64 (0.39)

Table 12. Bayes posterior median (half of interquartile range) of BC herring reference points derived from the SISCAH model via simulation for Haida Gwaii (HG), Prince Rupert District (PRD), Central Coast (CC), Strait of Georgia (SOG), and West Coast of Vancouver Island (WCVI). Reference points include USR = Upper stock reference biomass (parentheses show posterior standard error), U_{USR} = Equilibrium harvest rate associated with the USR , Y_{USR} = Equilibrium yield associated with the USR , SB_{MSY} = Equilibrium biomass associated with maximum sustainable yield (MSY), U_{MSY} = Equilibrium harvest rate associated with MSY, MSY = Maximum sustainable yield, SB_{crash} = Equilibrium biomass at the estimated crash point, U_{crash} = Equilibrium harvest rate at the estimated crash point.

SAR	USR	U_{USR}	Y_{USR}	SB_{MSY}	U_{MSY}	MSY	SB_{crash}	U_{crash}
HG	37.68 (3.68)	0.000 (0.000)	0.000 (0.000)	1.94 (3.07)	0.139 (0.093)	0.228 (0.543)	0.20 (0.41)	0.308 (0.224)
PRD	36.13 (2.03)	0.069 (0.021)	2.663 (0.796)	16.54 (2.16)	0.227 (0.027)	4.911 (0.420)	0.01 (0.01)	0.511 (0.071)
CC	48.87 (2.84)	0.082 (0.061)	3.115 (2.541)	25.86 (3.70)	0.218 (0.065)	5.106 (2.334)	3.73 (1.42)	0.335 (0.109)
SOG	69.42 (3.50)	0.166 (0.090)	14.049 (8.519)	44.46 (6.33)	0.276 (0.076)	17.403 (7.278)	5.81 (0.84)	0.455 (0.123)
WCVI	39.54 (2.56)	0.008 (0.048)	0.277 (1.909)	17.35 (11.40)	0.100 (0.046)	1.724 (1.979)	2.15 (2.40)	0.185 (0.185)

Table 13. Performance metric values calculated over the 15 year projections for each SAR and MP combination. Metrics include $P(SB > 0.3SB_0)$ = probability of SB being above the LRP, $P(SB > USR)$ = probability of SB being above the USR, $P(SB > B_{crash})$ = probability of SB being above B_{crash} , $\bar{C}$ = median average yearly catch, AAV_C = average annual variation in catch, $\bar{K}$ = median average landed SOK product, AAV_K = average annual variation in SOK product, $pUnviable$ = probability of catches below the historical minimum, B_{2036} = median biomass in 2036, D_{2036} = median depletion (relative to stochastic SB_0) in 2036.

MP	Objectives		Crash Points		Additional Metrics				Terminal States	
	$P(SB > 0.3SB_0)$	$P(SB > USR)$	$P(SB > B_{crash})$	$\bar{C}$	AAV_C	$\bar{K}$	AAV_K	$pUnviable$	B_{2036}	D_{2036}
HG										
NoFish	0.923	0.164	0.981	0.0	0.0	0.0	0.0	1.00	18.549	2.635
PerfHS3060Umsy	0.879	0.057	0.973	841.9	31.5	26.0	31.5	0.15	8.993	1.278
PerfHS30600.5Umsy	0.905	0.105	0.979	456.6	27.5	14.2	27.5	0.14	13.135	1.866
PRD										
NoFish	1.000	0.811	0.920	0.0	0.0	0.0	0.0	1.00	49.101	0.914
PerfHS3060Umsy	0.985	0.096	0.920	5347.5	19.9	111.8	19.9	0.00	24.136	0.455
PerfHS3060Uusr	1.000	0.567	0.920	2358.7	10.5	49.5	10.5	0.01	38.300	0.715
PerfHS30600.5Umsy	1.000	0.379	0.920	3526.8	12.2	73.9	12.2	0.01	32.886	0.616
CC										
NoFish	0.945	0.546	0.995	0.0	0.0	0.0	0.0	1.00	58.512	0.893
PerfHS3060Umsy	0.913	0.060	0.993	4337.4	27.5	176.7	27.5	0.09	30.191	0.461
PerfHS3060Uusr	0.933	0.331	0.994	2321.3	17.1	94.7	17.1	0.07	44.572	0.680
PerfHS30600.5Umsy	0.929	0.261	0.994	2877.6	18.3	117.4	18.3	0.07	40.911	0.624
SOG										
NoFish	0.981	0.843	1.000	0.0	0.0	0.0	0.0	1.00	105.968	0.931
PerfHS3060Umsy	0.944	0.224	0.999	18368.8	29.5	0.0	0.0	0.06	49.148	0.432
PerfHS3060Uusr	0.961	0.496	1.000	13811.6	20.9	0.0	0.0	0.04	64.556	0.567
PerfHS30600.5Umsy	0.964	0.583	1.000	12061.2	19.3	0.0	0.0	0.04	69.923	0.615
WCVI										
NoFish	0.877	0.437	0.992	0.0	0.0	0.0	0.0	1.00	42.158	1.022
PerfHS3060Umsy	0.839	0.257	0.987	2551.9	28.7	19.9	28.7	0.17	26.201	0.635
PerfHS3060Uusr	0.873	0.425	0.992	269.0	21.6	2.1	21.6	0.17	40.506	0.982
PerfHS30600.5Umsy	0.862	0.345	0.990	1473.7	25.5	11.5	25.5	0.15	32.991	0.800

7. FIGURES

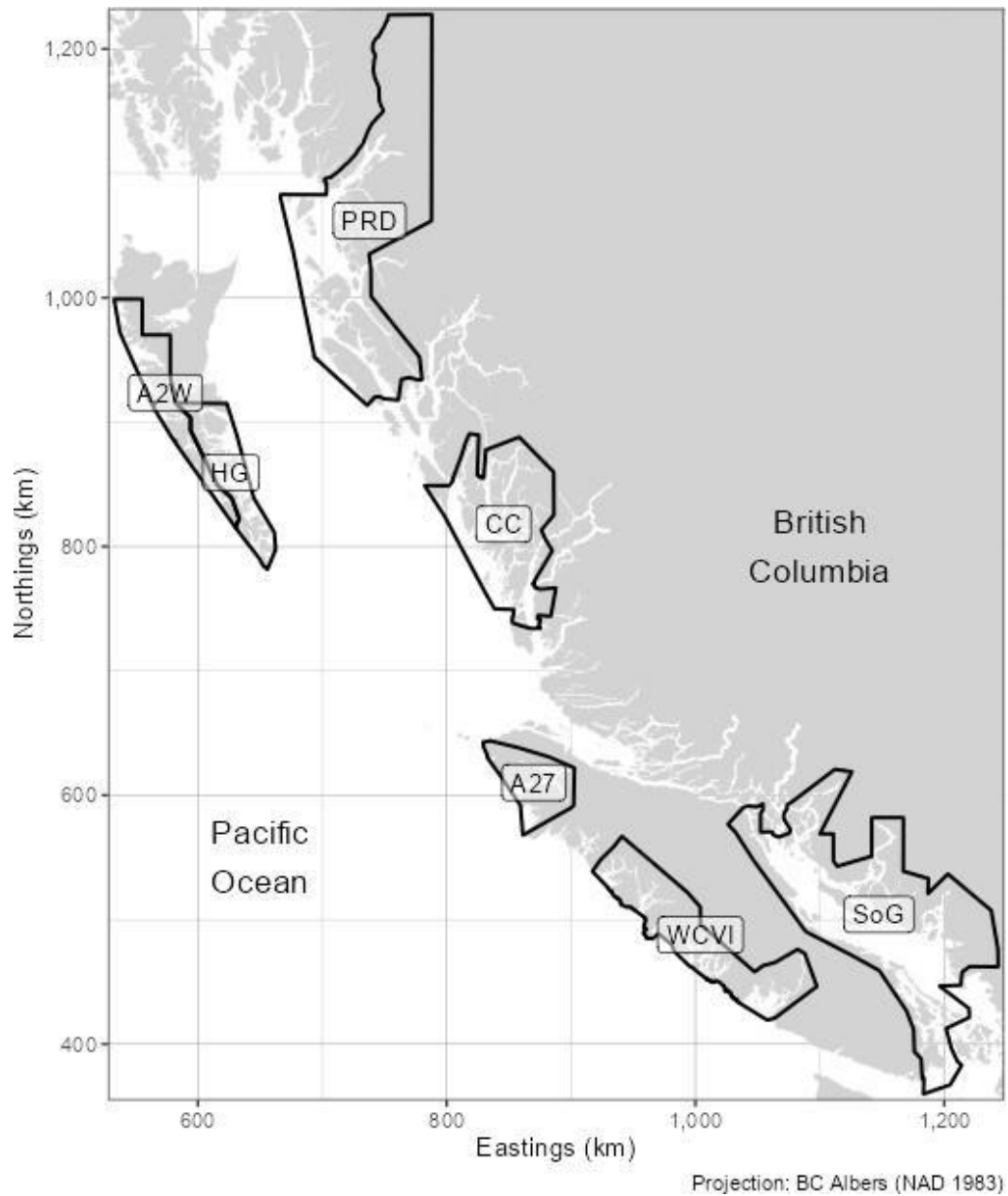


Figure 1. Boundaries for Pacific Herring SARs in British Columbia. The major SARs are Haida Gwaii (HG), Prince Rupert District (PRD), Central Coast (CC), Strait of Georgia (SOG), and West Coast of Vancouver Island (WCVI). The minor SARs are Area 27 (A27) and Area 2 West (A2W). Units: kilometres (km).

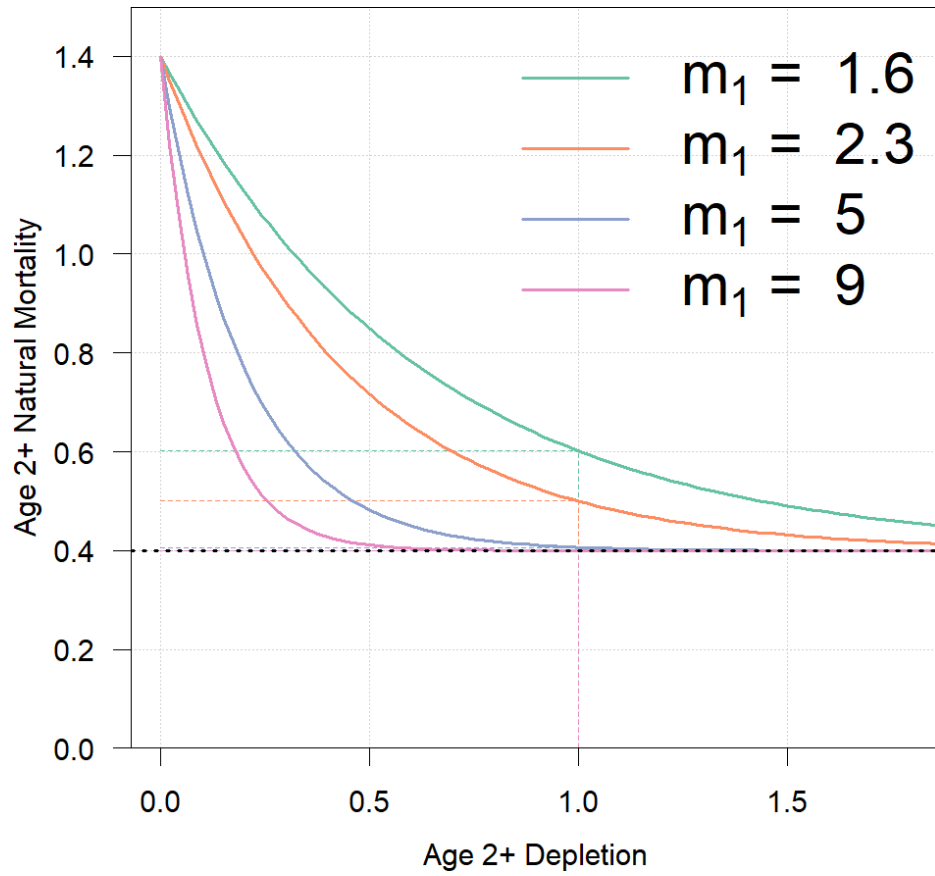


Figure 2. Examples of density-dependent age-2+ natural mortality relationships (coloured curves) with age-2+ biomass depletion. Each curve shows a different value of the m_1 parameter, controlling the steepness of the relationship. Dashed segments show the derived unfished equilibrium M_0 for each m_1 value, which converge to M_b as m_1 increases.

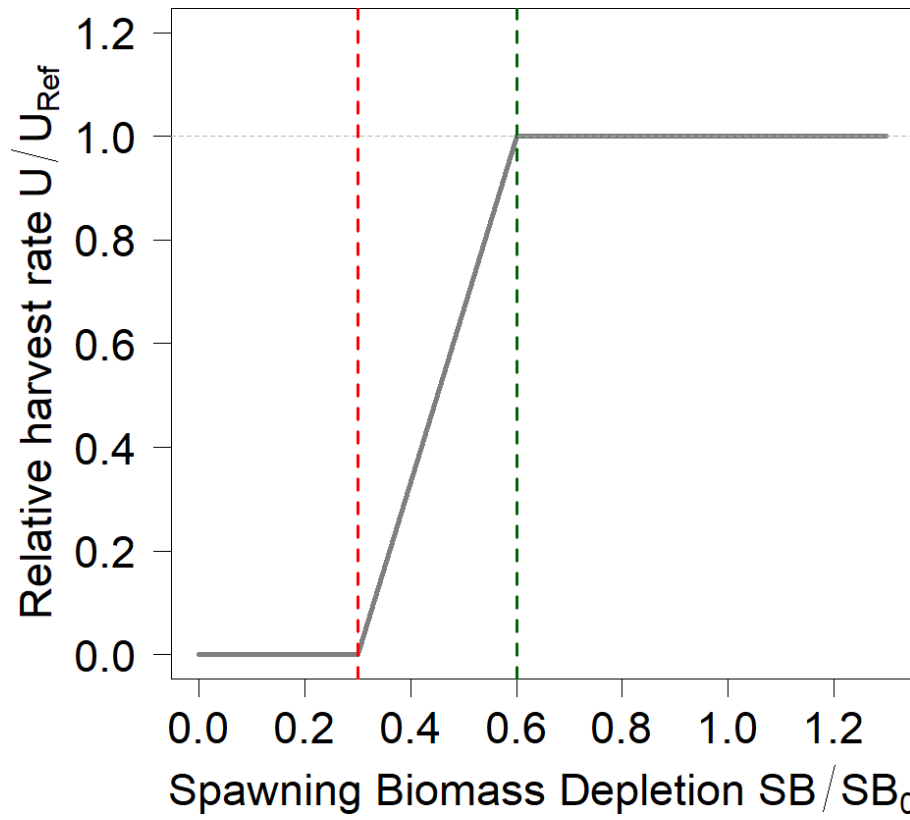


Figure 3. The 'HS-3060' hockey-stick harvest control rule, with operational control points at 30% and 60% of unfished biomass SB_0 , and a maximum target harvest rate of U_{Ref} .

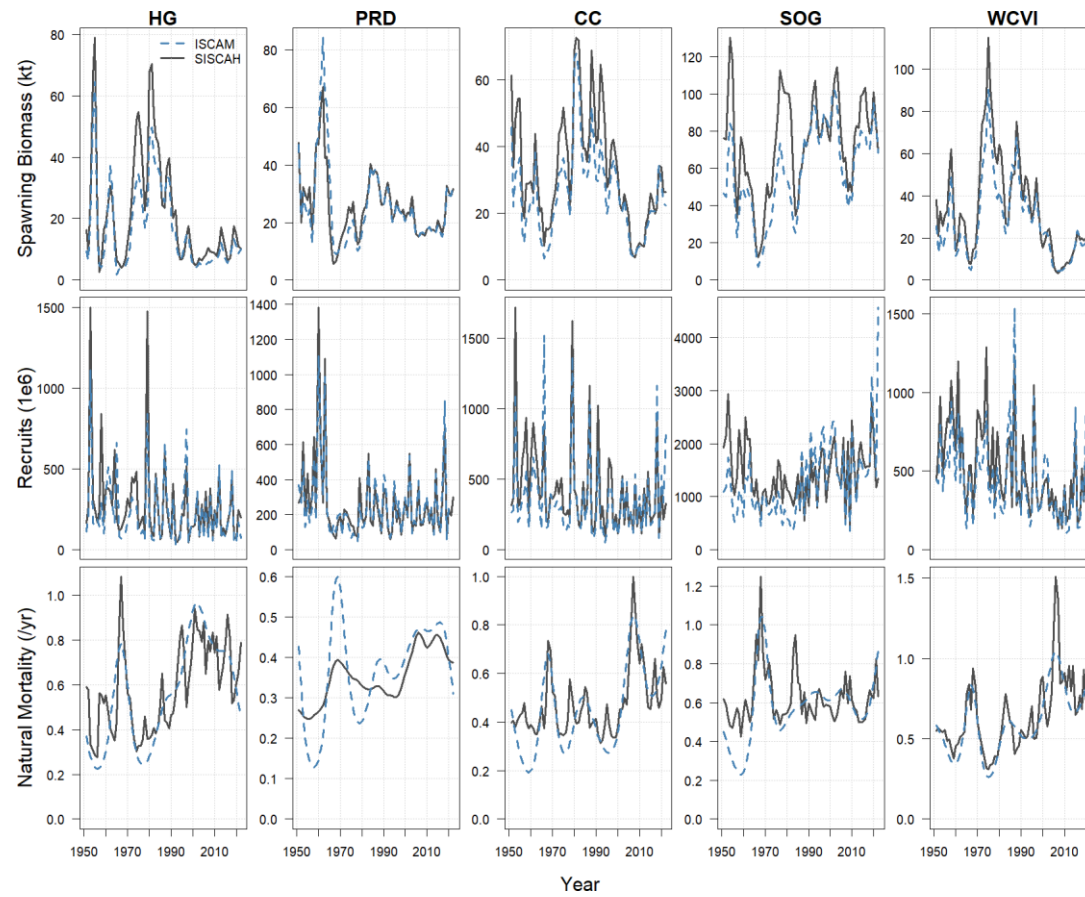


Figure 4. Comparison of biomass, recruitment, and natural mortality estimates for the 5 SARs between ISCAM and the full SISCAH model (with discrete F , spawn-on-kelp, density-dependent M , and a blended survey index).

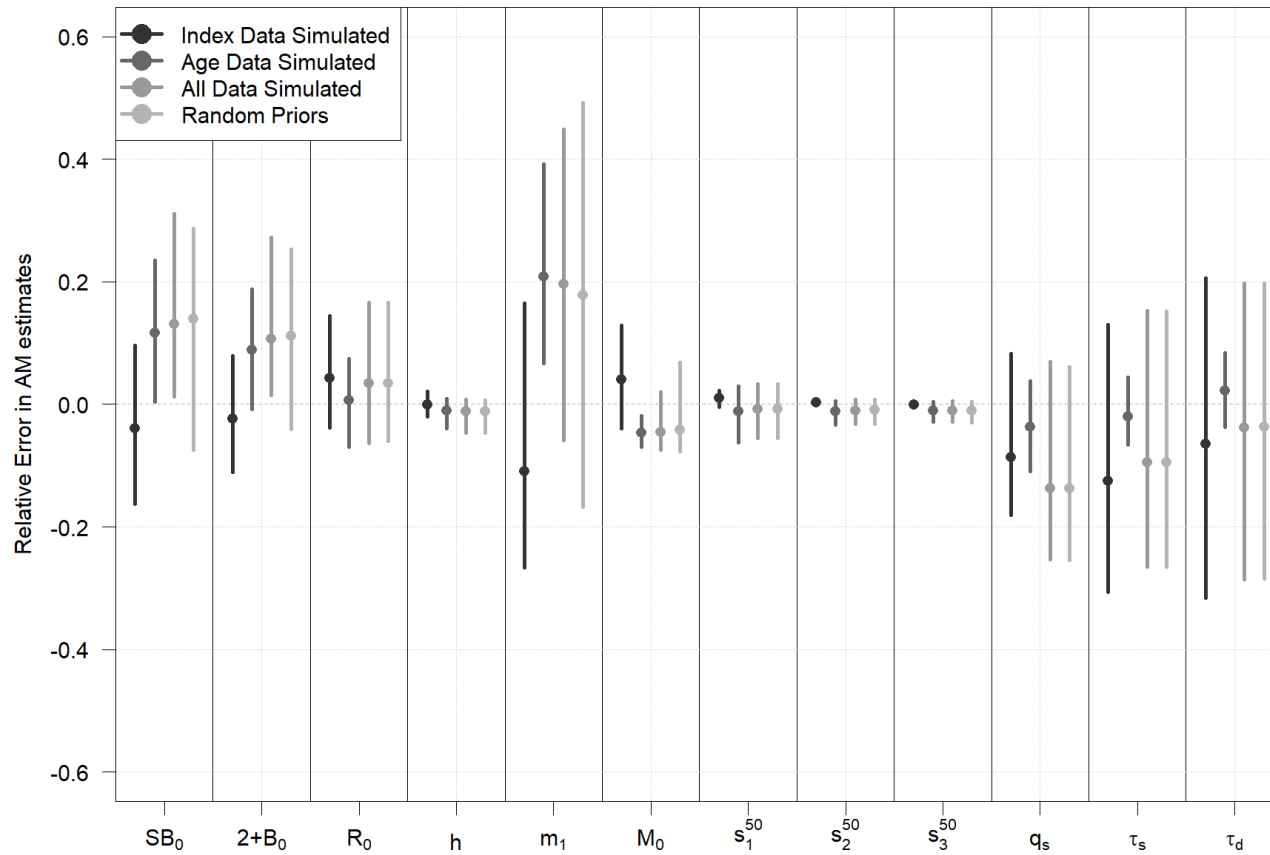


Figure 5. Central Coast: Relative errors in leading parameter estimates in the simulation self test of SISCAH on simulated data. Parameter estimates include: life-history parameters (SB_0 , $2 + B_0$, R_0 , h , m_1 , M_0), selectivity parameters (s_1^{50} , s_2^{50} , s_3^{50}), and survey observation model parameters (q_s , τ_s , τ_d). Points represent 50th percentile and the line segments extend to the 2.5th and 97.5th percentiles of relative error distributions.

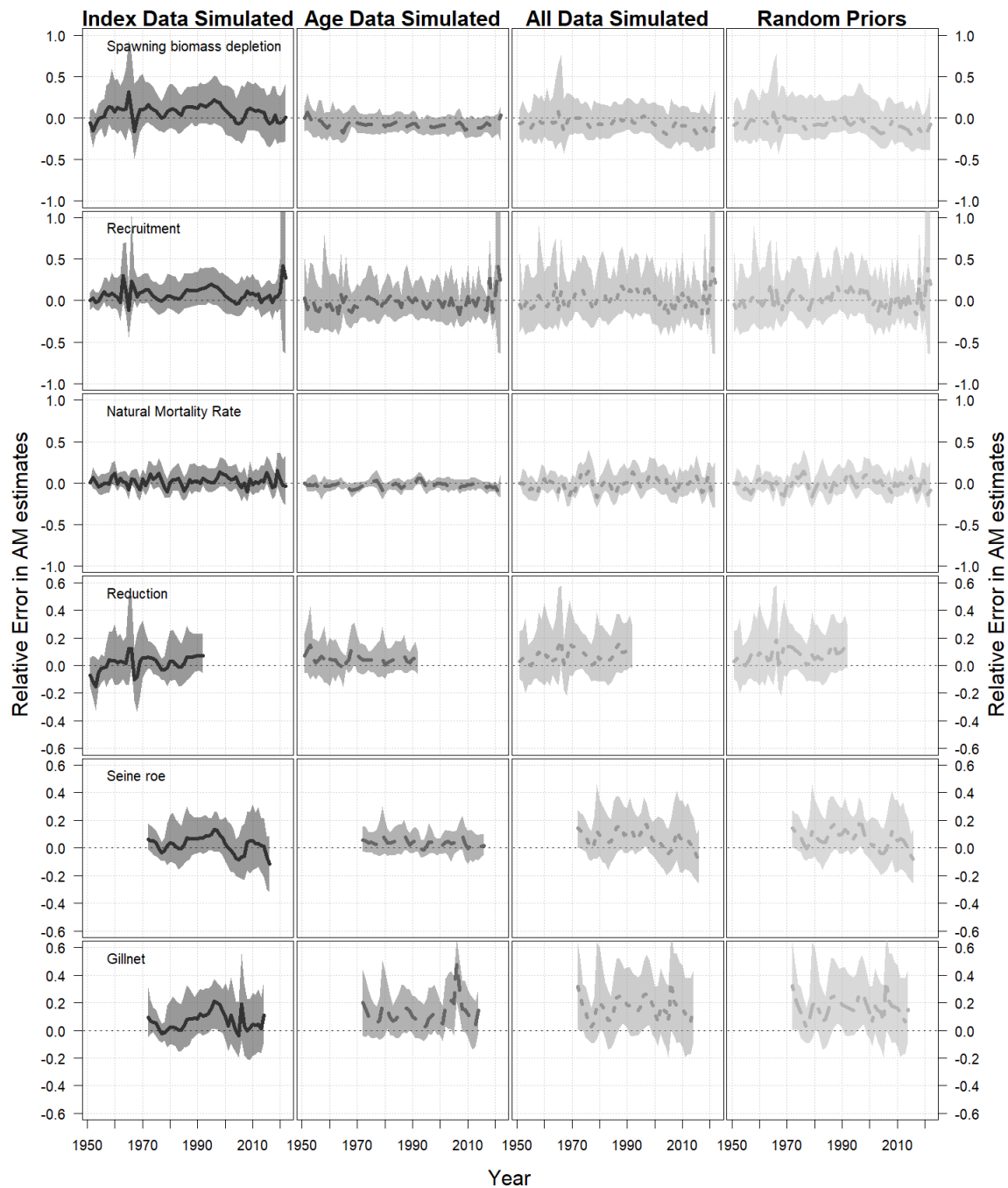


Figure 6. Central Coast: Relative errors in time series estimates of (from top to bottom) spawning biomass depletion, recruitment, natural mortality, and vulnerable biomass for each commercial fleet under the four simulation self test scenarios for SISCAH. Thick lines represent 50th percentiles and the shaded regions extend to the 2.5th and 97.5th percentiles of relative error distribution time series.

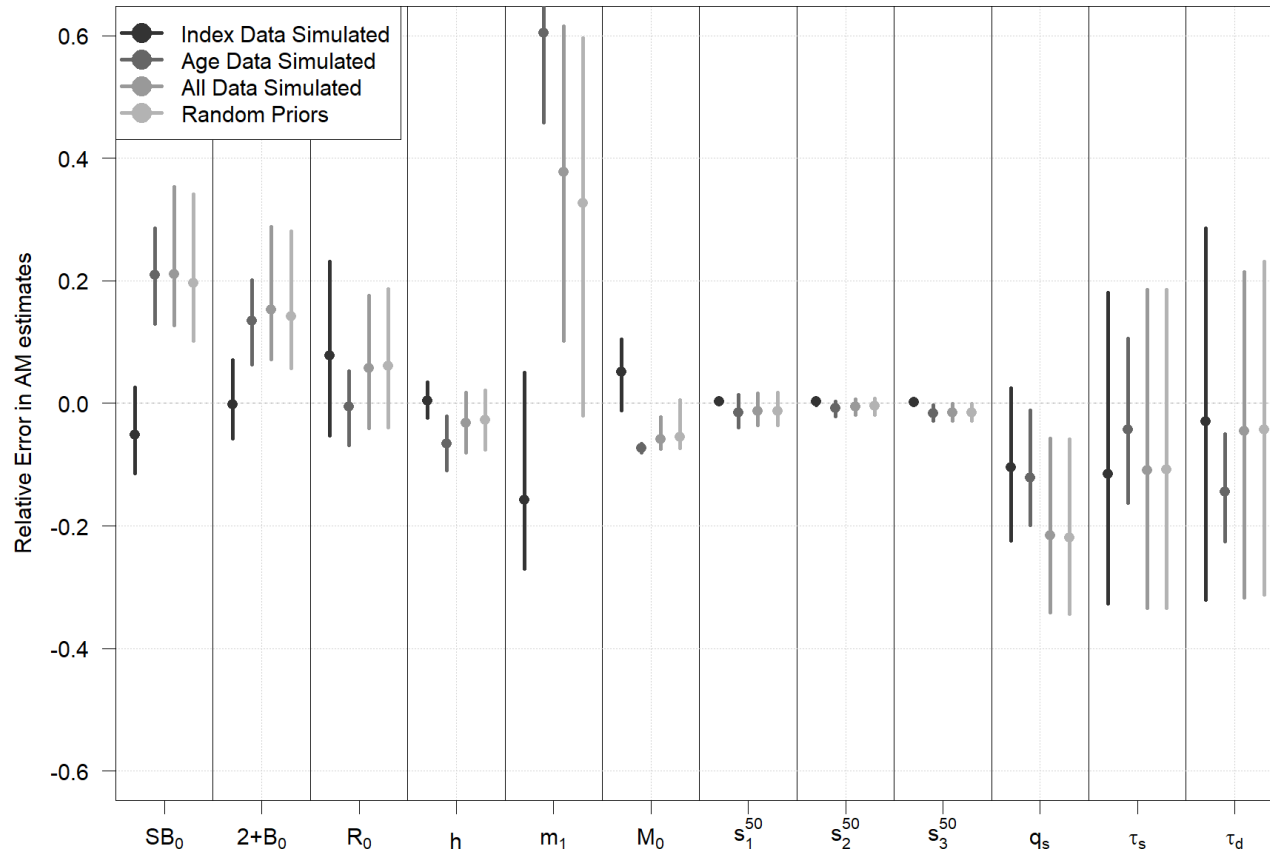


Figure 7. Strait of Georgia: Relative errors in leading parameter estimates in the simulation self test of SISCAH on simulated data. Parameter estimates include: life-history parameters (SB_0 , $2 + B_0$, R_0 , h , m_1 , M_0), selectivity parameters (s_1^{50} , s_2^{50} , s_3^{50}), and survey observation model parameters (q_s , τ_s , τ_d). Points represent 50th percentile and the line segments extend to the 2.5th and 97.5th percentiles of relative error distributions.

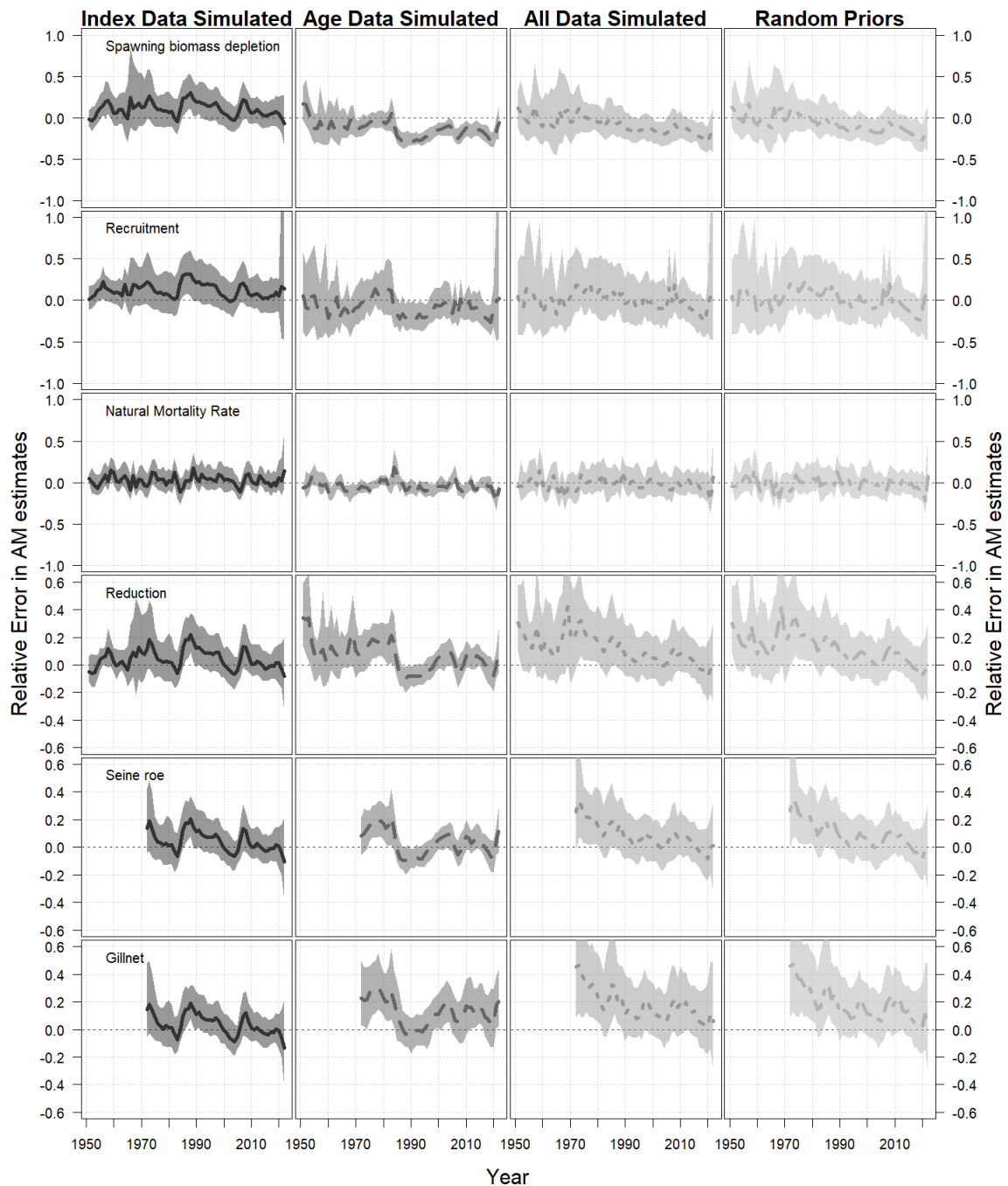


Figure 8. Strait of Georgia: Relative errors in time series estimates of (from top to bottom) spawning biomass depletion, recruitment, natural mortality, and vulnerable biomass for each commercial fleet under the four simulation self test scenarios for SISCAH. Thick lines represent 50th percentiles and the shaded regions extend to the 2.5th and 97.5th percentiles of relative error distribution time series.

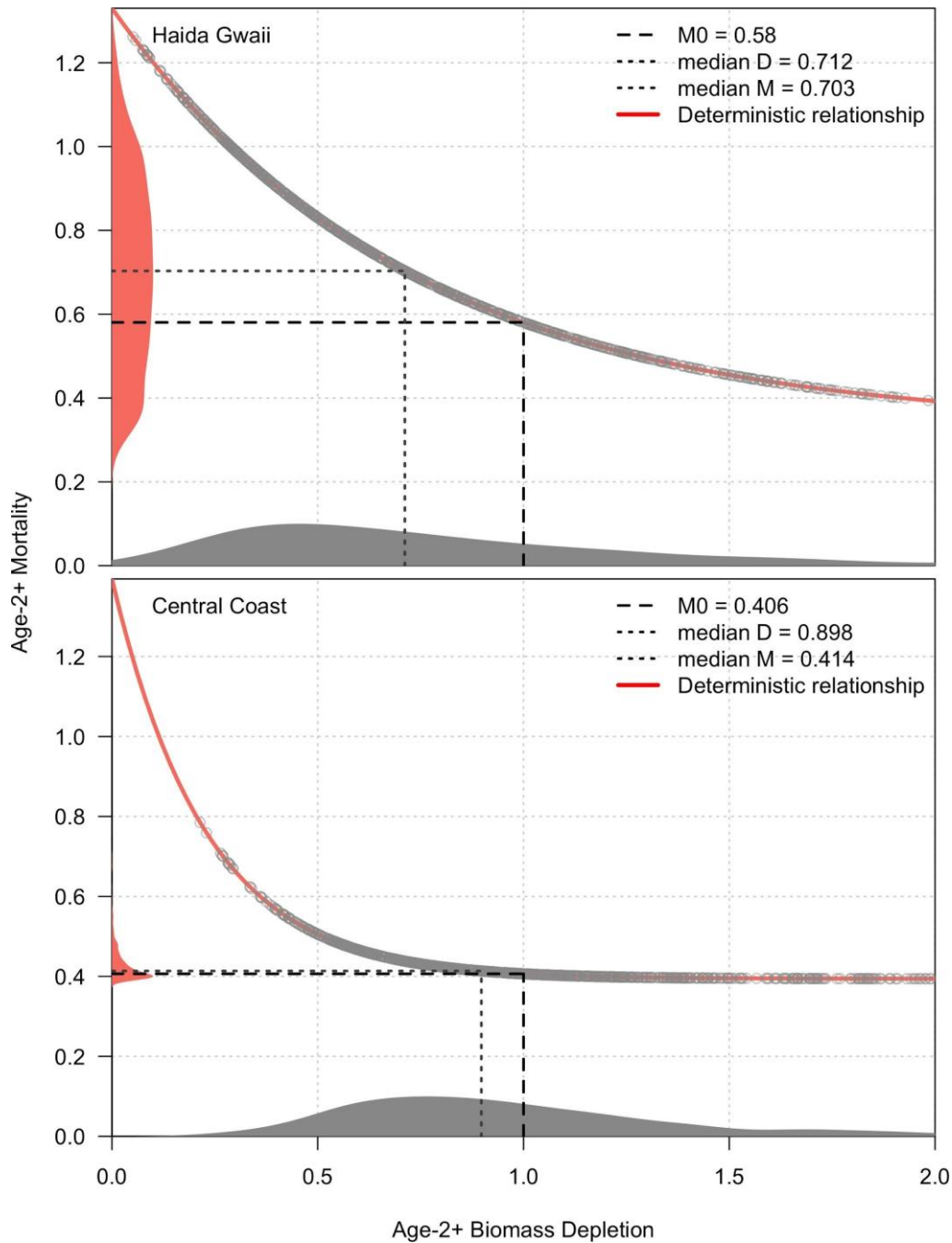


Figure 9. Examples showing the interaction of recruitment variability (σ_R) with density dependent M for two example SARs. Grey points show random log-normally distributed depletion values (x-axis) with a mean of 1 (unfished biomass) but a log-normal bias correction added, to emulate the effect of simulated random recruitment. The resulting distribution of age-2+ biomass depletion is shown as a density plot along the x-axis. The implied mortality values (ignoring mortality process error) are taken from the red curve, and the resulting M distribution is shown as a density along the y-axis. Deterministic unfished biomass and mortality is shown by the segments of long dashes, and the median of both depletion and mortality are connected via the line segments with short dashes.

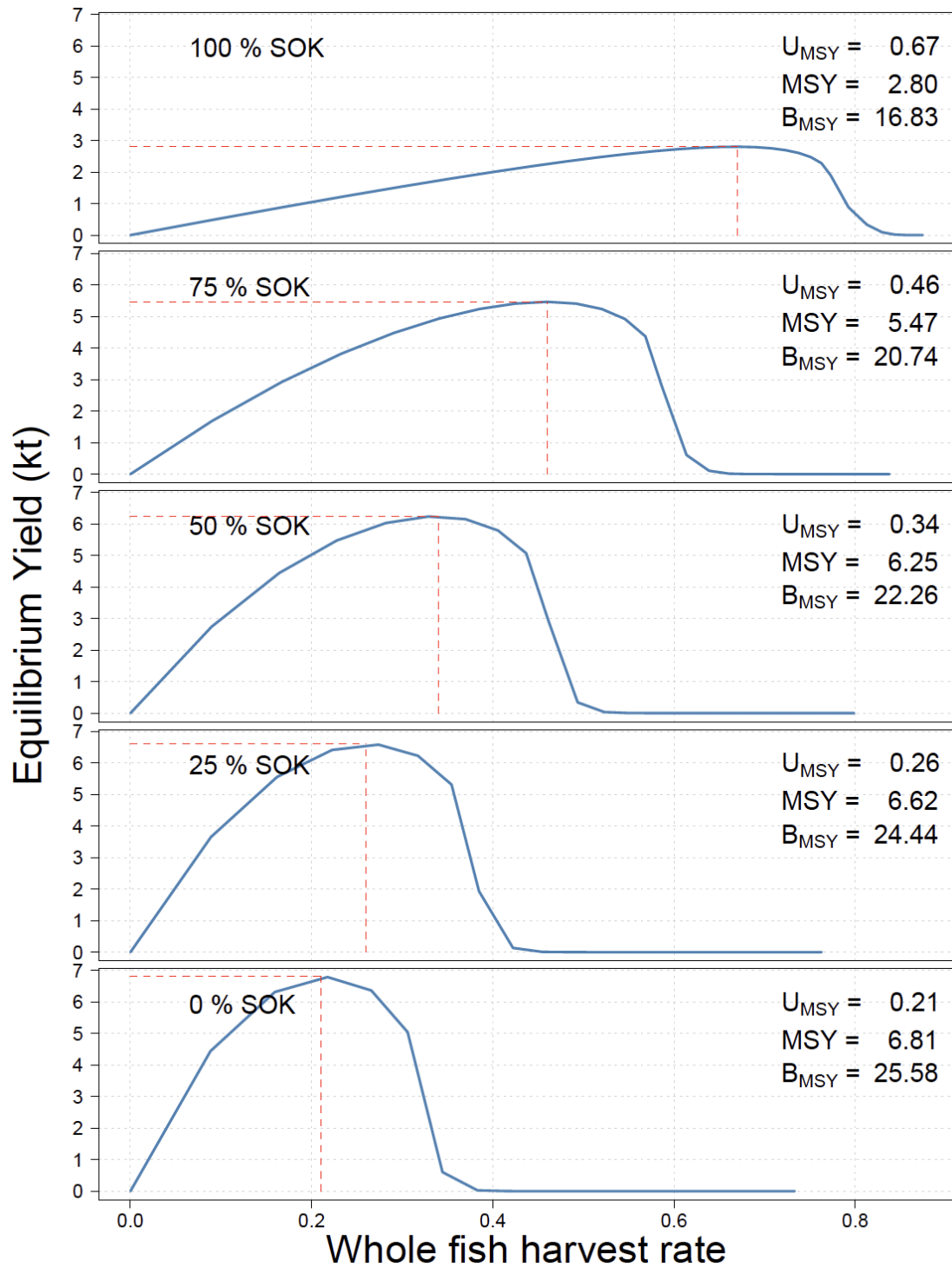


Figure 10. Central coast SAR yield (y-axis) curves with respect to whole fish harvest rate (x-axis), which is the capture rate of mature fish. Each panel shows the effect of SOK allocation between SOK and Seine fisheries on optimal yield and UMSY harvest rates, with the top showing 100% SOK, and the bottom showing 100% Seine. These curves are not completely smooth as they are estimated over a coarse harvest rate grid, and are also estimated based on one posterior draw with no recruitment or mortality process errors, so optima do not reflect stochastic values estimated when integrating over all uncertainties.

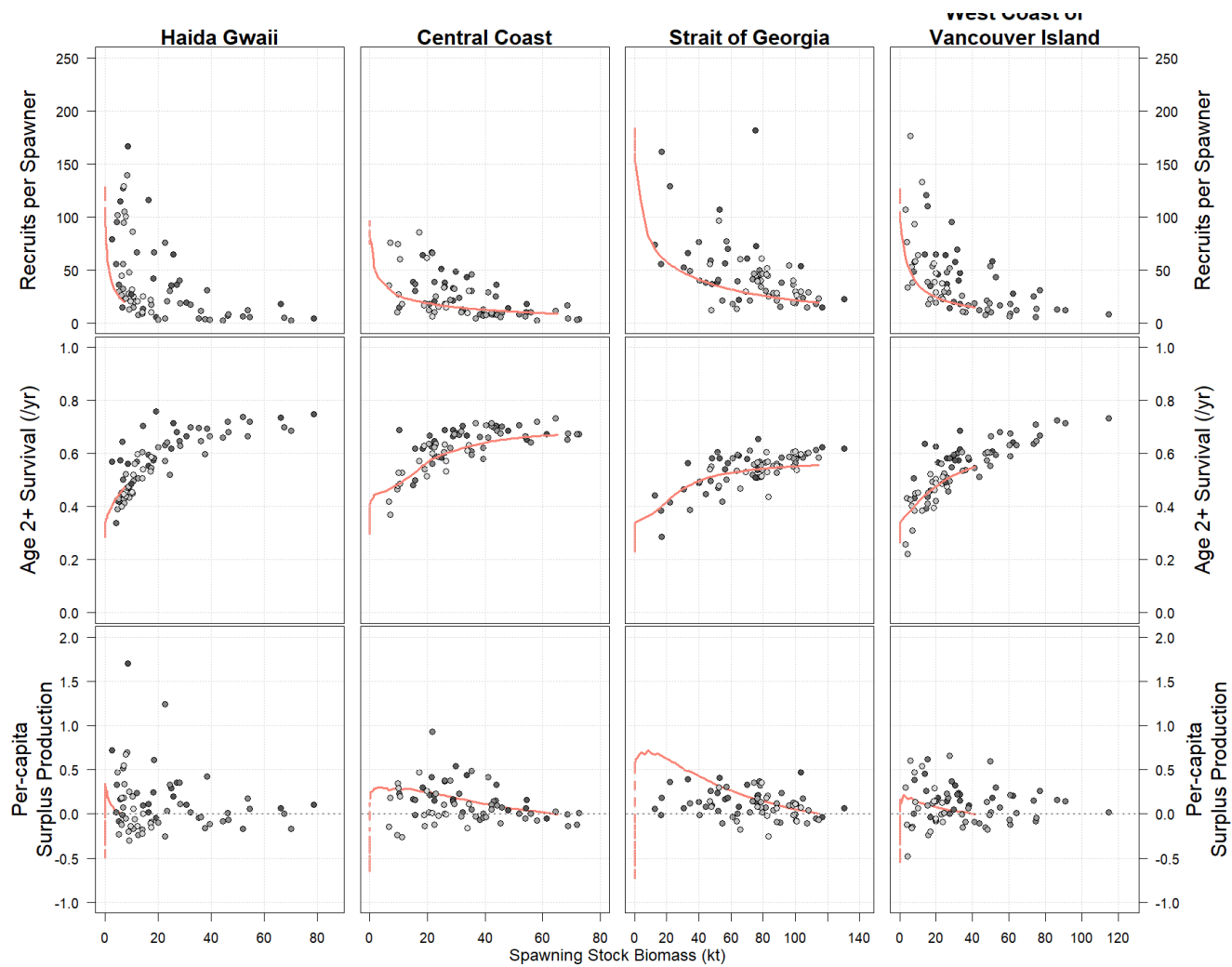


Figure 11. SISCAN model estimates (points) and stochastic equilibria (red lines) of recruits-per-spawner (top), density dependent age-2+ mortality (middle), and per-capita surplus production (bottom) with respect to spawning stock biomass (x-axis) in all SARs. Points are coloured to show phase, with light points for later years. Red lines show simulated stochastic equilibrium values derived from 200 year simulations used to estimate fishery reference points.

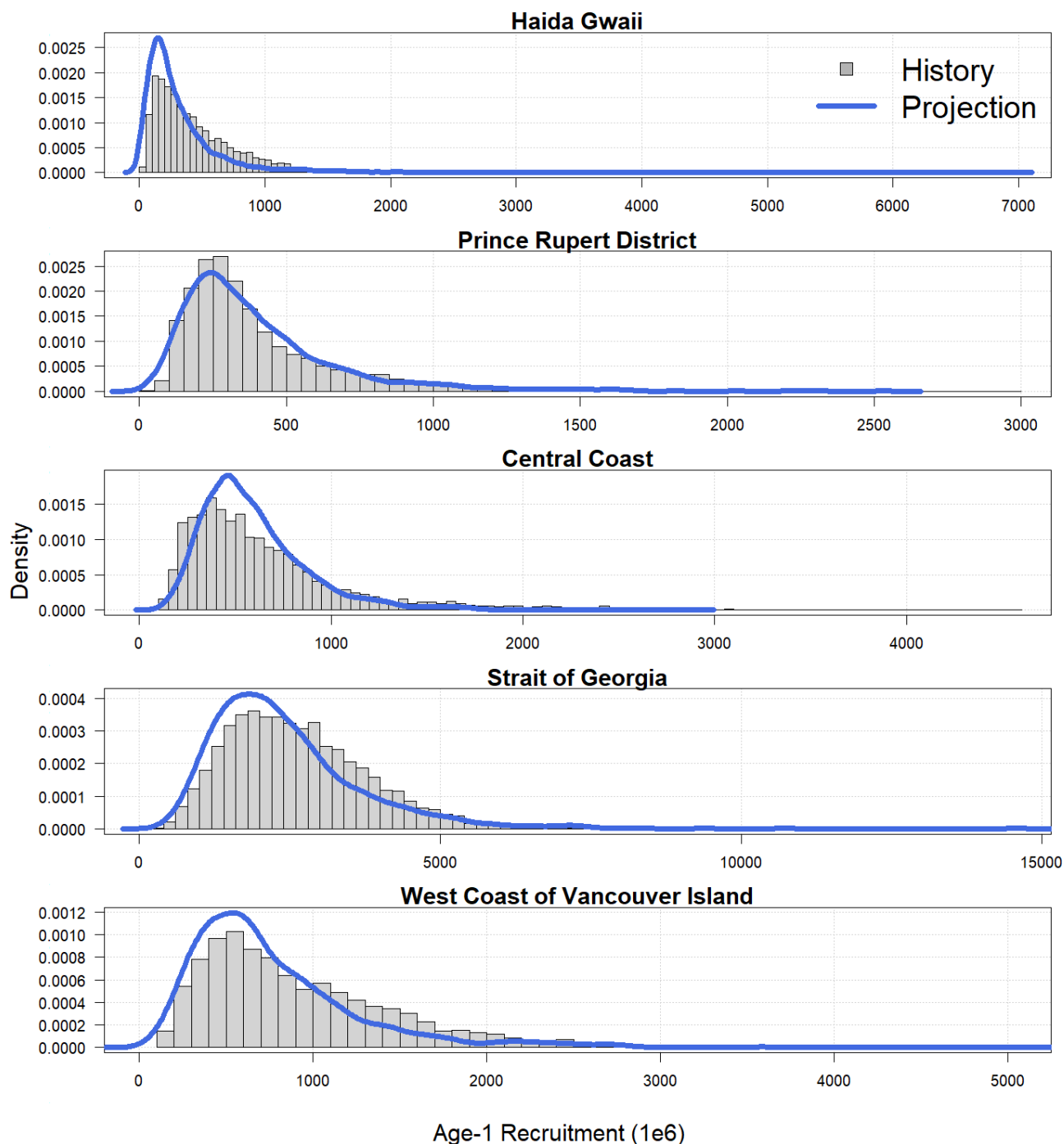


Figure 12. Recruitment distributions from the historical period (grey bars) and projection (blue density) for all SARs under the No Fishing management procedure.

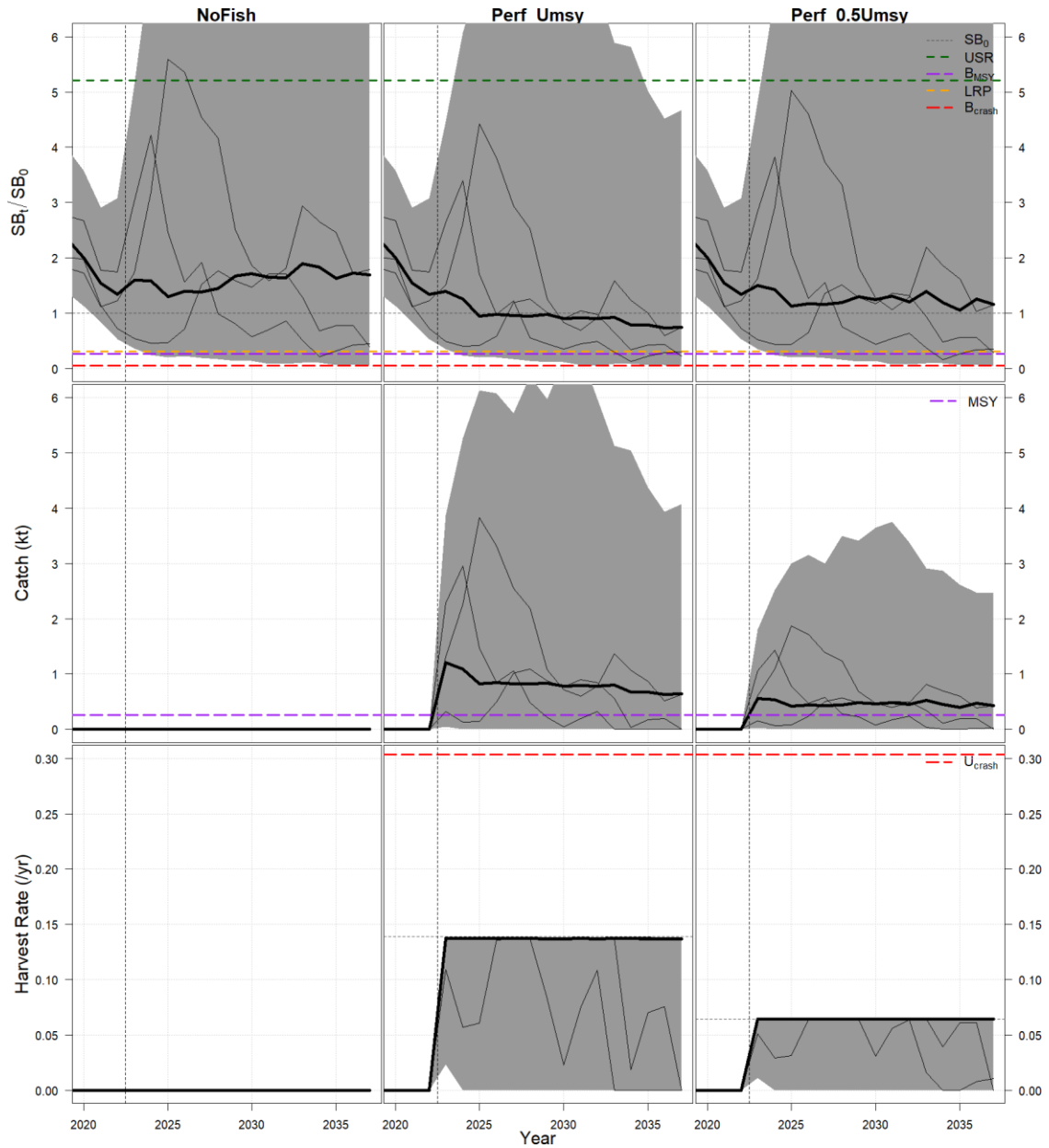


Figure 13. Haida Gwaii simulation envelopes of spawning biomass depletion (top), total allowable catch (middle), and harvest rate (bottom) under multiple management procedures indicated at the top of each column. In all panels, heavy black lines indicate the median, and shaded regions show the central 95% of each quantity's simulated distribution, thin black lines show individual random simulation replicates, and the vertical dashed line shows the start of the projection period. In spawning biomass depletion plots, the horizontal dashed lines show reference points with colours indicated in the legend (B_0 = unfished spawning biomass, USR = upper stock reference, B_{MSY} = equilibrium biomass at MSY , LRP = 30% of unfished biomass, and B_{crash} = biomass at largest decline in yield). In the catch panel, the horizontal dashed purple line shows maximum sustainable yield MSY , and in harvest rate panels the reference removal rate U_{ref} is shown as a horizontal grey dashed line. Column headers indicate management procedures: NoFish = no fishing, and Perf = Perfect information with harvest rate U_{MSY} or $U_{0.5MSY}$.

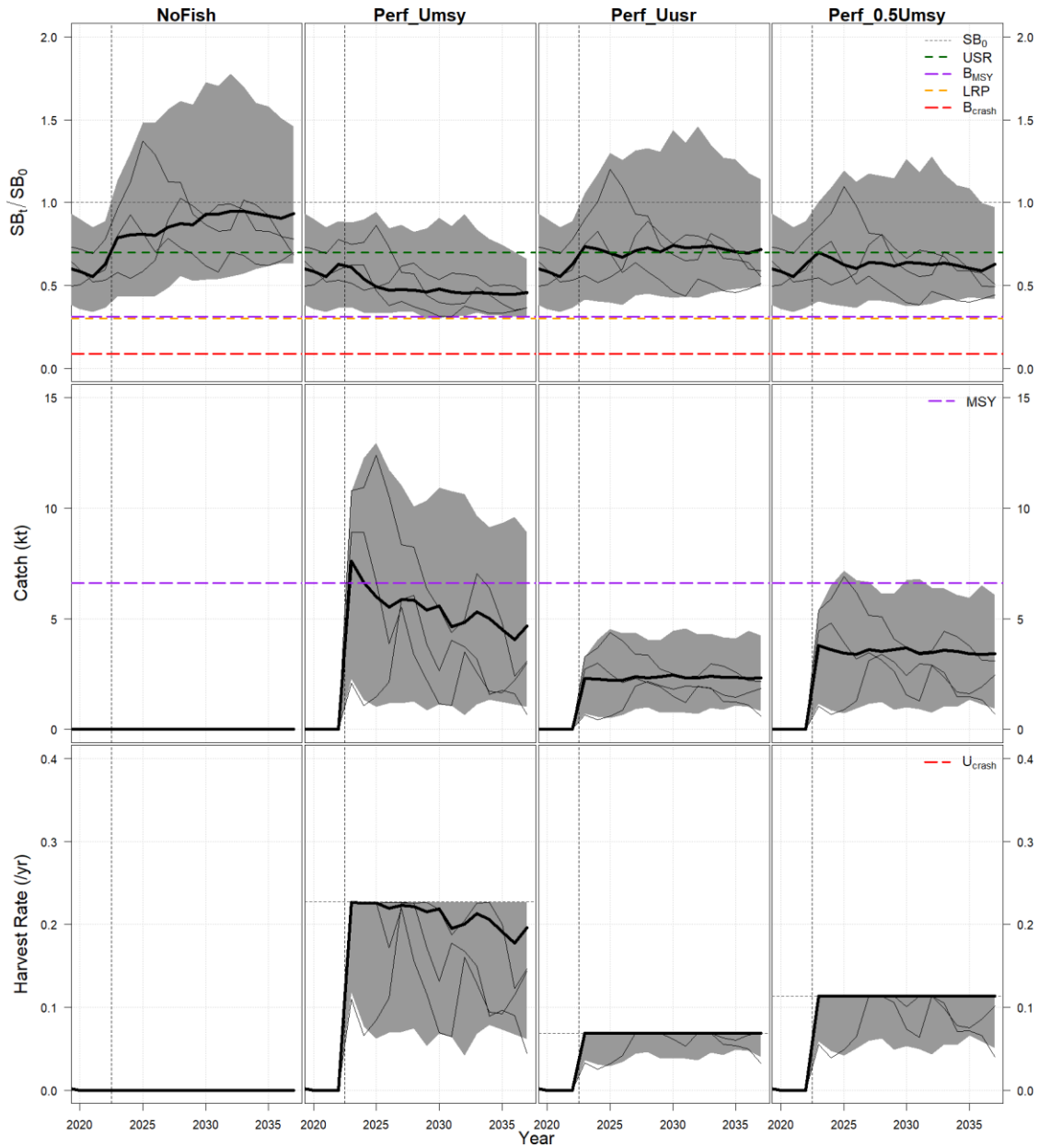


Figure 14. Prince Rupert District simulation envelopes of spawning biomass depletion (top), total allowable catch (middle), and harvest rate (bottom) under multiple management procedures indicated at the top of each column. In all panels, heavy black lines indicate the median, and shaded regions show the central 95% of each quantity's simulated distribution, thin black lines show individual random simulation replicates, and the vertical dashed line shows the start of the projection period. In spawning biomass depletion plots, the horizontal dashed lines show reference points with colours indicated in the legend (B_0 = unfished spawning biomass, USR = upper stock reference, B_{MSY} = equilibrium biomass at MSY , LRP = 30% of unfished biomass, and B_{crash} = biomass at largest decline in yield). In the catch panel, the horizontal dashed purple line shows maximum sustainable yield MSY , and in harvest rate panels the reference removal rate U_{ref} is shown as a horizontal grey dashed line. Column headers indicate management procedures: NoFish = no fishing, and Perf = Perfect information with harvest rate U_{MSY} or $U_{0.5MSY}$.

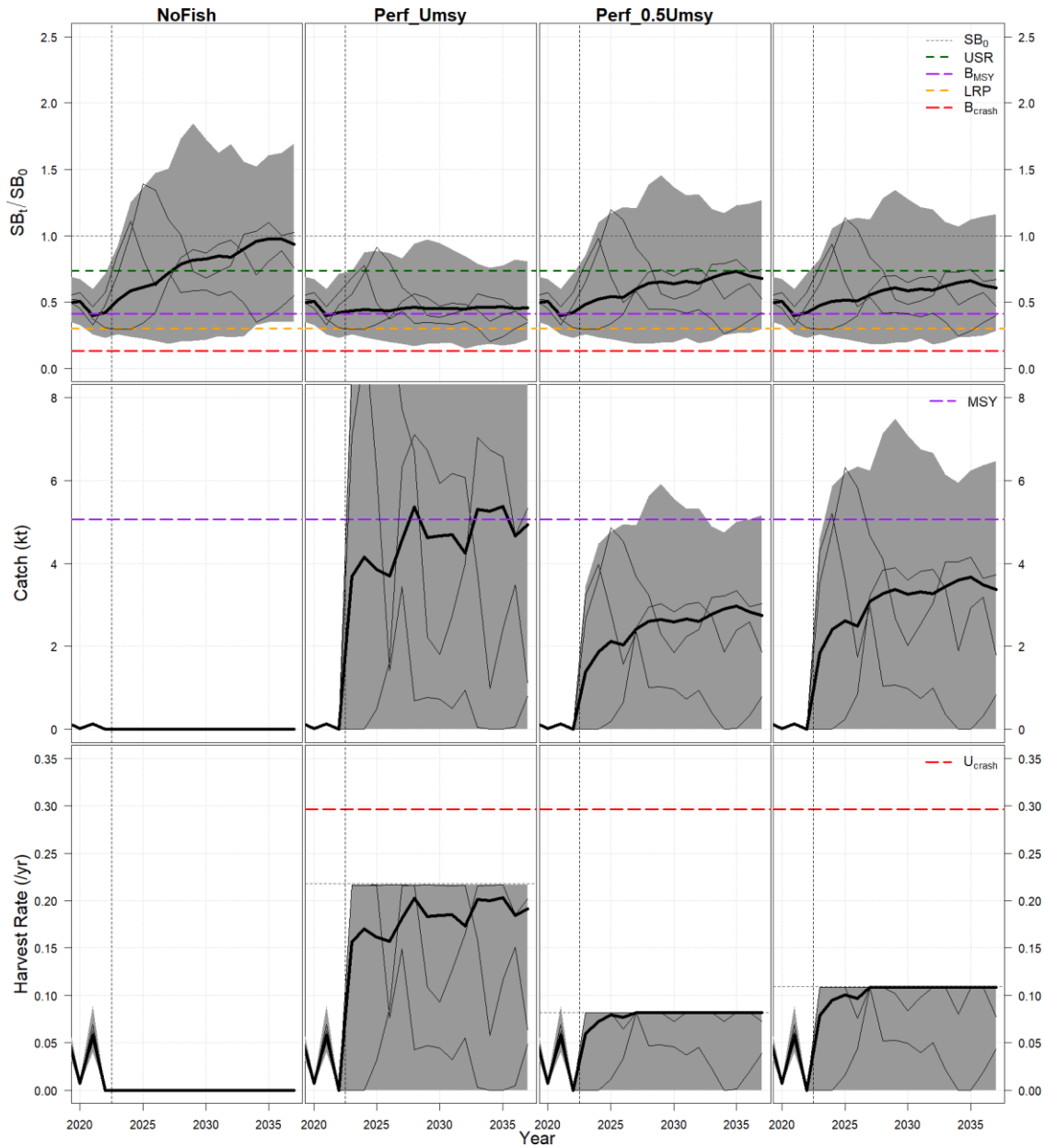


Figure 15. Central Coast simulation envelopes of spawning biomass depletion (top), total allowable catch (middle), and harvest rate (bottom) under multiple management procedures indicated at the top of each column. In all panels, heavy black lines indicate the median, and shaded regions show the central 95% of each quantity's simulated distribution, thin black lines show individual random simulation replicates, and the vertical dashed line shows the start of the projection period. In spawning biomass depletion plots, the horizontal dashed lines show reference points with colours indicated in the legend (B_0 = unfished spawning biomass, USR = upper stock reference, B_{MSY} = equilibrium biomass at MSY , LRP = 30% of unfished biomass, and B_{crash} = biomass at largest decline in yield). In the catch panel, the horizontal dashed purple line shows maximum sustainable yield MSY , and in harvest rate panels the reference removal rate U_{ref} is shown as a horizontal grey dashed line. Column headers indicate management procedures: NoFish = no fishing, and Perf = Perfect information with harvest rate U_{MSY} or $U_{0.5MSY}$.

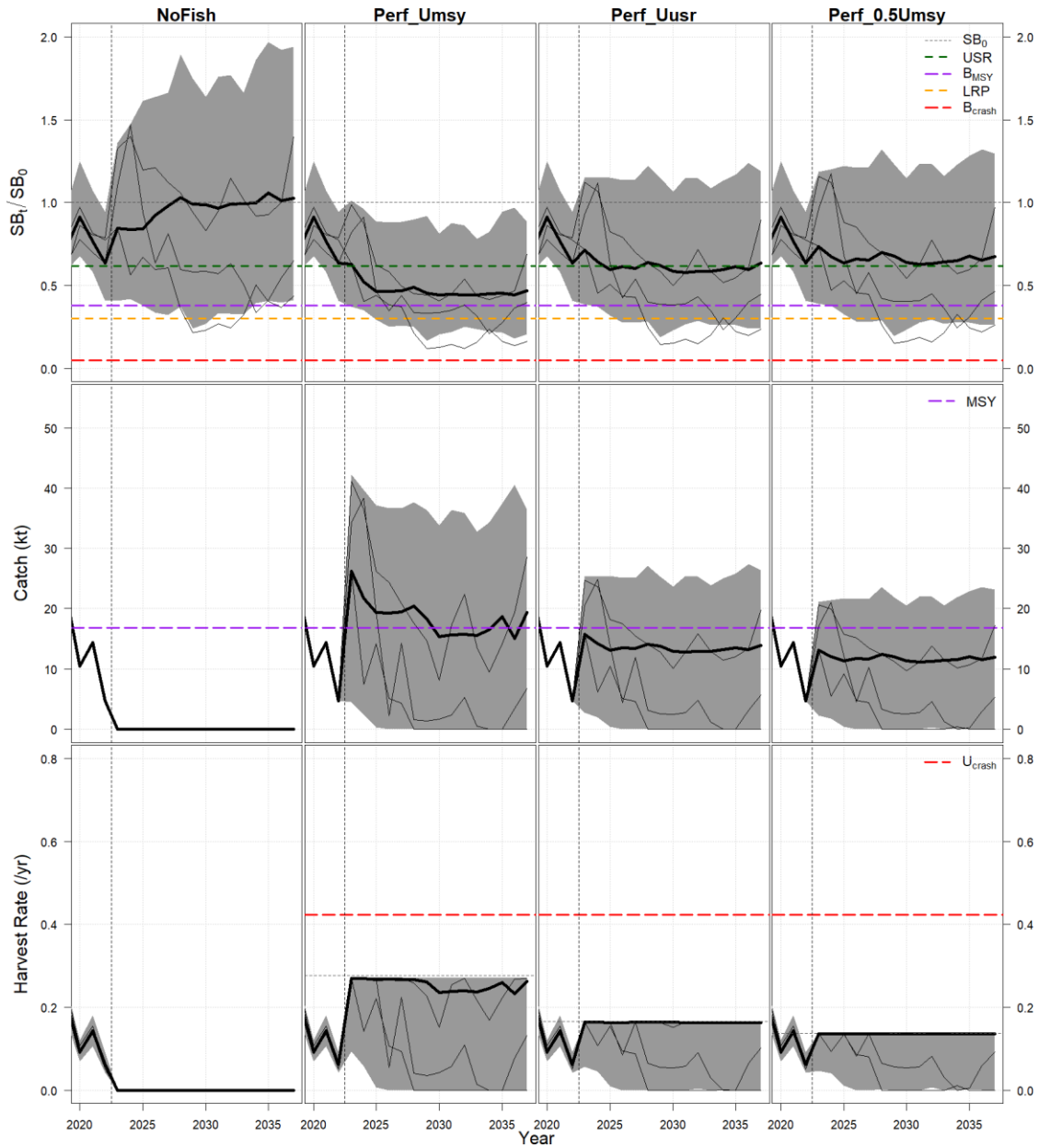


Figure 16. Strait of Georgia simulation envelopes of spawning biomass depletion (top), total allowable catch (middle), and harvest rate (bottom) under multiple management procedures indicated at the top of each column. In all panels, heavy black lines indicate the median, and shaded regions show the central 95% of each quantity's simulated distribution, thin black lines show individual random simulation replicates, and the vertical dashed line shows the start of the projection period. In spawning biomass depletion plots, the horizontal dashed lines show reference points with colours indicated in the legend (B_0 = unfished spawning biomass, USR = upper stock reference, B_{MSY} = equilibrium biomass at MSY , LRP = 30% of unfished biomass, and B_{crash} = biomass at largest decline in yield). In the catch panel, the horizontal dashed purple line shows maximum sustainable yield MSY , and in harvest rate panels the reference removal rate U_{ref} is shown as a horizontal grey dashed line. Column headers indicate management procedures: NoFish = no fishing, and Perf = Perfect information with harvest rate U_{MSY} or $U_{0.5MSY}$.

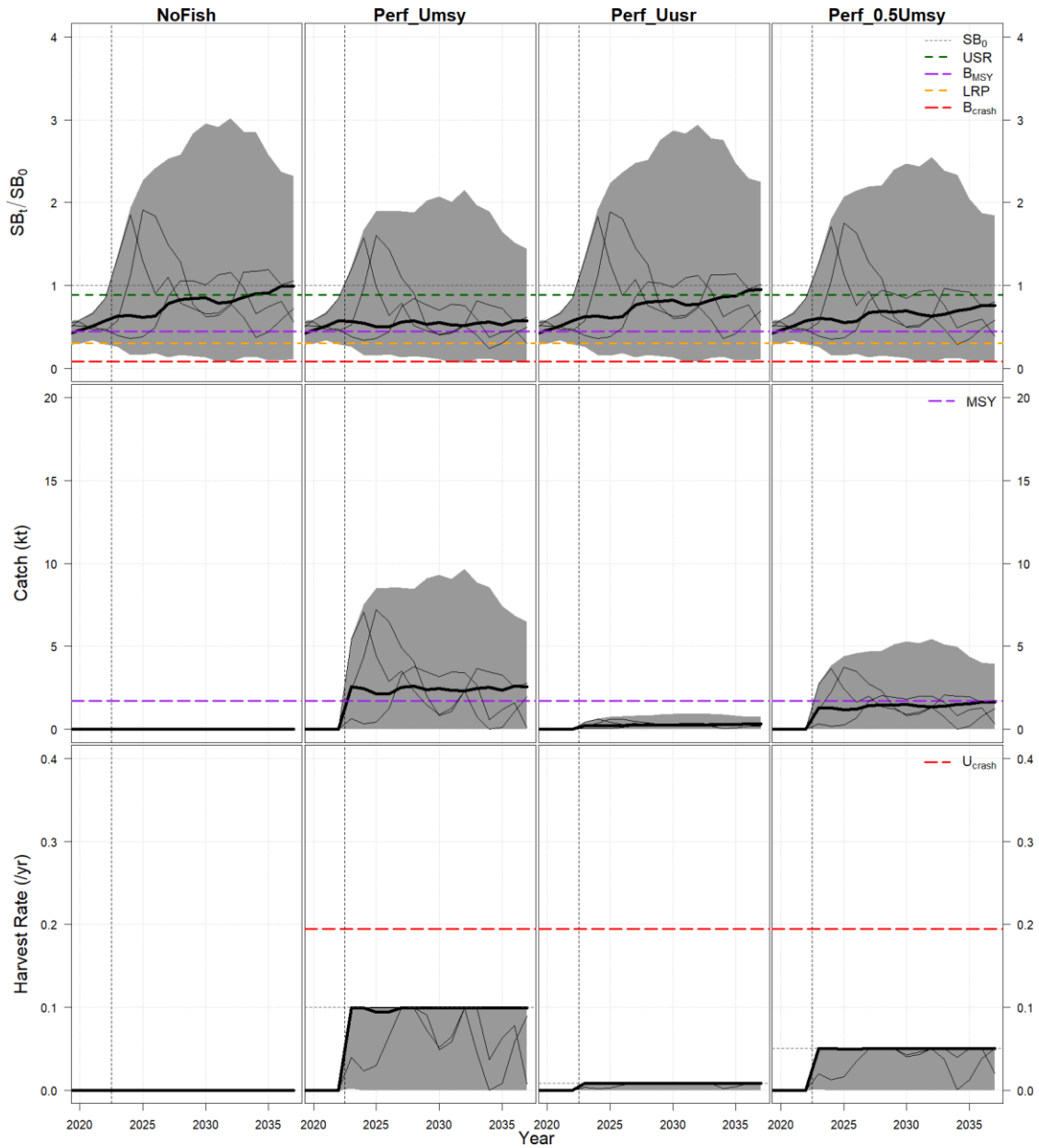


Figure 17. West Coast of Vancouver Island simulation envelopes of spawning biomass depletion (top), total allowable catch (middle), and harvest rate (bottom) under multiple management procedures indicated at the top of each column. In all panels, heavy black lines indicate the median, and shaded regions show the central 95% of each quantity's simulated distribution, thin black lines show individual random simulation replicates, and the vertical dashed line shows the start of the projection period. In spawning biomass depletion plots, the horizontal dashed lines show reference points with colours indicated in the legend (B_0 = unfished spawning biomass, USR = upper stock reference, B_{MSY} = equilibrium biomass at MSY , LRP = 30% of unfished biomass, and B_{crash} = biomass at largest decline in yield). In the catch panel, the horizontal dashed purple line shows maximum sustainable yield MSY , and in harvest rate panels the reference removal rate U_{ref} is shown as a horizontal grey dashed line. Column headers indicate management procedures: NoFish = no fishing, and Perf = Perfect information with harvest rate U_{MSY} or $U_{0.5MSY}$.

APPENDIX A. CATCH, BIOLOGICAL DATA, AND FISHERY INDEPENDENT SURVEYS

Data used in this model come from two sources: commercial fisheries and independent surveys. The sections below present each type data used in this paper.

A.1. DESCRIPTION OF THE FISHERIES

At present, there are several Pacific Herring fisheries in BC. First Nations have priority access, after conservation, to fish for food, social, and ceremonial (FSC) purposes. Commercial fishing opportunities consist of four directed fisheries: food and bait (FB), special use (SU), spawn-on-kelp (SOK), and roe herring (seine and gillnet). There is also a small recreational fishery.

First Nations fish for whole herring, herring roe, and herring eggs for FSC purposes. Whole herring are fished by seine, gillnet, rake, dip net, and jig. Herring eggs are collected as spawn on seaweed such as kelp (i.e., SOK), or spawn on tree boughs placed in spawning locations. Indigenous harvest of herring for FSC purposes may occur coast wide where authorized by a communal license.

The history of Pacific Herring commercial fisheries is described in Cleary et al. (2019), and the latest treaty and Aboriginal commercial fisheries are described in the latest stock assessment report (DFO 2022a). SOK fisheries from 1972–2016 are documented in Schweigert et al. (2018).

A.2. COMMERCIAL CATCH DATA

The commercial catch time series extends from in 1951 to 2022. Pacific Herring were commercially harvested as early as 1930, however catches prior to 1951 are not reliably attributable to each region or stock area and thus are excluded.

Figure A.1 presents total landed catch for the historical reduction fishery (1951–1965) and present-day licensed fisheries: FB and SU (combined), roe seine, and roe gillnet. Catch validation for these fisheries occurs at offloading, through dockside monitoring and validation programs, with 100% validation since inception of the roe fishery in 1972. Figure A.2 presents the same data, truncated from 1970 to 2022. SOK removals are not combined into the previous two figures, however the data are shown Figure A.3 and a description of the fishery appears below.

A.2.1. Spawn-on-kelp

Commercial SOK fisheries are licensed as either closed or open pond operations. Generally, closed ponding is licensed for HG, PRD, CC (limited), and WCVI, while open ponding is licensed in the CC (Area 07).

In closed pond fisheries, herring are captured using a purse seine net and then towed to and subsequently transferred into closed net-pens (ponds) which contain kelp blades strung on submerged lines. Ponded herring will spawn on blades of kelp (usually *Macrocystus integrifolia*) and spawned out herring are released from ponds following spawning (Schweigert et al. 2018). In open pond fisheries, herring are attracted to a site where kelp is laid out to collect spawn, or alternatively, frames strung with kelp are towed to sites where herring are already spawning.

The SOK fishery is licensed as weight (lbs) of landed product. SOK fishery data, 1975–2022, are available as total landings of SOK product (drained wet weight of eggs adhered to kelp), with dockside weight validation since 1996. Landed product for the major stock areas is presented in Figure A.3.

Generally, stock assessment models assume that all removals from the population are known and accounted for in reconstructing abundance and forecasting future productivity, and involve specifying uncertainty (as variance) in commercial catch weight. The herring SOK fishery is an anomaly since no fish are removed from the population although there is some difficulty to quantify mortality that occurs within the net-pens. In addition, the removal of eggs has an impact on future productivity however accounting for this loss in stock assessment modeling is complicated.

Schweigert et al. (2018) recommend an assumption of 65 short tons herring mortality for each closed pond licence and that mortality be treated as seine fishery removals. In addition, we suggest that the total validated egg removals by the SOK fishery be added to the estimate of the spawn index in the assessment model thereby accounting for the foregone egg production. Taken together the inclusion of catch and egg removal will directly affect the calculation of fishing and natural mortality rates in the assessment model and indirectly the determination of spawning biomass and recruitment analogous to the Shelton et al. (2014) approach.

Our approach for modelling SOK egg removals and fishing mortality is outlined in the Methods section.

A.3. SPAWN SURVEY PROGRAM AND DATA

Pacific Herring spawn surveys in BC have evolved over time. Between 1951 and 1987 spawn surveys were primarily done either from the beach or using small vessels to search for spawning activity and a surface survey method used to estimate egg deposition. From 1988 to present day aircraft has been the primary way to identify spawning activity and dive surveys have been the primary means of estimating egg deposition. During the surface survey era more effort was devoted to identifying spawning activity (from the ground and the water) and less was spent on quantifying egg deposition, whereas for the dive survey era, aerial surveys allow us to identify spawn activity quickly and dive surveys allow us to quantify egg deposition with more accuracy and precision.

Prior to this paper, differences in accuracy and precision of the two survey eras were accounted for in the model-fitting using two independent survey catchability coefficients (q_s and q_d). However, in years since 1987, sometimes timing, weather and geographic location precludes use of a dive survey in which case surface surveys are still used. In this paper we account for the additional uncertainty in surface survey estimates by using the proportion of observations from each survey method to estimate q_s and q_d and further model a blended survey index. Surface and dive survey protocols can be found in Fort et al.¹ and calculation of survey biomass index is described in Grinnell et al. (2023).

All spawn data are presented in Figure A.4.

A.4. BIOLOGICAL SAMPLING PROGRAM AND DATA

Herring biological samples are collected from pre-spawning aggregations through the seine test fishery sampling program, and as well from the commercial fisheries during catch validation and/or offloading (#ref sampling manual). The target sample size for each sampling event is 100 fish. To help reduce personal bias by the sampler multiple sampling events occur and these are subsampled to produce a single sample.

¹ Fort, C., Daniel, K., and Thompson, M. [Herring Spawn Survey Manual](#). Unpublished report.

Herring samples are processed each spring providing the following data: standard length, weight, gonad weight, maturity, sex, and age. Herring scales are used for ageing, with ageing conducted by the Schlerochronology Lab at the Pacific Biological Station. Cleary et al. (2019) provides further details on herring biological sampling program.

For each SAR, biological data are aggregated by year and gear type and from these data we derive two types of input data for the catch-age stock assessment model: weight-at-age (Figures A.5, A.6, A.7, A.8, and A.9), and proportion-at-age (Figures A.10, A.11, A.12, A.13, and A.14) by fleet (1951–2022). Sample sizes for ages vary greatly; tables of sample sizes by year and gear are included for each SAR. For herring age 10 and older biological data are combined into a single 10+ plus group.

A.5. FIGURES

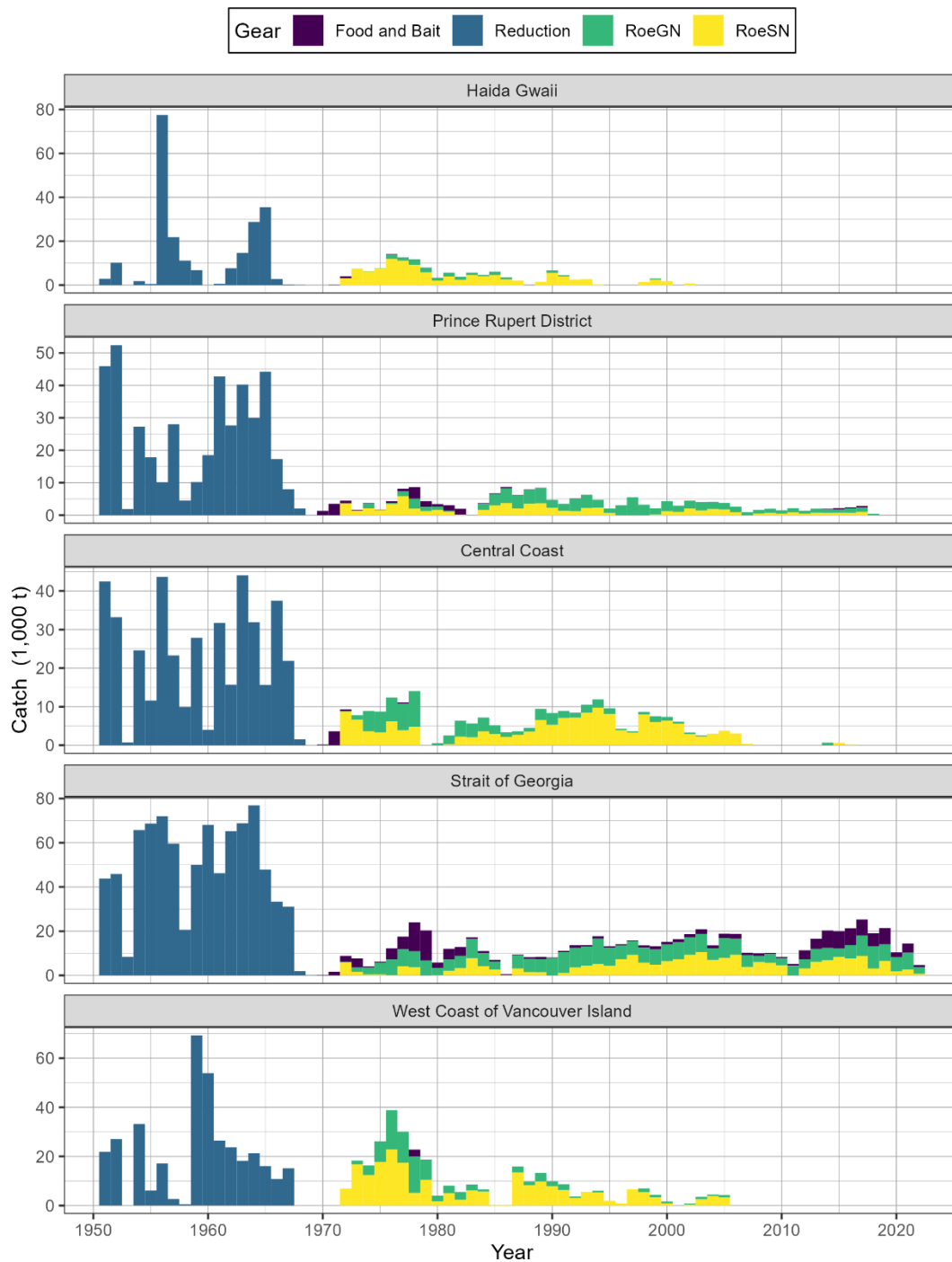


Figure A.1. Total landed Pacific Herring catch in thousands of tonnes (t) from 1951 to 2022 for the major SARs. Reduction fishery (blue), food and bait and special use (purple), roe seine (yellow), roe gillnet (green).

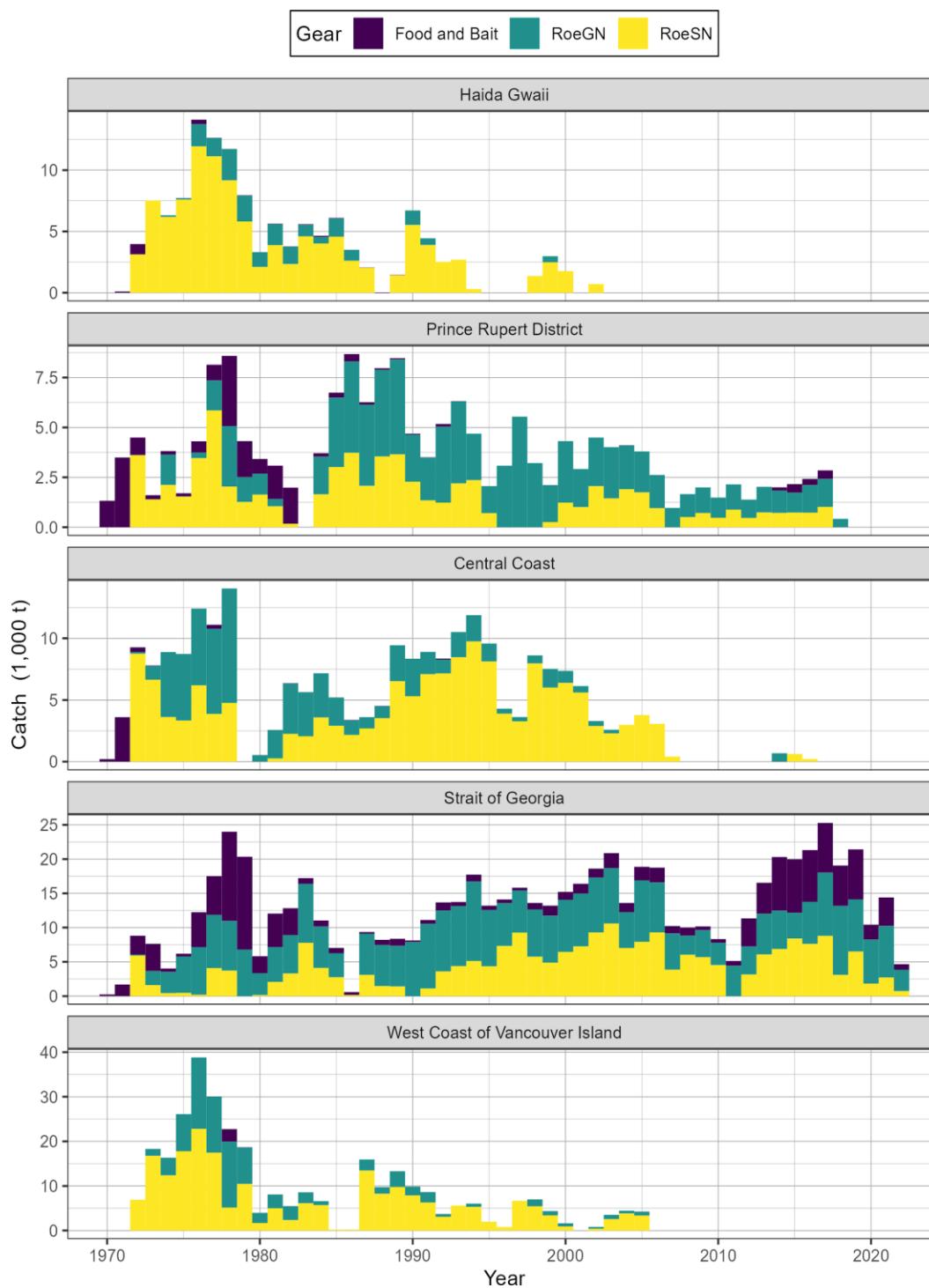


Figure A.2. Total landed Pacific Herring catch in thousands of tonnes (t) from 1970 to 2022 for the major SARs. Food and bait and special use (purple), roe seine (yellow), roe gillnet (green).

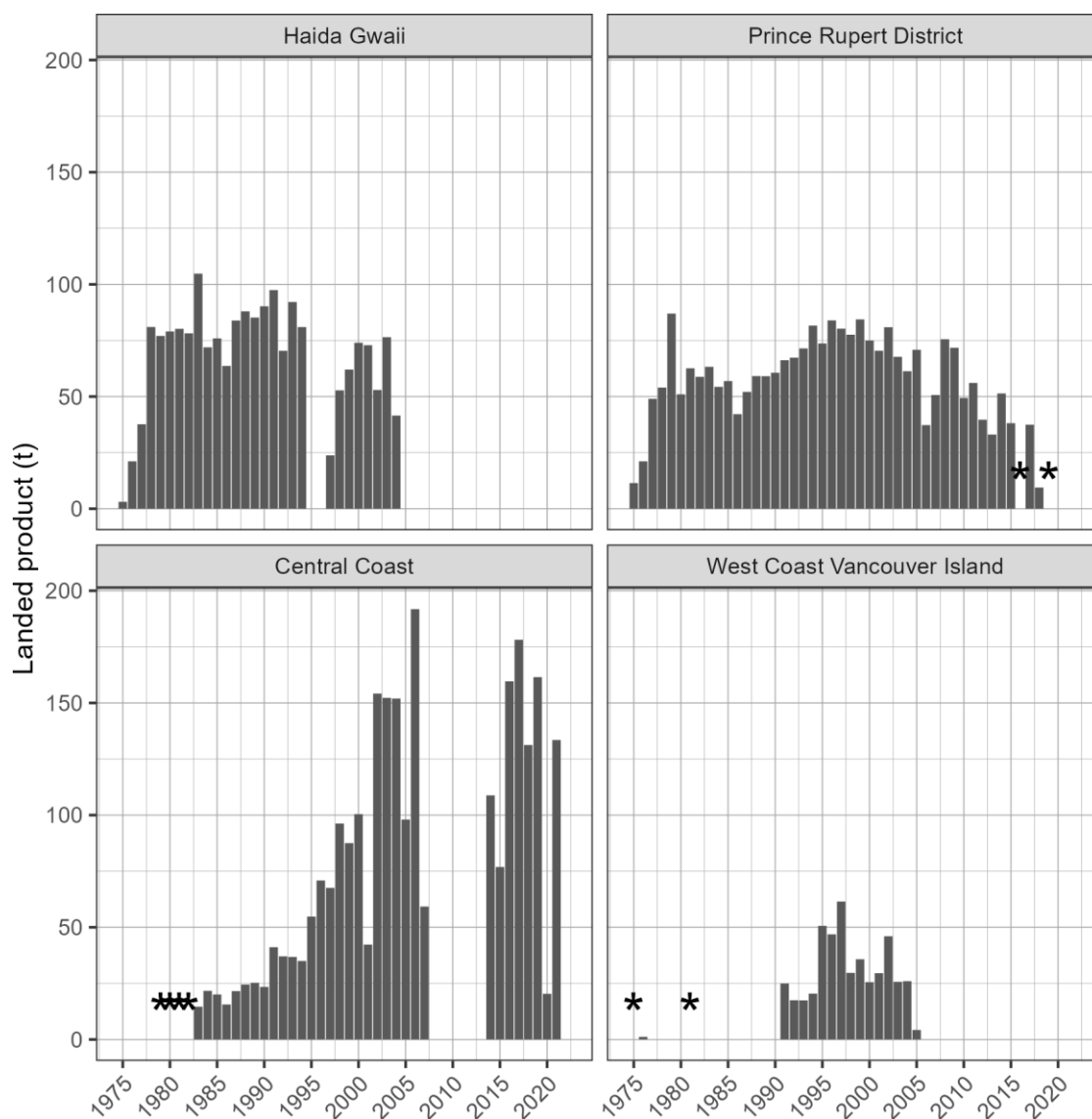


Figure A.3. Total landed commercial spawn-on-kelp product by region and year in metric tonnes (t).
 * indicates data in plot withheld due to privacy.

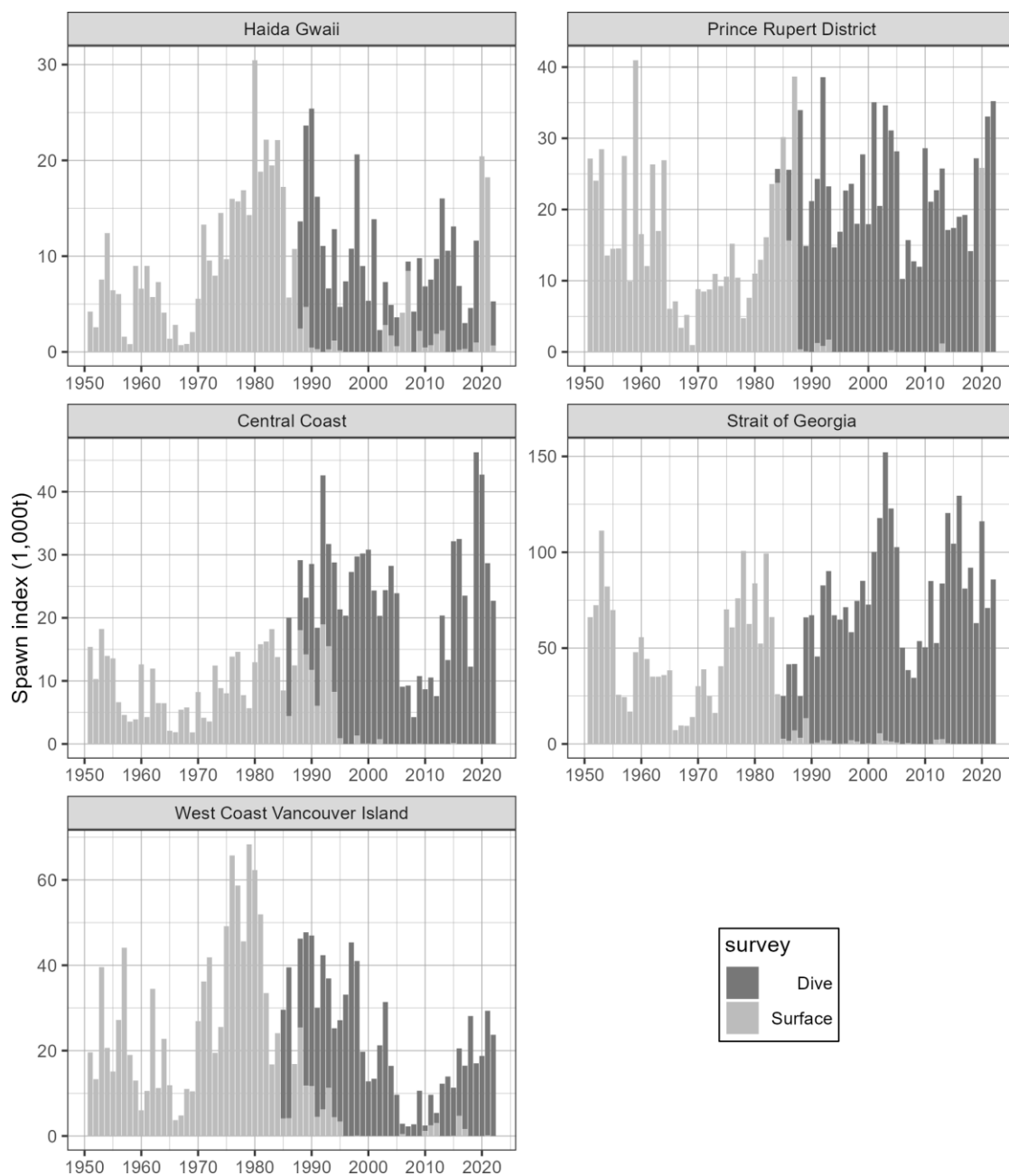


Figure A.4. Spawn index in thousands of tonnes (t) for Pacific Herring from 1951 to 2022 in the major SARs, using the two survey methods. The 'spawn index' is not scaled by q . Note: For Haida Gwaii in 2021 data were collected via a modified survey using an underwater camera due to the dive charter not being available due to the Covid-19 pandemic, for our study this was more akin to and treated as a dive survey.

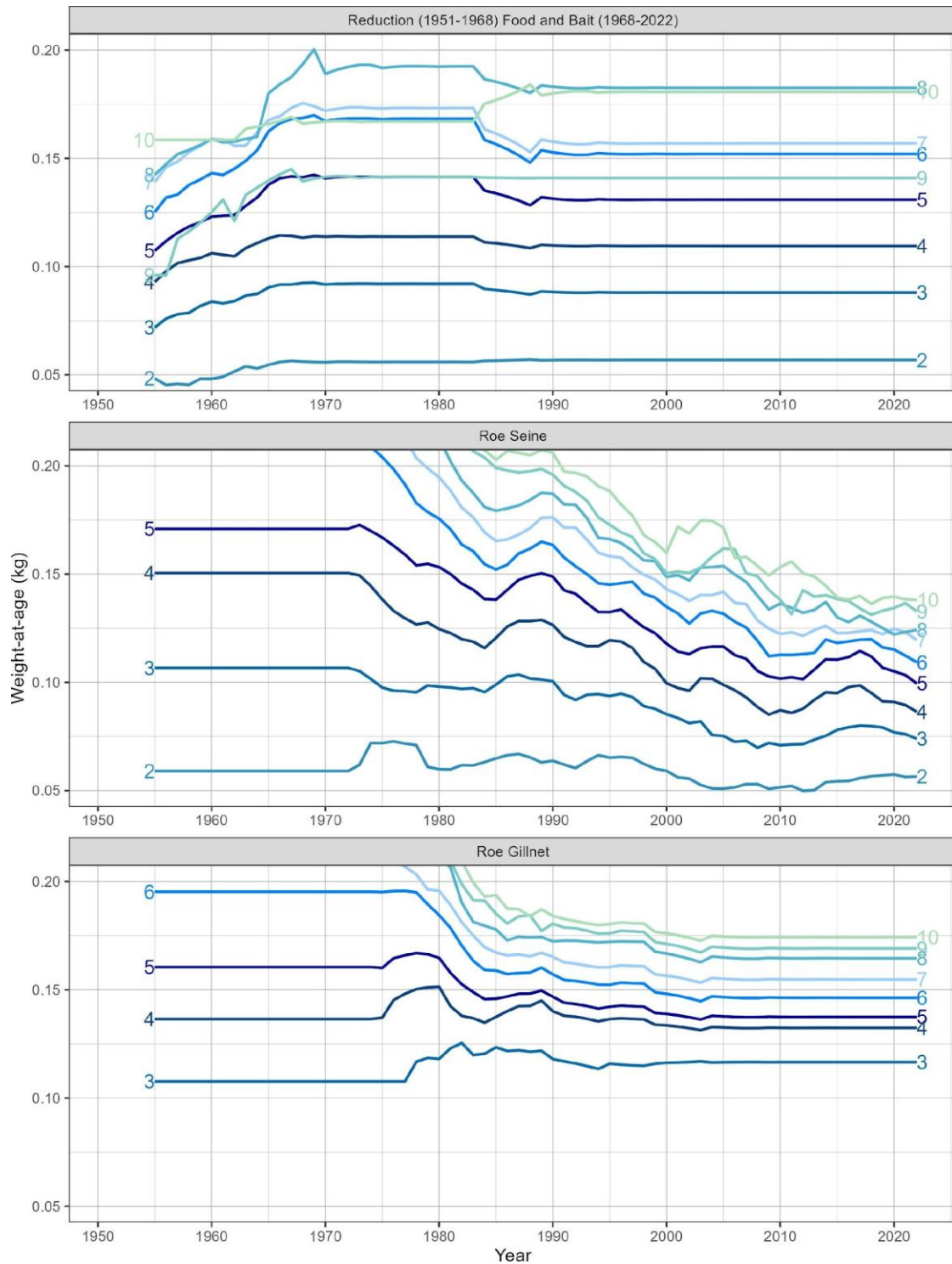


Figure A.5. Haida Gwaii: Mean weight-at-age (kg) for herring 1951–2022. Lines show 5-year running means incrementally age 2 or 3 to age-10+, shaded from darker to lighter, where age-10+ is ages 10 and up. In years without age samples for an age class, values are imputed as the mean of the previous 5 years, except at the beginning of the series where the first value is imputed backwards. (Hence straight lines.) Biological summaries use only commercial and test seine nets samples due to size-selectivity of other gear types. Vertical axes are cropped at 0.05 to 0.20 kg.

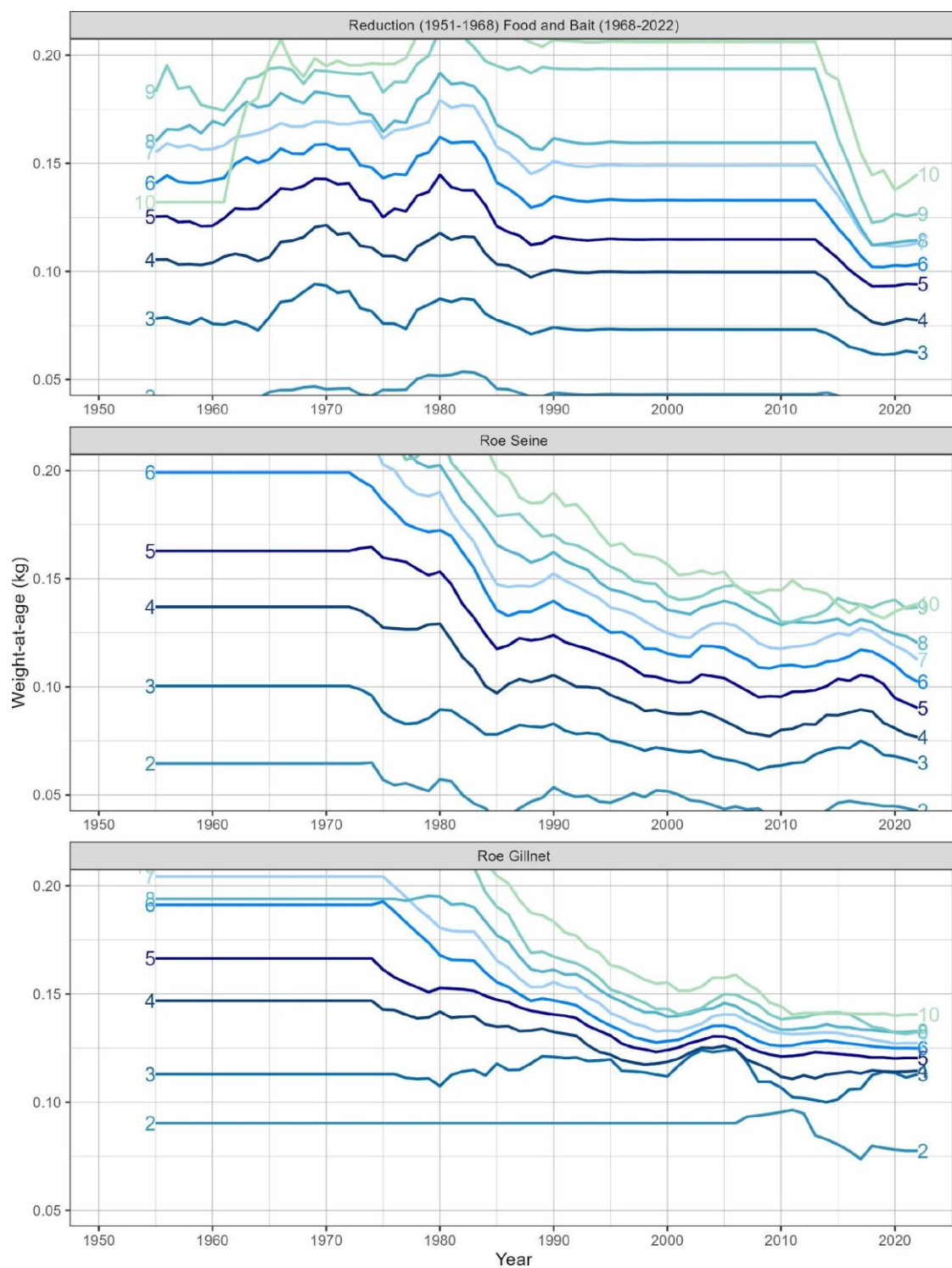


Figure A.6. Prince Rupert District: Mean weight-at-age (kg) for herring 1951–2022. Lines show 5-year running means incrementally age 2 or 3 to age-10+, shaded from darker to lighter, where age-10+ is ages 10 and up. In years without age samples for an age class, values are imputed as the mean of the previous 5 years, except at the beginning of the series where the first value is imputed backwards. (Hence straight lines.) Biological summaries use only commercial and test seine nets samples due to size-selectivity of other gear types. Vertical axes are cropped at 0.05 to 0.20 kg.

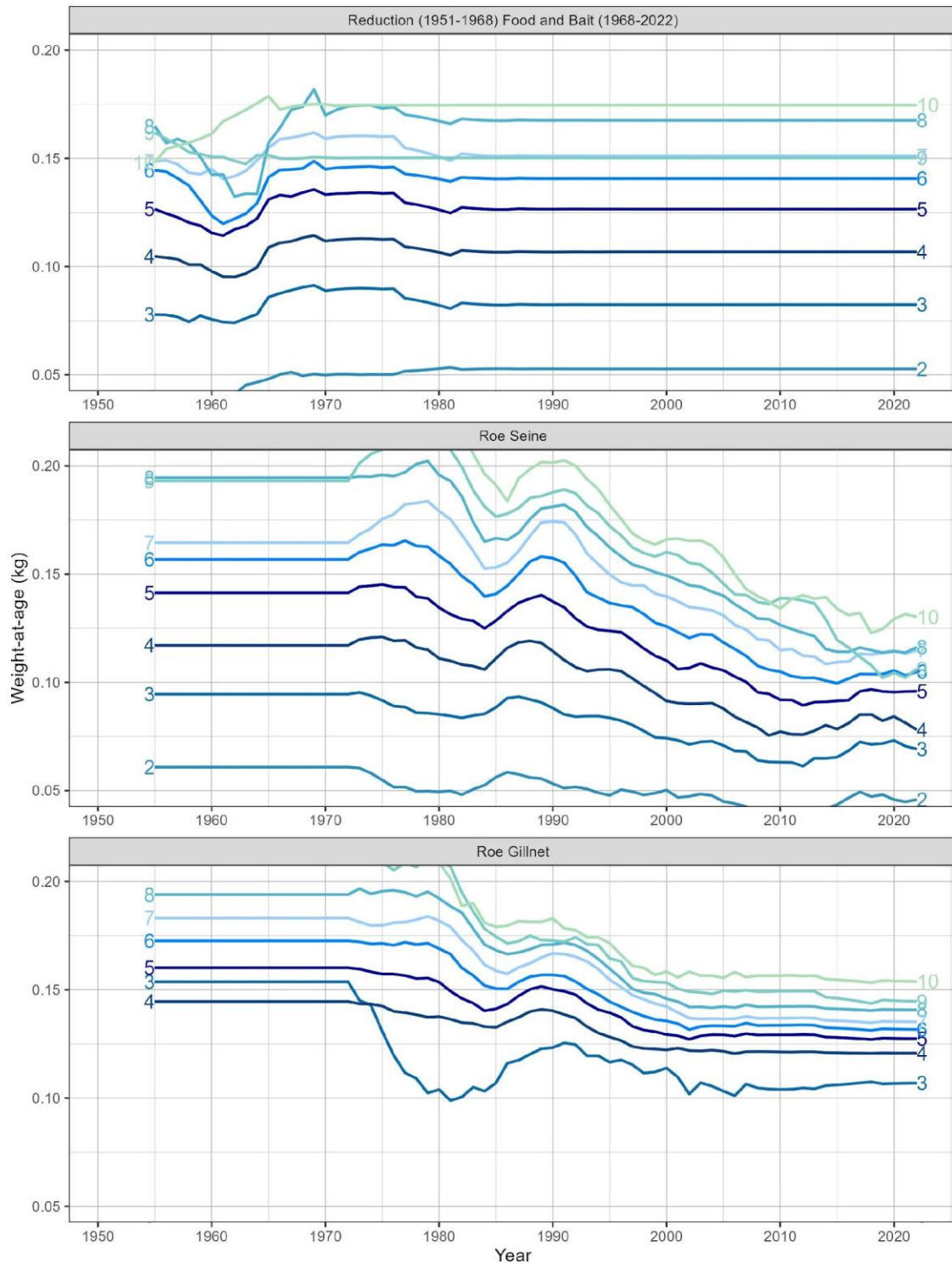


Figure A.7. Central Coast: Mean weight-at-age (kg) for herring 1951–2022. Lines show 5-year running means incrementally age 2 or 3 to age-10+, shaded from darker to lighter, where age-10+ is ages 10 and up. In years without age samples for an age class, values are imputed as the mean of the previous 5 years, except at the beginning of the series where the first value is imputed backwards. (Hence straight lines.) Biological summaries use only commercial and test seine nets samples due to size-selectivity of other gear types. Vertical axes are cropped at 0.05 to 0.20 kg.

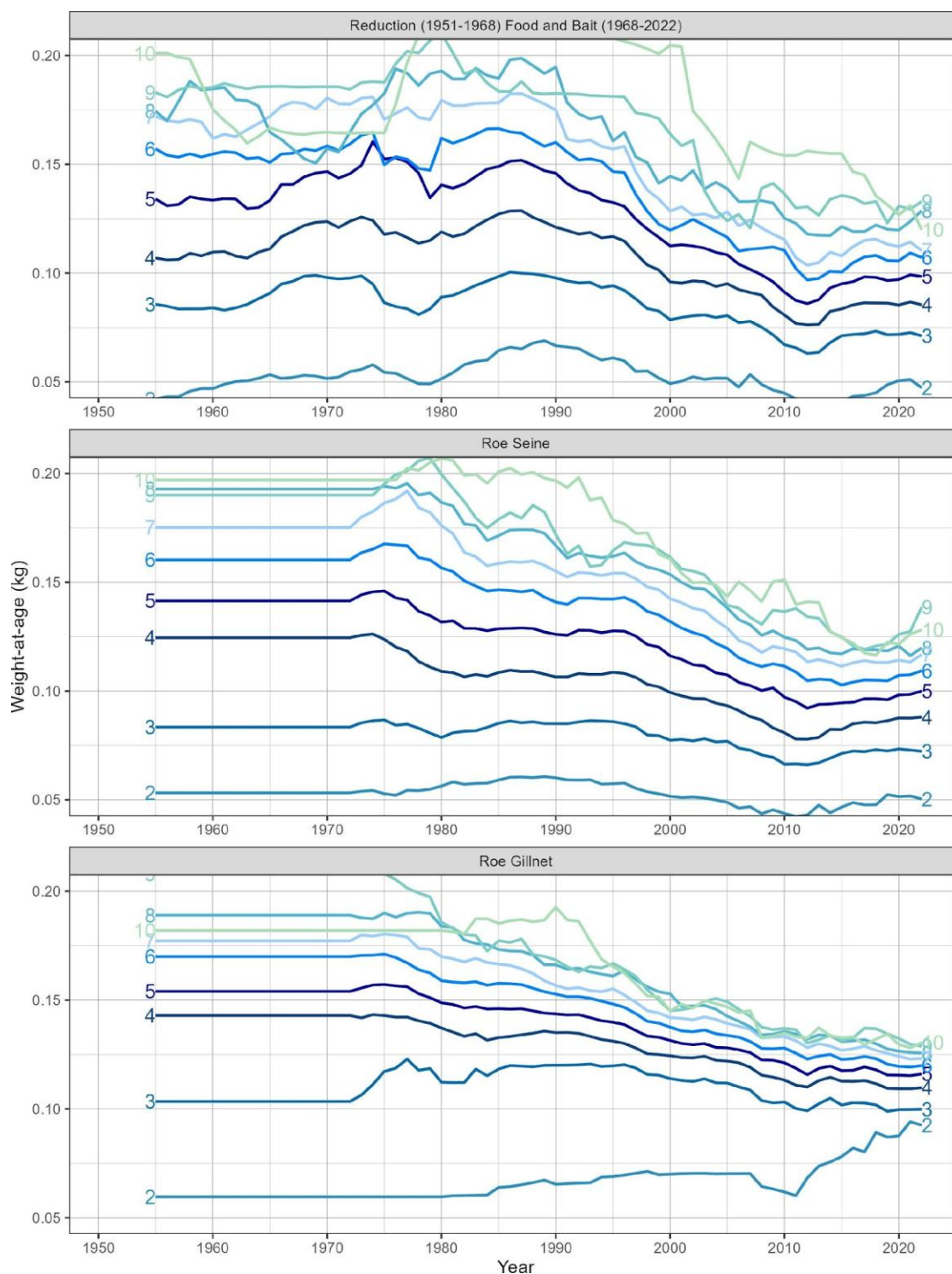


Figure A.8. Strait of Georgia: Mean weight-at-age (kg) for herring 1951–2022. Lines show 5-year running means incrementally age 2 or 3 to age-10+, shaded from darker to lighter, where age-10+ is ages 10 and up. In years without age samples for an age class, values are imputed as the mean of the previous 5 years, except at the beginning of the series where the first value is imputed backwards. (Hence straight lines.) Biological summaries use only commercial and test seine nets samples due to size-selectivity of other gear types. Vertical axes are cropped at 0.05 to 0.20 kg.

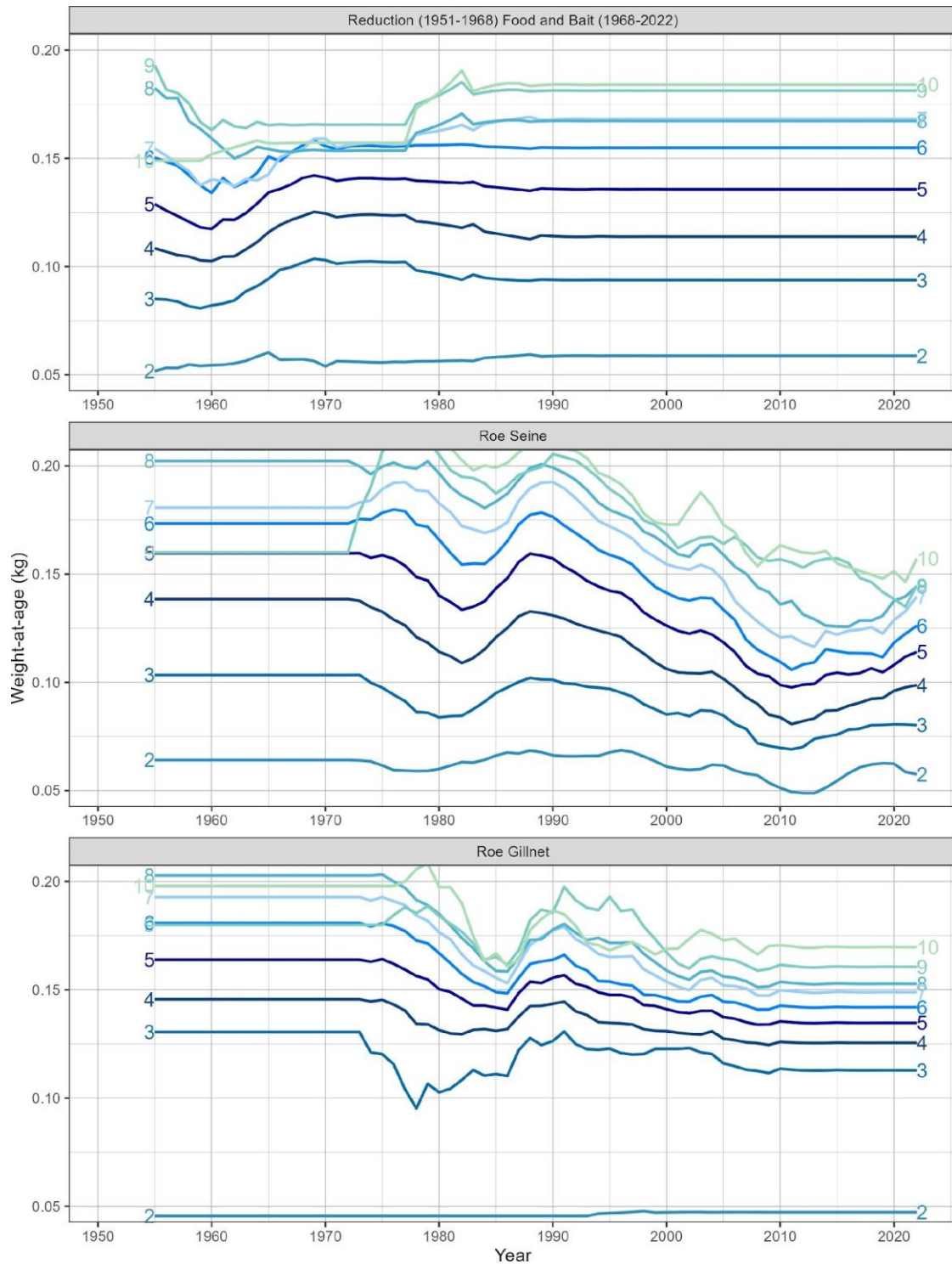


Figure A.9. West Coast Vancouver Island: Mean weight-at-age (kg) for herring 1951–2022. Lines show 5-year running means incrementally age 2 or 3 to age-10+, shaded from darker to lighter, where age-10+ is ages 10 and up. In years without age samples for an age class, values are imputed as the mean of the previous 5 years, except at the beginning of the series where the first value is imputed backwards. (Hence straight lines.) Biological summaries use only commercial and test seine nets samples due to size-selectivity of other gear types. Vertical axes are cropped at 0.05 to 0.20 kg.

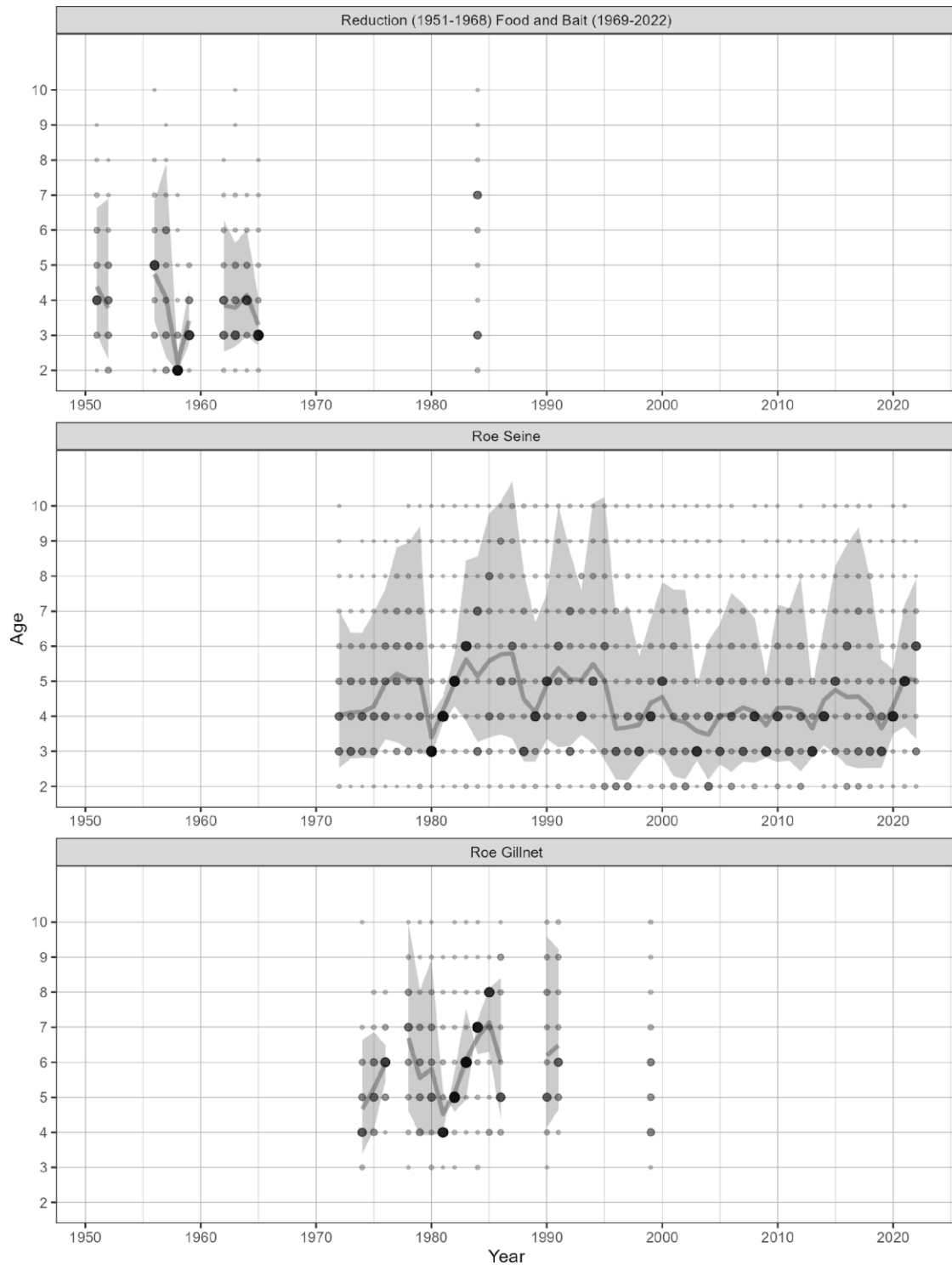


Figure A.10. Haida Gwaii: Proportion-at-age for Pacific Herring from 1951 to 2022. Dot size and colour indicates age class proportion for the year; each year adds up to 1.0. The gray line is the mean age, and the shaded area is the approximate 90 percent distribution. Biological summaries are presented by gear type (reduction, food and bait, seine roe and gillnet roe), where seine roe combines samples across the commercial and test fisheries. The age-10 plus class includes fish ages 10 and older.

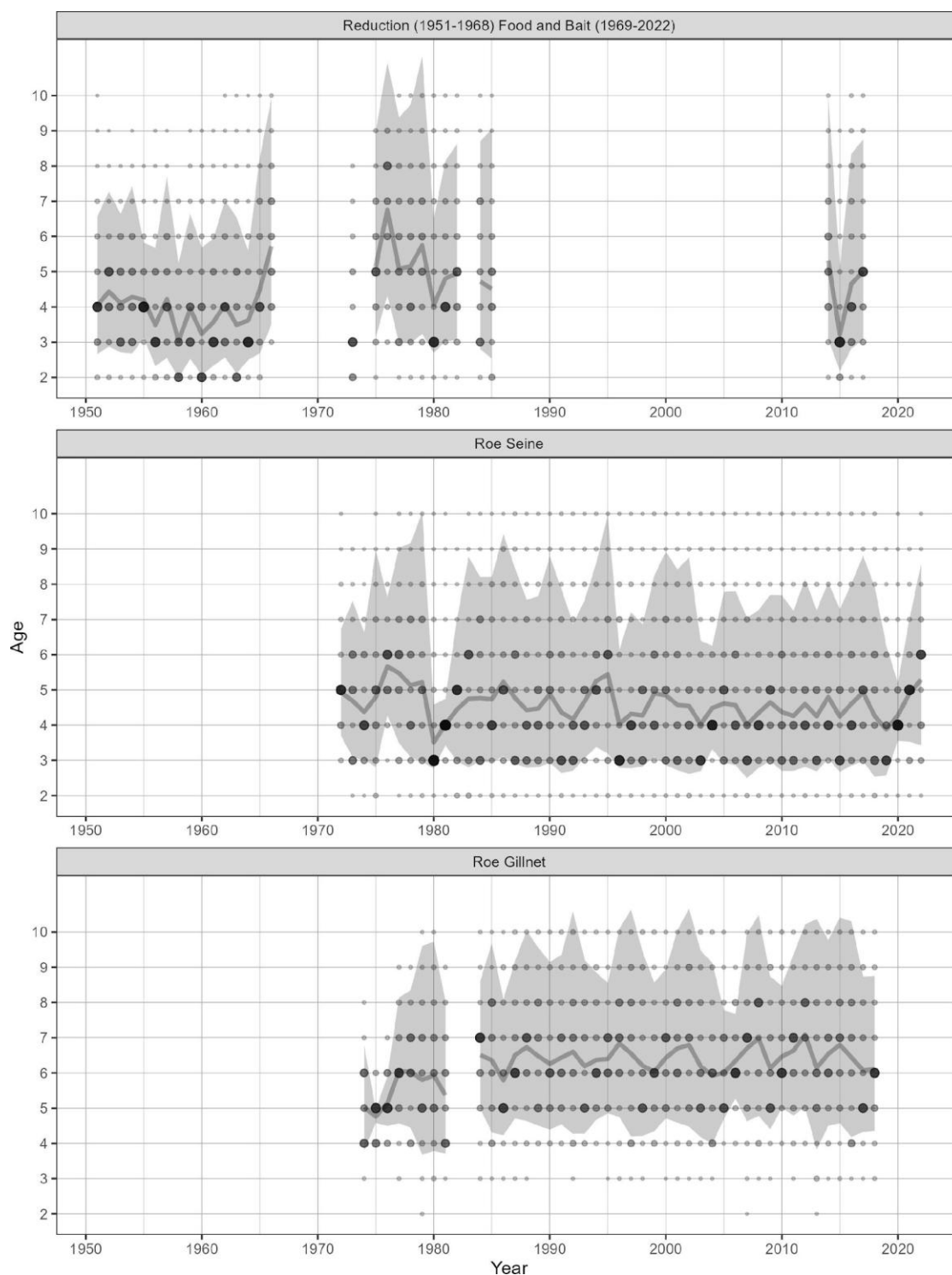


Figure A.11. Prince Rupert District: Proportion-at-age for Pacific Herring from 1951 to 2022. Dot size and colour indicates age class proportion for the year; each year adds up to 1.0. The gray line is the mean age, and the shaded area is the approximate 90 percent distribution. Biological summaries are presented by gear type (reduction, food and bait, seine roe and gillnet roe), where seine roe combines samples across the commercial and test fisheries. The age-10 plus class includes fish ages 10 and older.

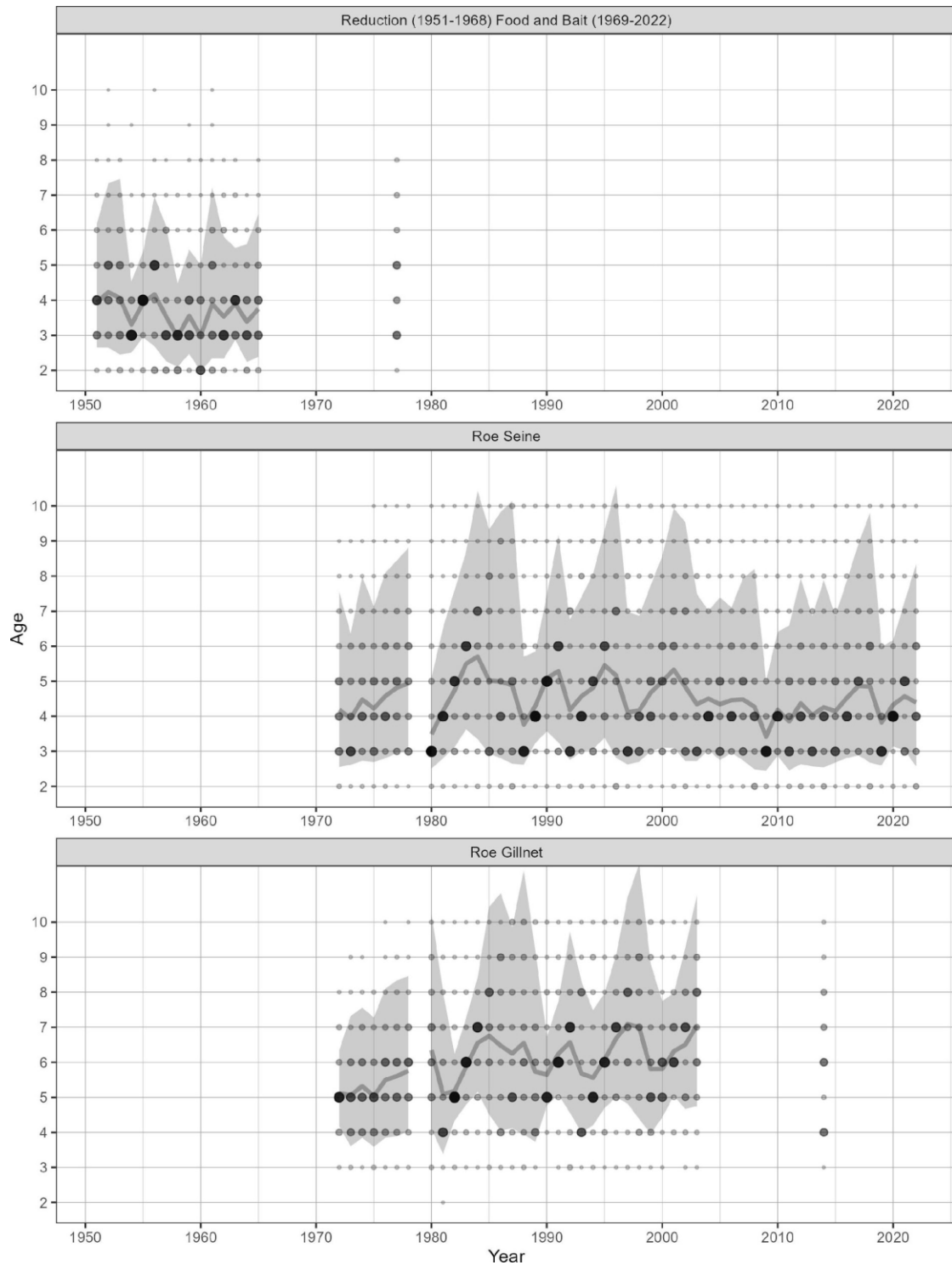


Figure A.12. Central Coast: Proportion-at-age for Pacific Herring from 1951 to 2022. Dot size and colour indicates age class proportion for the year; each year adds up to 1.0. The gray line is the mean age, and the shaded area is the approximate 90 percent distribution. Biological summaries are presented by gear type (reduction, food and bait, seine roe and gillnet roe), where seine roe combines samples across the commercial and test fisheries. The age-10 plus class includes fish ages 10 and older.

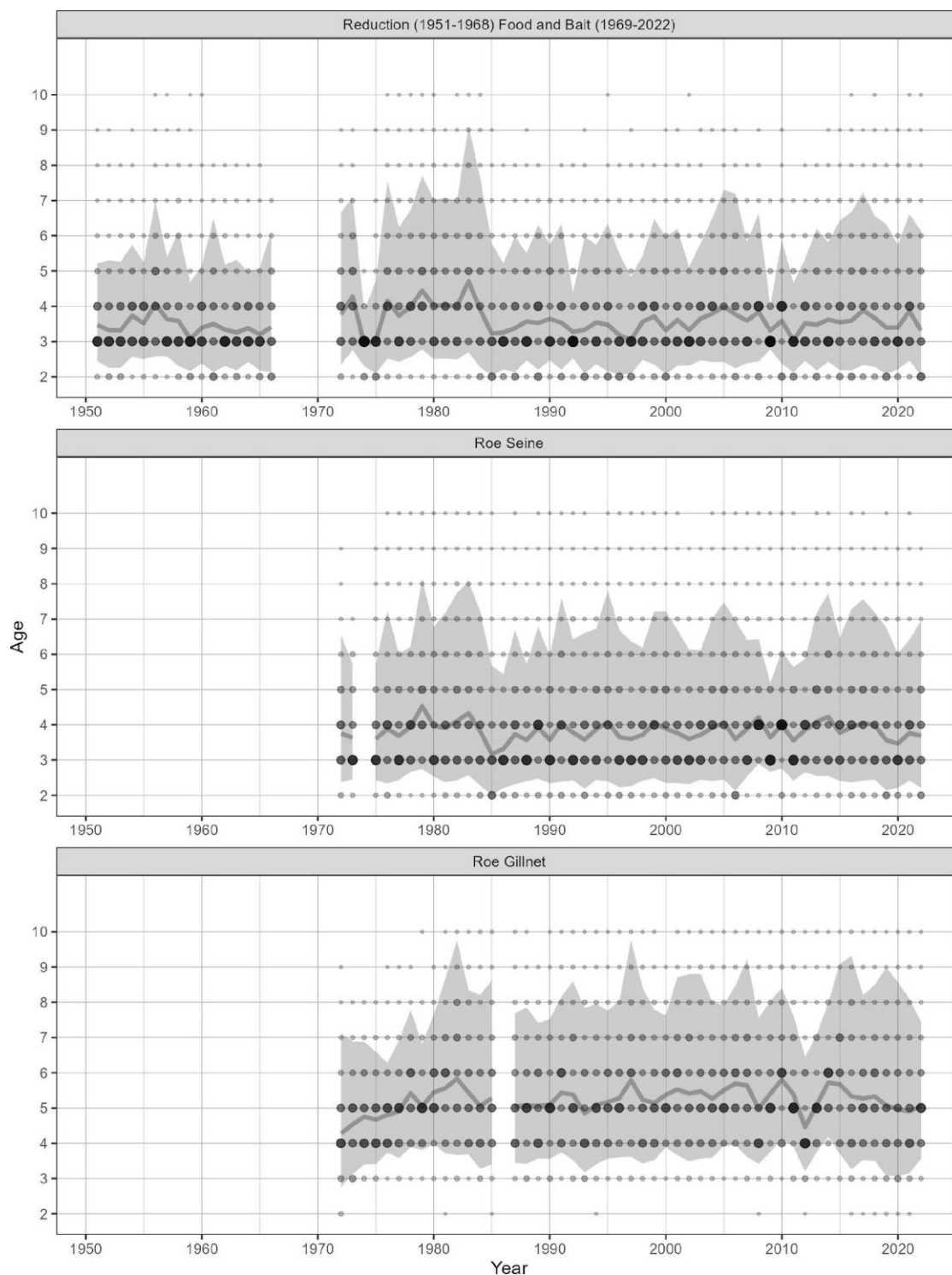


Figure A.13. Strait of Georgia: Proportion-at-age for Pacific Herring from 1951 to 2022. Dot size and colour indicates age class proportion for the year; each year adds up to 1.0. The gray line is the mean age, and the shaded area is the approximate 90 percent distribution. Biological summaries are presented by gear type (reduction, food and bait, seine roe and gillnet roe), where seine roe combines samples across the commercial and test fisheries. The age-10 plus class includes fish ages 10 and older.

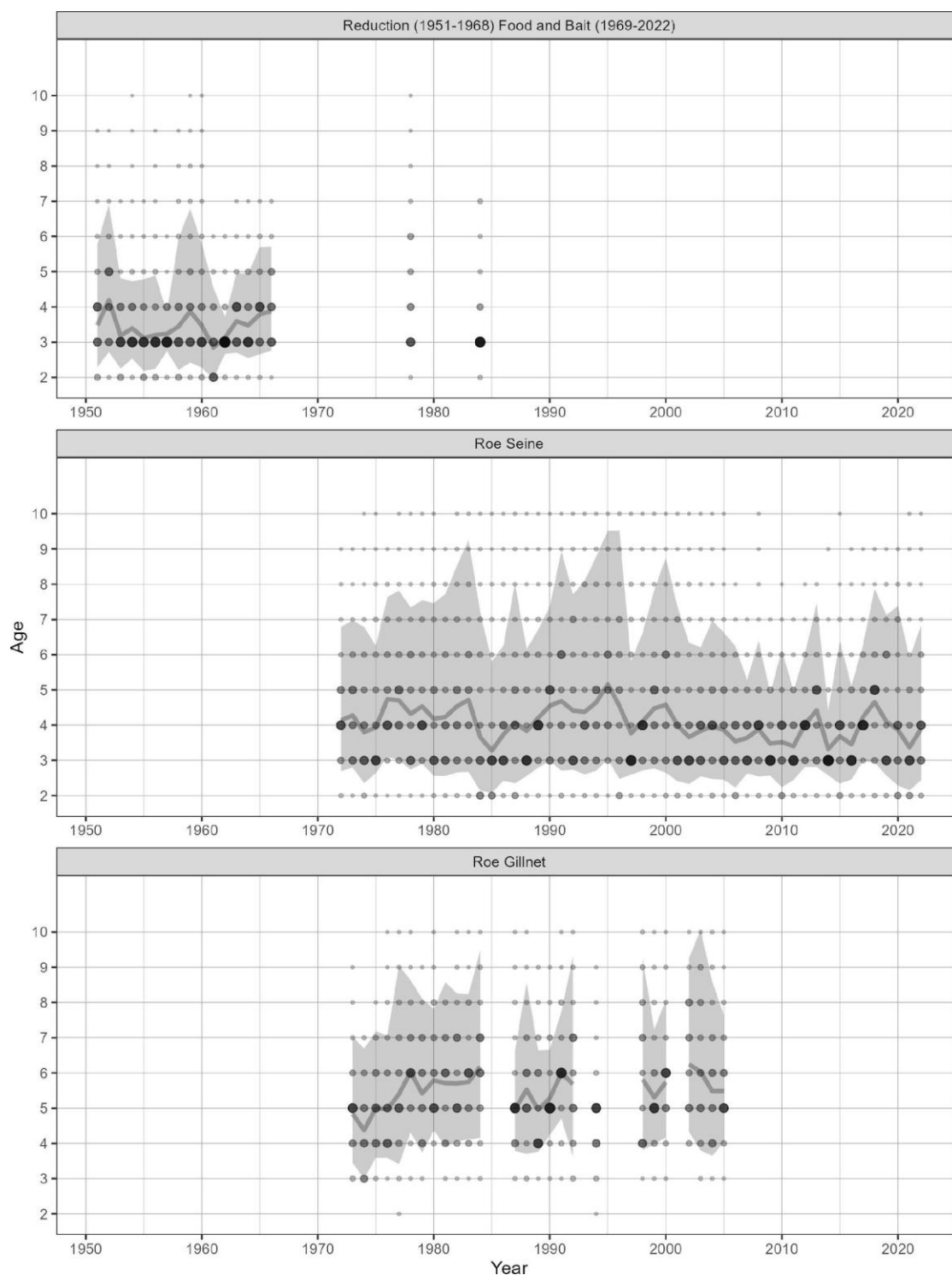


Figure A.14. West Coast Vancouver Island: Proportion-at-age for Pacific Herring from 1951 to 2022. Dot size and colour indicates age class proportion for the year; each year adds up to 1.0. The gray line is the mean age, and the shaded area is the approximate 90 percent distribution. Biological summaries are presented by gear type (reduction, food and bait, seine roe and gillnet roe), where seine roe combines samples across the commercial and test fisheries. The age-10 plus class includes fish ages 10 and older.

APPENDIX B. DATA USE AND TRANSITION ANALYSIS FOR THE HERRING ASSESSMENT MODEL

B.1. METHODS

SISCAH contains a number of features and/or assumptions that differ from the assessment model previously accepted to provide BC herring management advice, ISCAM, (Martell et al. 2012; Cleary et al. 2019). To understand how SISCAH behaves differently from ISCAM, we compared model estimates between ISCAM and several implementations of SISCAH. Specifically, we first compared ISCAM to a “base” implementation of SISCAH containing assumptions that broadly matched ISCAM (e.g., continuous fishing mortality, separate survey indices, density-independent M). We then changed assumptions from and/or added features to the base SISCAH implementation and examined the resulting changes to model estimates.

The density-independent M model in SISCAH is implemented as a simple random walk with log-normal deviations, i.e.

$$M_t = M_{t-1} \cdot e^{\epsilon_t}, \quad (\text{B.1})$$

where M_t is the instantaneous natural mortality rate at time t , and $\epsilon_t \sim N(0, \sigma_M)$ is a log-normal random walk deviation. The particular changes to base SISCAH that we examined were:

1. Discrete fishery removals (“DiscF”) and SOK removals (“DiscF+SOK”)
2. Blended survey index (“Blended”)
3. Density dependent mortality (“DDM”)

This approach allows us to detect whether differences between ISCAM and SISCAH estimates arise due to a change in modelling platform or due to the specific new features implemented in SISCAH for Pacific Herring. Finally we ran the “Full” SISCAH model with all the features simultaneously to show the combined effects on model estimates, and as a method of posterior predictive checks. Also the 5 stocks further act as a posterior predictive check under different conditions.

Differences in the base SISCAH model and ISCAM are explored by comparing model estimates of mortality, recruitment, and spawning biomass. The differences shown in these base comparisons are due to structural differences in these models, and not due to the additional features (1–3) proposed for Pacific Herring.

Differences due to changes in fishing mortality are explored by modifying the base SISCAH model, which modelled continuous fishing mortality, to an alternative “discrete F ” implementation in which fishery catches were removed at discrete points in the year to match the behaviour of the fishing fleet (Branch 2009). Again model estimates of mortality, recruitment and spawning biomass are compared. We further modify the discrete F model to take into account spawn-on-kelp removals and again compare model estimates.

Differences due to changes in the survey index are explored by modifying the base SISCAH model. The base model treats the spawn survey time series as two separate survey eras and thus estimates two spawn survey catchability parameters: “ q_s ” for the surface survey (1951–1987) and “ q_d ” the dive survey (post 1987). However, even in years since dive surveys became widely adopted, there are still areas and years in which surface surveys are used and currently these post-1987 surface observations are assumed to be from dive surveys.

Modifications to base SISCAH include treating surface and dive spawn observations as components of a single blended relative abundance index which includes a yearly catchability

scalar q_t derived via weighted averaging of annual proportions of surface and dive survey observations (Section 2.5.1, main text, Table 3 eq L.2). Then, as is the case with base SISCAH and ISCAM, surface and dive survey catchability components are estimated using a log-normal prior for the less precise surface survey ($\mu_{\log q} = -.69$, $\tau_q = 1$) and an assumption of a census (i.e., $q_d = 1$) for the dive survey component.

Differences due to changes in natural mortality (M) are explored by comparing ISCAM, which models time varying M using a spline function fitted to 12 nodes, to the base SISCAH model, where estimated time varying M is allowed to vary annually as a random walk in log space. The SISCAH base approach is different from ISCAM, but is similar in the sense that it proposes no specific mechanism causing changes in M . We further modified the base SISCAH model by modelling M as a depensatory process where M varies year-to-year along a density-dependent relationship with biomass (Equation 1, Section 2 of the main text). Model estimates of M , recruitment and spawning biomass are compared.

A comparison of ISCAM with the “full” SISCAH model that contained discrete fishing mortality (with SOK in all areas except SOG), a blended survey index, and density-dependent M is presented in the main text.

Finally, in base SISCAH the standard error in annual M log-normal deviations (σ_M) was set to 0.1. This value of σ_M is more constraining on interannual M deviations than the variance used to constrain spline nodes in ISCAM. To test the sensitivity of SISCAH to the choice of σ_M , we compare estimates between base SISCAH to alternative SISCAH implementations with $\sigma_M = 0.2$ and $\sigma_M = 0.5$.

B.2. RESULTS AND DISCUSSION

B.2.1. Haida Gwaii

B.2.1.1. Transition from ISCAM to base SISCAH

Spawning biomass, recruitment, and F estimates followed similar trends in ISCAM and base SISCAH for most of the time-series (Figure B.1). SISCAH M often mimicked the mean behaviour of ISCAM M , but with more year to year variability. From the mid-1970s to the mid-1980s spawning biomass was higher, and fishing mortality was lower in the seine roe and reduction fisheries under SISCAH compared to ISCAM.

B.2.1.2. Transition to discrete fishing mortality and inclusion of SOK

Converting SISCAH from continuous F to discrete F had little effect on model estimates of spawning biomass, recruitment, and M (Figure B.1). With discrete- F SISCAH estimated higher levels of gillnet F compared to continuous- F -SISCAH. Accounting for SOK removals resulted in some higher biomass estimates and lower gillnet F at peak times in the mid-1970s and the early 1980s, with similar estimates of recruitment to the discrete F model with no SOK. However all these model differences may arise from the approximation of parameters rather than any intrinsic model behaviour.

B.2.1.3. Transition to blended index

Converting SISCAH to fit to a blended survey index instead of a separate index had minor effects on model estimates (Figure B.2).

B.2.1.4. Transition to density-dependent mortality

Converting SISCAH to have density-dependent M rather than a simple random walk in M resulted estimates of M with considerably more interannual variation, including slightly lower minima and significantly higher maxima. In particular, density-dependent M spiked in the late 1960s (a period in which biomass was very low) to levels higher than both base SISCAH and ISCAM. There were relatively small effects on estimates of biomass, recruitment, and F (Figure B.3).

B.2.1.5. Sensitivity analysis of variability in natural mortality

Varying σ_M from 0.1 to 0.5 produced time-series of estimated M that had identical means and overall trends but larger amplitude, i.e., increasing σ_M produced higher maxima and lower minima but the timing of the minima and maxima did not change. The largest discrepancy occurred in the late 1960s, when M reached a peak of 0.46, 0.58 and 0.92 under $\sigma_M = 0.1$, $\sigma_M = 0.2$ and $\sigma_M = 0.5$, respectively. Each model also produced very similar trajectories of spawning biomass and fishing mortality. Discrepancies arose in total mortality estimates when σ_M was increased to 0.5 as the large spikes in M were apparent in total mortality. Models with higher σ_M estimated lower SB_0 and R_0 , and higher catchability (h) and surface survey catchability (q_s) (Table B.2).

B.2.2. Prince Rupert District

B.2.2.1. Transition from ISCAM to base SISCAH

ISCAM and base SISCAH produced divergent estimates in the 1950s and 1960s but were similar thereafter (Figure B.5). The main difference between the two models is that ISCAM estimates a fairly “wavy” M pattern, varying from approximately 0.12/yr in the 1950s to 0.60/yr in the 1960s, whereas base SISCAH M estimates ranged between 0.25–0.5/yr over this period. SISCAH estimates of reduction F in the 1950s and early 1960s were generally well below ISCAM estimates.

B.2.2.2. Transition to discrete fishing mortality and inclusion of SOK

SISCAH with discrete F produced broadly similar estimates to SISCAH with continuous F (Figure B.5); SISCAH estimated lower M under discrete F than continuous F throughout the time series, however since this trend didn’t occur in other areas, it isn’t representative of the discrete F feature.

Accounting for SOK led to virtually no change in parameter estimates.

B.2.2.3. Transition to blended index

Converting SISCAH to fit to a blended survey index instead of a separated index had virtually no effect on model estimates (Figure B.6); estimated spawning biomass, recruitment and mortality were nearly identical under base SISCAH and SISCAH with the blended survey index.

B.2.2.4. Sensitivity analysis of variability in natural mortality

Varying σ_M from 0.1 to 0.5 produced time-series of estimated M that had identical means and overall trends but larger amplitude, i.e., increasing σ_M produced higher maxima and lower minima but the timing of the minima and maxima did not change. The largest discrepancy occurred in the late 1960s, when M reached a peak of 0.45 under $\sigma_M = 0.1$, but spiked to 0.59 and 0.95 under $\sigma_M = 0.2$ and $\sigma_M = 0.5$, respectively. Each model also produced very similar trajectories of spawning biomass and fishing mortality. Annual spawning biomass estimates

under $\sigma_M = 0.2$ and $\sigma_M = 0.5$ tended to be 2% lower and 4% lower, respectively than under $\sigma_M = 0.1$. Discrepancies arose in ISCAM and base SISCAH estimates of spawning biomass after 1970, recruitment, and fishing mortality from seine and gillnet fisheries are very similar (Figure B.8), but there are some differences in spawning biomass, recruitment and M during the 1950s and 1960s. SISCAH estimates of spawning biomass and recruitment tend to be higher, and the amplitude on M greater than ISCAM estimates during this time period. After the mid-1990s all the estimates are very similar between the two models.

B.2.3. Central Coast

B.2.3.1. Transition from ISCAM to base SISCAH

ISCAM and base SISCAH estimates of spawning biomass after 1970, recruitment, and fishing mortality from seine and gillnet fisheries are very similar (Figure B.8), but there are some significant differences in spawning biomass, M , reduction fishery F , and total mortality Z during the 1950s and 1960s. SISCAH estimates of spawning biomass tend to be higher than ISCAM estimates, but recruitment is similar, which is an effect of differences in natural mortality and, to a lesser extent, total mortality. M estimates after the mid-1990s are very similar between the two models.

B.2.3.2. Transition to discrete fishing mortality and inclusion of SOK

Converting SISCAH from continuous F to discrete F made little difference except for M which decreased for the early part of the time series. (Figure B.8). Adding SOK removals had very minimal effects on model estimates.

B.2.3.3. Transition to blended index

Converting SISCAH to fit to a blended survey index instead of a separated index had little effect on model estimates; estimated spawning biomass, recruitment and mortality were nearly identical between base SISCAH and SISCAH with the blended survey index (Figure B.9).

B.2.3.4. Transition to density-dependent mortality

Converting SISCAH M from a random walk to account for density-dependence produced similar estimates overall but also created some minor differences (Figure B.10). In particular, spawning biomass estimates were lower under density-dependent M in the early 1980s and higher in the late 1980s and 1990s. Estimated M also differed between the two models; while most of the peaks and valleys in the time series occurred at the same time SISCAH-density-dependent mortality had more variability and higher peaks than SISCAH-random-walk mortality (Figure B.10).

B.2.3.5. Sensitivity analysis of variability in natural mortality

Varying σ_M from 0.1 to 0.5 produced time-series of estimated M that had identical means and overall trends but larger amplitude, i.e., increasing σ_M produced higher maxima and lower minima but the timing of the minima and maxima did not change. The largest discrepancy occurred in the late 1960s, when M reached a peak of 0.44 under $\sigma_M = 0.1$, but spiked to 0.56 and 0.95 under $\sigma_M = 0.2$ and $\sigma_M = 0.5$, respectively. Each model also produced very similar trajectories of spawning biomass and fishing mortality. Annual spawning biomass estimates under $\sigma_M = 0.2$ and $\sigma_M = 0.5$ tended to be 4% lower and 7% lower, respectively than under $\sigma_M = 0.1$. Discrepancies arose in total mortality estimates when σ_M was increased to 0.5 as the

large spikes in M were apparent in total mortality. Models with higher σ_M estimated lower SB_0 and R_0 , and q_s (Table B.2). There was no consistent effect of σ_M on estimates of h .

B.2.4. Strait of Georgia

B.2.4.1. Transition from ISCAM to base SISCAH

ISCAM and base SISCAH estimated similarly “wavy” M trends, with local minima and maxima usually occurring concurrently (Figure B.12). Notable periods of divergence in M estimates between the two models occurs in the 1950s and early 1960s and again in the 1980s, where SISCAH M was higher than ISCAM M . Spawning biomass was consistently higher under SISCAH than ISCAM, particularly with peak biomass levels in the 1950s and late 1970s/early 1980s.

Since then biomass estimates track very closely, with biomass estimates since 2020 are nearly identical. Estimated recruitment in SISCAH was higher than ISCAM recruitment between 1950 and the mid-1980s, but was slightly lower between 1990 and the early 2000s. Estimated fishing and total mortality had similar peaks and valleys, albeit with peaks sometimes higher for ISCAM especially for seine roe and gillnet fisheries in the 1970s and 1980s.

B.2.4.2. Transition to discrete fishing mortality

Converting SISCAH from continuous F to discrete F had minimal effects on model estimates of spawning biomass, recruitment, and M (Figure B.12). Divergences in F estimates did arise, as SISCAH with discrete F estimated higher levels of seine roe F and gillnet F compared to SISCAH with continuous F ; however these differences may arise from the approximation of F rather than intrinsic model behaviour. Total mortality was similar between continuous and discrete F SISCAH models.

B.2.4.3. Transition to blended index

Converting SISCAH to fit to a blended survey index instead of a separated index had little effect on model estimates (Figure B.13); estimated spawning biomass, recruitment and mortality were nearly identical between base SISCAH and SISCAH with the blended survey index.

B.2.4.4. Transition to density-dependent mortality

Converting SISCAH to have density-dependent M rather than a simple random walk in M had small effects on estimates of biomass and total mortality, but a few differences in M emerged (Figure B.14). In particular, the density-dependent M trajectory had slightly higher amplitudes and more variability. However, mean values of M were similar between the two models.

B.2.4.5. Sensitivity analysis of variability in natural mortality

Varying σ_M from 0.1 to 0.5 produced time-series of estimated M that had identical means and overall trends but larger amplitude, i.e., increasing σ_M produced higher maxima and lower minima but the timing of the minima and maxima did not change. The largest discrepancy occurred in the late 1960s, when M reached a peak of 0.83 under $\sigma_M = 0.1$, but spiked to 1.03 and 1.37 under $\sigma_M = 0.2$ and $\sigma_M = 0.5$, respectively. Each model also produced very similar trajectories of spawning biomass and fishing mortality. Annual spawning biomass estimates under $\sigma_M = 0.2$ and $\sigma_M = 0.5$ tended to be 2% lower and 3% lower, respectively than under $\sigma_M = 0.1$.

Discrepancies arose in reduction fishery F in the 1960s with higher F associated with higher σ_M and this translated to higher total mortality estimates. Models with higher σ_M estimated lower SB_0 and R_0 , and higher h and q_s (Table B.2).

B.2.5. West Coast of Vancouver Island

B.2.5.1. Transition from ISCAM to base SISCALH

ISCAM and base SISCALH estimated similarly “wavy” M trends, with local minima and maxima usually occurring concurrently (Figure B.16). Notable periods of divergence in M estimates between the two models include the late 1950s and 1960s, when ISCAM M increased from 0.35/yr to 0.82/yr, while SISCALH M increased more gradually, from 0.45/yr to 0.61/yr. Also in the mid 2000s to 2020 SISCALH estimated a higher M . Spawning biomass was higher under SISCALH than ISCAM up to the mid 1980s, but biomass estimates after this point were similar. Estimated recruitment in SISCALH was higher than ISCAM recruitment in the 1950s and 1980s, but was similar otherwise. Estimated fishing and total mortality was similar between ISCAM and SISCALH but influenced by differences in M .

B.2.5.2. Transition to discrete fishing mortality

Converting SISCALH from continuous F to discrete F had minimal effects on model estimates of spawning biomass, and recruitment (Figure B.16). The amplitudes of M were smaller with discrete M . Divergences in F estimates did arise; compared to SISCALH with continuous F , SISCALH with discrete F estimated lower reduction F but higher seine roe F and gillnet F during some time periods. However these differences may arise from the approximation of F rather than intrinsic model behaviour.

B.2.5.3. Transition to blended index

Converting SISCALH to fit to a blended survey index instead of a separated index had little effect on model estimates (Figure B.17); estimated spawning biomass, recruitment and mortality were nearly identical between base SISCALH and SISCALH with the blended survey index.

B.2.5.4. Transition to density-dependent mortality

Converting SISCALH to have density-dependent M rather than a simple random walk in M had small effects on estimates of biomass and total mortality (Figure B.18). SISCALH with density-dependent M estimated similar M trends to base SISCALH but with greater interannual variability.

B.2.5.5. Sensitivity analysis of variability in natural mortality

Varying σ_M from 0.1 to 0.5 produced time-series of estimated M that had identical means and overall trends but larger amplitude, i.e., increasing σ_M produced higher maxima and lower minima but the timing of the minima and maxima did not change. The largest discrepancy occurred in around 2006, when M reached a peak of 1.09 under $\sigma_M = 0.1$, but spiked to 1.41 and 1.86 under $\sigma_M = 0.2$ and $\sigma_M = 0.5$, respectively. Each model also produced very similar trajectories of spawning biomass and fishing mortality. Annual spawning biomass estimates under $\sigma_M = 0.2$ and $\sigma_M = 0.5$ tended to be 4% lower and 7% lower, respectively than under $\sigma_M = 0.1$. Discrepancies arose in total mortality estimates when σ_M was increased to 0.5 as the large spikes in M were apparent in total mortality.

B.3. TABLES

Table B.1. Estimated quantities of interest and biological reference points for BC herring populations (SOG, CC, PRD, HG, WCVI) from ISCAM and implementations of SISCALH that varied in hypotheses about F (hypF) (continuous or discrete), survey indices (hypSurv) (Separate or Blended), and M (hypM). (Spline, Random Walk, or Density Dependent). DDM hypothesis rejected for PRD, so not presented here. SB_0 = estimated unfished equilibrium spawning biomass (deterministic), R_0 = estimated unfished equilibrium recruitment, R_{init} = estimated initial recruitment, m_1 = depensation rate in density dependent mortality, M_b = asymptotic lower limit on natural mortality, M_{1951} = estimated mortality in 1951 (for DIM models), M_0 = unfished equilibrium natural mortality (or time-averaged for DIM), h = stock-recruit steepness, q_s = surface survey catchability.

Model	Hypothesis	SB_0	R_0	R_{init}	m_1	M_b	M_0	M_{1951}	h	q_s
HG										
ISCAM	ISCAM	21.820	249.530	31.730	–	–	0.564	–	0.810	0.420
SISCAH	Base	19.073	381.913	262.991	–	–	0.581	0.360	0.665	0.282
SISCAH	DiscF	20.117	373.791	232.770	–	–	0.563	0.343	0.667	0.281
SISCAH	Blended	20.683	405.541	268.569	–	–	0.576	0.367	0.685	0.297
SISCAH	DDM	19.899	377.555	325.420	1.434	0.330	0.568	–	0.705	0.308
SISCAH	Full	17.209	368.121	–	1.324	0.330	0.596	–	0.698	0.325
SISCAH	DiscFSOK	19.096	356.326	356.326	–	–	0.564	0.390	0.628	0.252
PRD										
ISCAM	ISCAM	55.480	309.080	250.510	–	–	0.367	–	0.717	0.549
SISCAH	Base	35.984	297.803	231.052	–	–	0.384	0.448	0.651	0.492
SISCAH	DiscF	43.106	257.158	113.373	–	–	0.327	0.217	0.672	0.582
SISCAH	Blended	35.748	286.221	240.740	–	–	0.378	0.476	0.656	0.503
SISCAH	Full	48.986	339.080	246.176	–	–	0.352	0.271	0.638	0.540
SISCAH	DiscFSOK	44.241	264.261	113.813	–	–	0.327	0.219	0.674	0.581
CC										
ISCAM	ISCAM	49.630	404.410	267.820	–	–	0.453	–	0.817	0.323
SISCAH	Base	37.382	524.634	842.526	3.560	–	0.488	0.587	0.657	0.239
SISCAH	DiscF	43.145	466.680	432.642	3.560	–	0.435	0.401	0.674	0.265
SISCAH	Blended	38.306	588.096	1058.833	3.560	–	0.507	0.611	0.653	0.214
SISCAH	DDM	36.827	460.563	724.255	2.657	0.394	0.464	–	0.678	0.247
SISCAH	Full	48.001	523.920	–	3.150	0.394	0.437	–	0.709	0.233

Model	Hypothesis	SB_0	R_0	R_{init}	m_1	M_b	M_0	M_{1951}	h	q_s
SISCAH	DiscFSOK	45.674	512.036	512.036	3.560	–	0.442	0.412	0.680	0.253
SOG										
ISCAM	ISCAM	133.570	1659.370	271.660	–	–	0.576	–	0.744	1.029
SISCAH	Base	108.576	3118.111	3445.624	6.970	–	0.670	0.674	0.696	0.554
SISCAH	DiscF	119.204	2657.237	1299.175	6.970	–	0.607	0.427	0.730	0.688
SISCAH	Blended	108.368	3076.484	3353.006	6.970	–	0.667	0.672	0.696	0.570
SISCAH	DDM	110.619	2957.659	3594.841	2.581	0.576	0.652	–	0.708	0.571
SISCAH	Full	102.034	2524.821	–	2.873	0.576	0.633	–	0.709	0.699
WCVI										
ISCAM	ISCAM	43.290	562.840	262.710	–	–	0.607	–	0.740	0.851
SISCAH	Base	38.249	1047.620	1183.920	1.490	–	0.674	0.610	0.649	0.537
SISCAH	Blended	39.565	1063.546	1248.732	1.490	–	0.669	0.633	0.658	0.504
SISCAH	DDM	49.637	1011.705	978.493	1.713	0.420	0.600	–	0.697	0.555
SISCAH	Full	46.092	849.099	683.938	1.856	0.420	0.576	–	0.689	0.615
SISCAH	DiscF	42.985	888.093	651.174	1.490	–	0.604	0.463	0.604	0.632
SISCAH	DiscFSOK	43.180	890.974	651.048	1.490	–	0.603	0.463	0.604	0.632

Table B.2. Base SISCAH model parameter estimates by SAR for three levels of σ_M for random walk deviations under a density independent M assumption.

SAR	σ_M	SB_0	R_0	R_{init}	h	q_s
HG						
HG	0.1	19.91	352.87	352.87	0.702	0.304
HG	0.2	18.89	330.64	330.64	0.720	0.334
HG	0.5	17.22	307.89	307.89	0.736	0.384
PRD						
PRD	0.1	43.97	377.34	887.36	–	0.476
PRD	0.2	43.58	367.13	868.47	–	0.491
PRD	0.5	42.70	361.31	882.55	–	0.511
CC						
CC	0.1	45.02	517.20	517.20	0.705	0.253
CC	0.2	44.51	483.17	483.17	0.714	0.266
CC	0.5	44.06	461.37	461.37	0.709	0.284
SOG						
SOG	0.1	112.82	2438.26	2438.26	0.698	0.732
SOG	0.2	110.96	2431.12	2431.12	0.702	0.758
SOG	0.5	111.05	2433.95	2433.95	0.694	0.781
WCVI						
WCVI	0.1	41.56	884.00	884.00	0.641	0.636
WCVI	0.2	39.39	843.04	843.04	0.668	0.670
WCVI	0.5	37.97	794.08	794.08	0.683	0.709

B.4. FIGURES

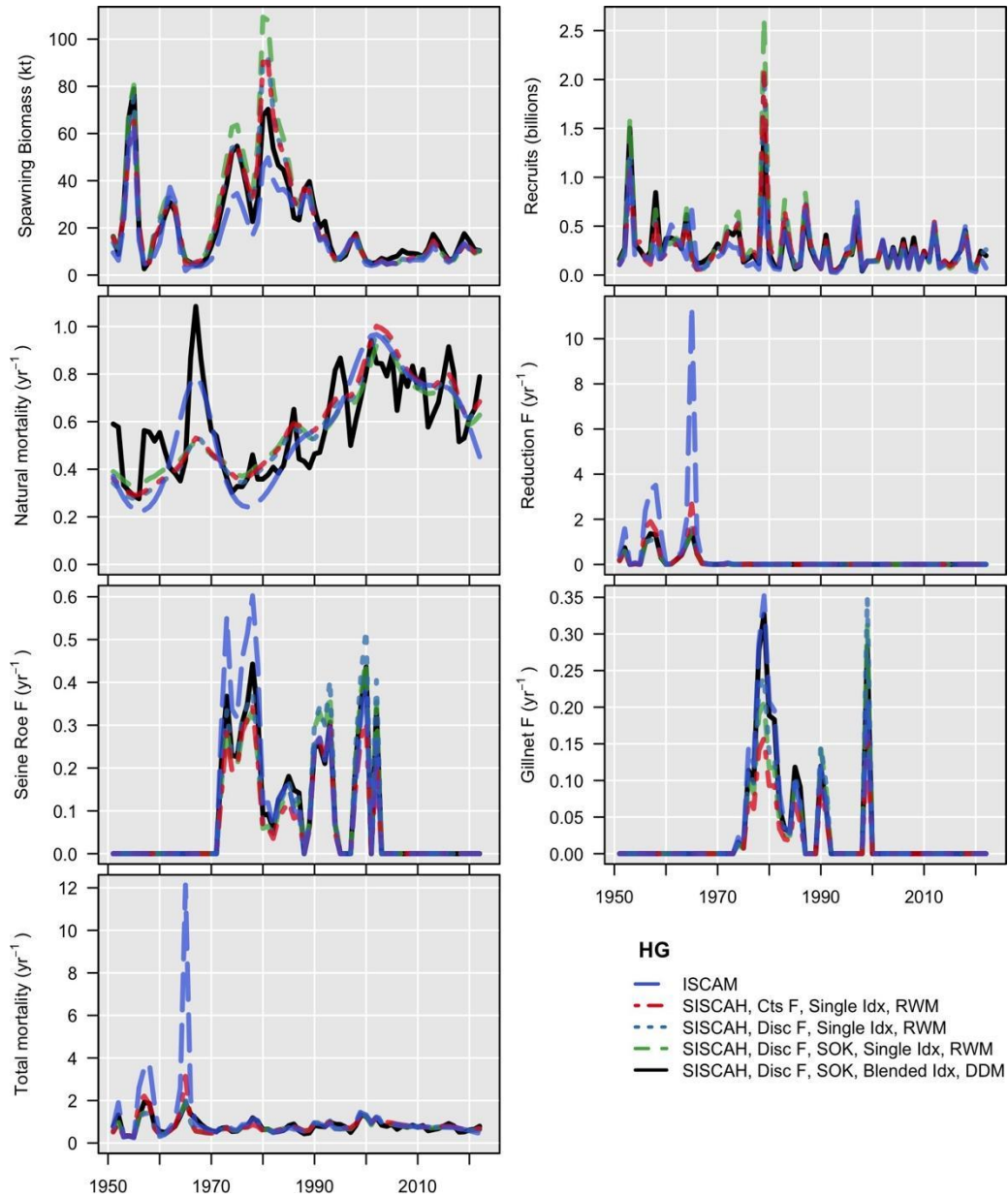


Figure B.1. Haida Gwaii: Comparison of biomass, recruitment, and mortality estimates between ISCAM with continuous F, single index (Idx), random walk mortality (RWM), and SISCAL models with step-wise implementations of discrete F (Disc F), spawn-on-kelp removals (SOK), the blended index (Idx), and density dependent mortality (DDM).

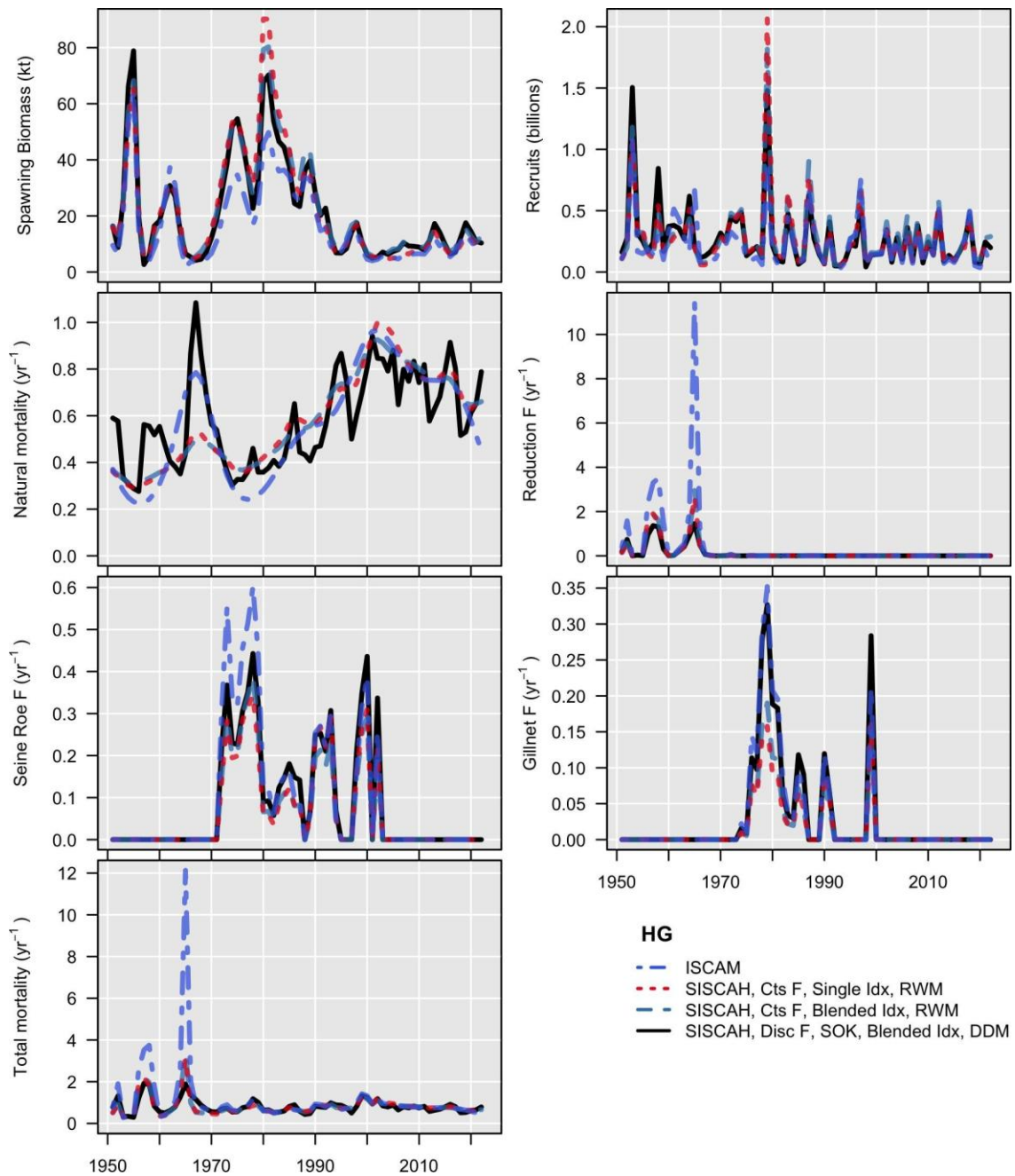


Figure B.2. Haida Gwaii: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAH, base SISCAH with blended index, and a fully implemented SISCAH model.

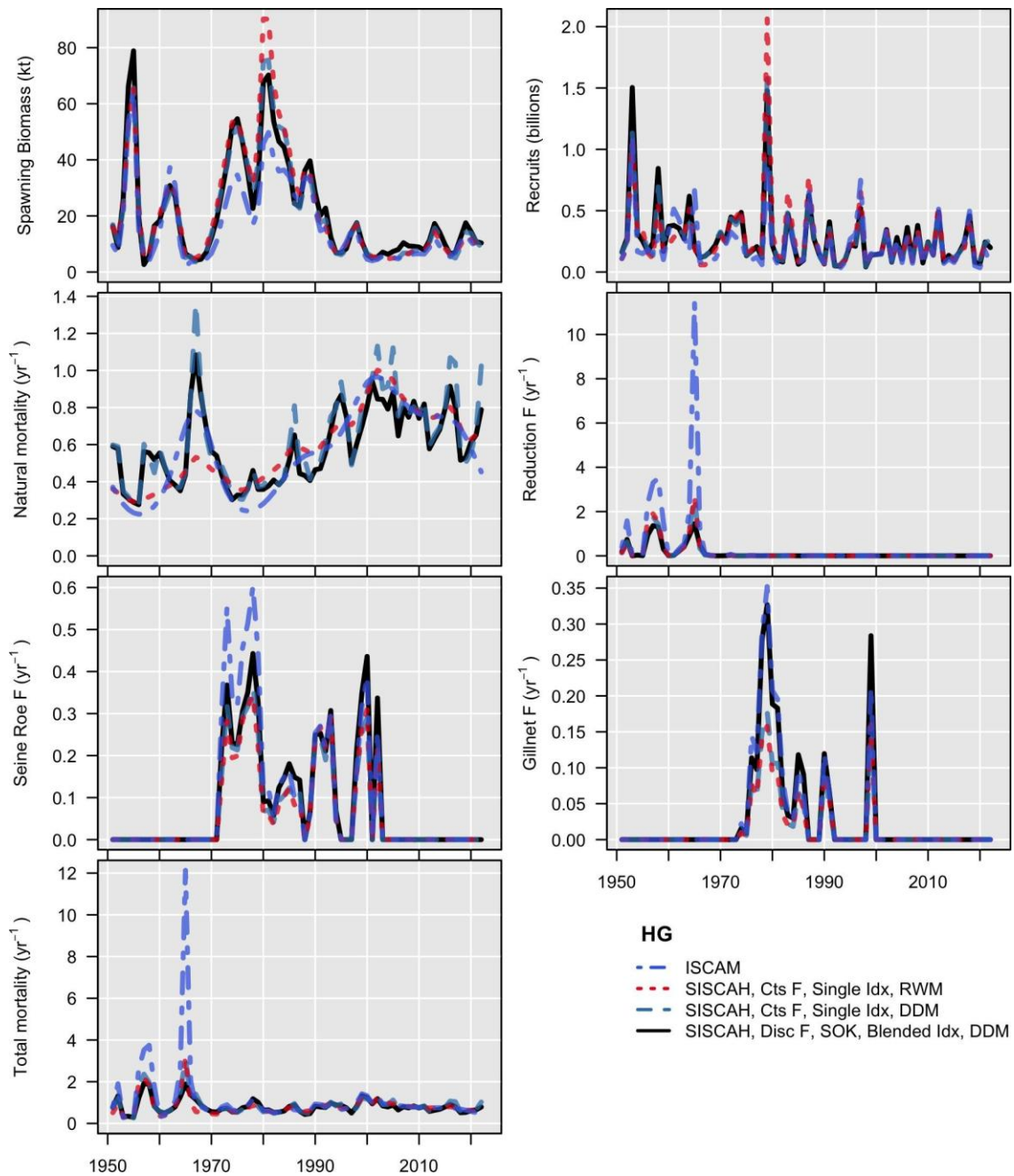


Figure B.3. Haida Gwaii: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAH, base SISCAH with density dependent mortality, and a fully implemented SISCAH model.

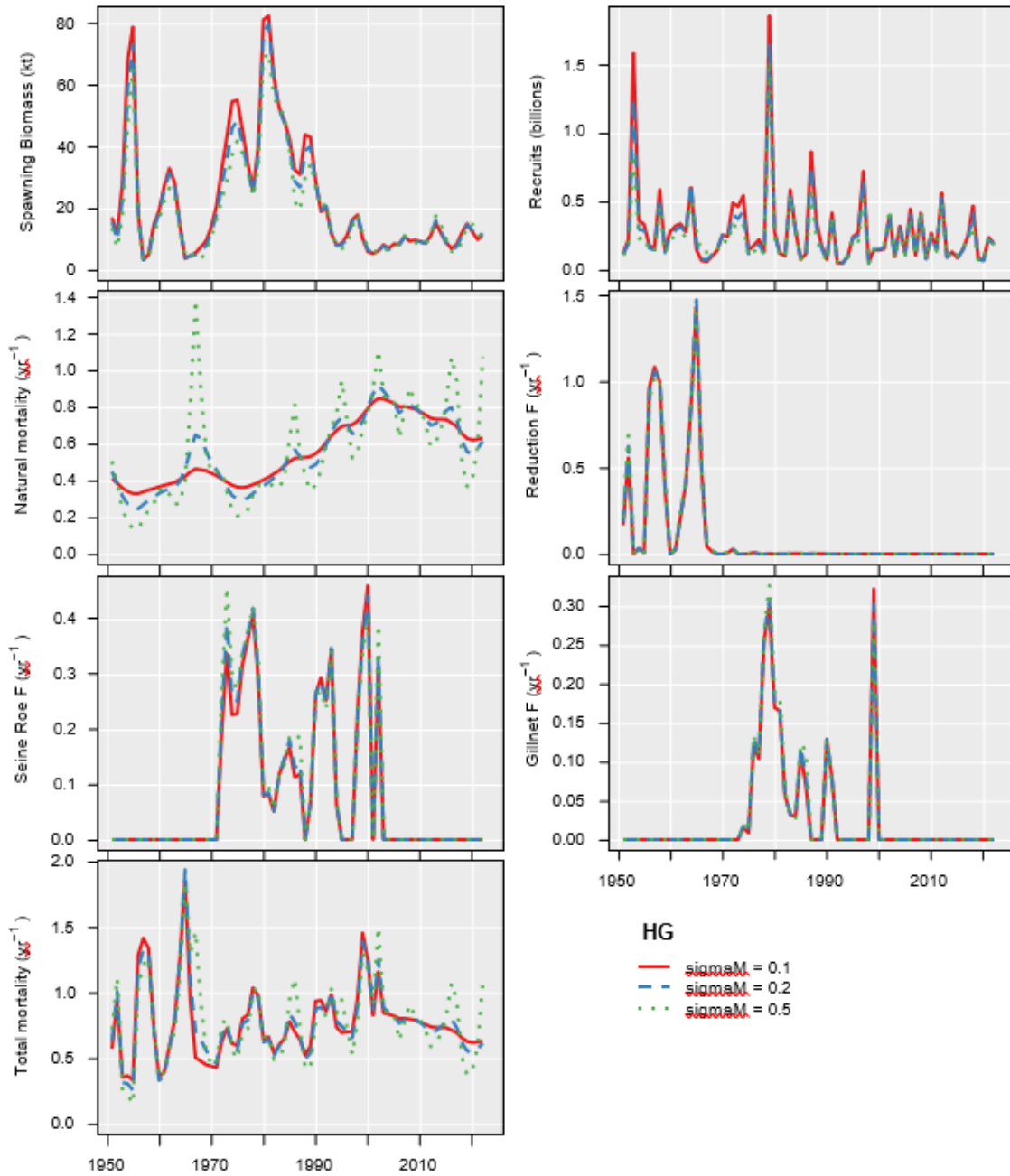


Figure B.4. Haida Gwaii: Comparison of biomass, recruitment, and mortality estimates between SISCAH with three fixed values (0.1, 0.2, 0.5) for the standard error in annual natural mortality log-normal deviations σ_M .

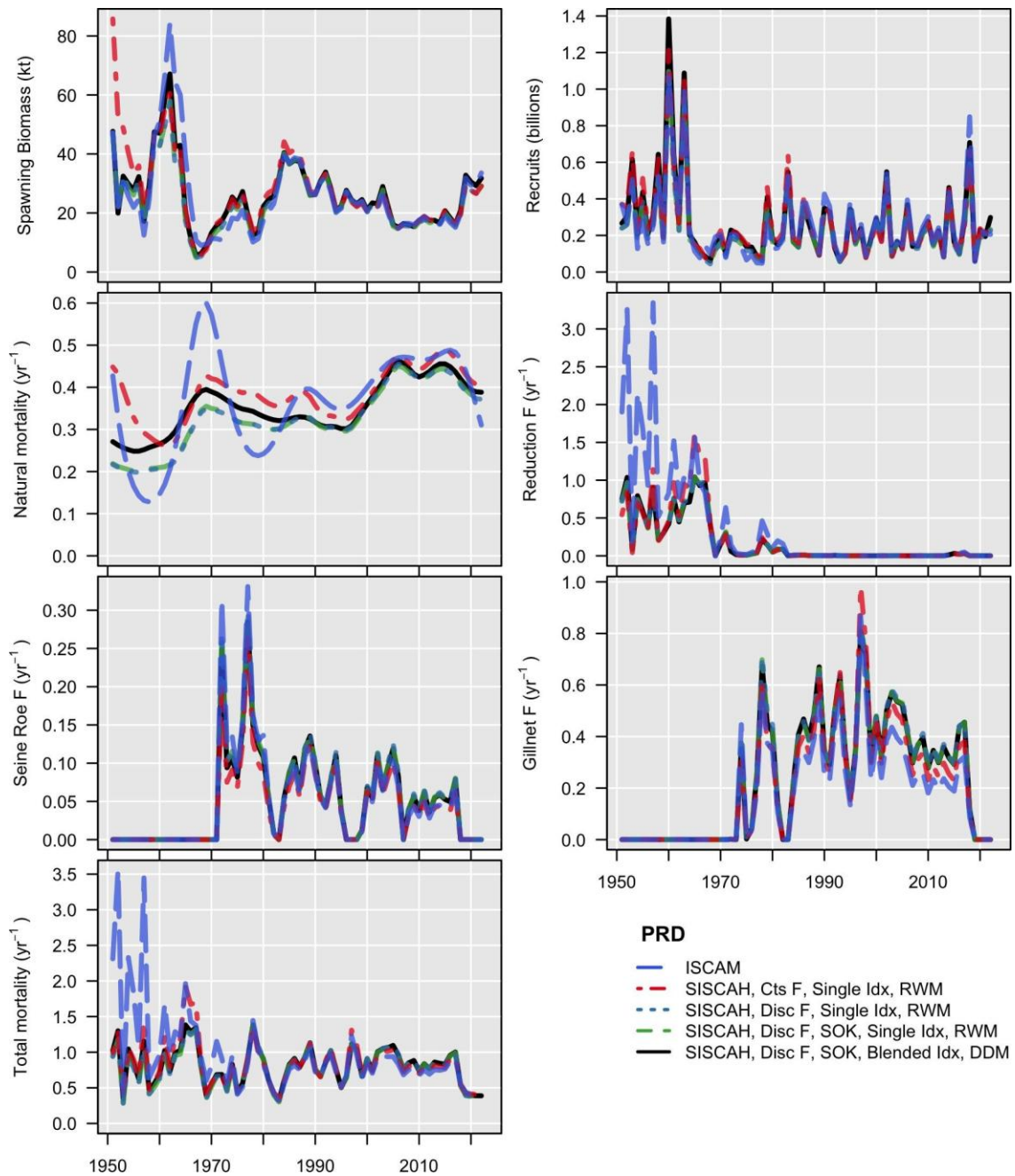


Figure B.5. Prince Rupert District: Comparison of biomass, recruitment, and mortality estimates between ISCAM with continuous F , single index (IdX), random walk mortality (RWM), and SISCAL models with step-wise implementations of discrete F ($Disc F$), spawn-on-kelp removals (SOK), the blended index (Idx), and density dependent mortality (DDM).

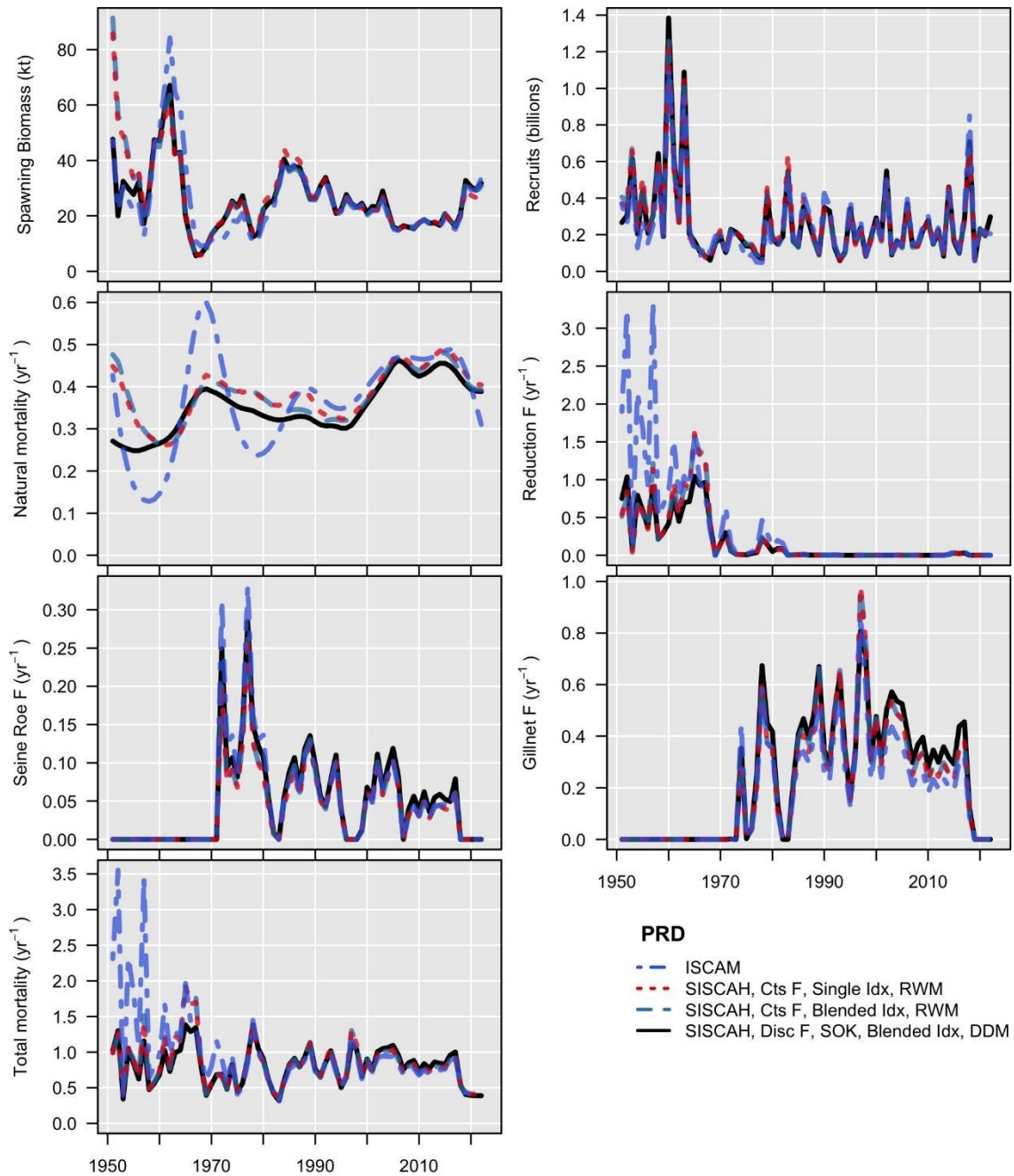


Figure B.6. Prince Rupert District: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAL, base SISCAL with blended index, and a fully implemented SISCAL model.

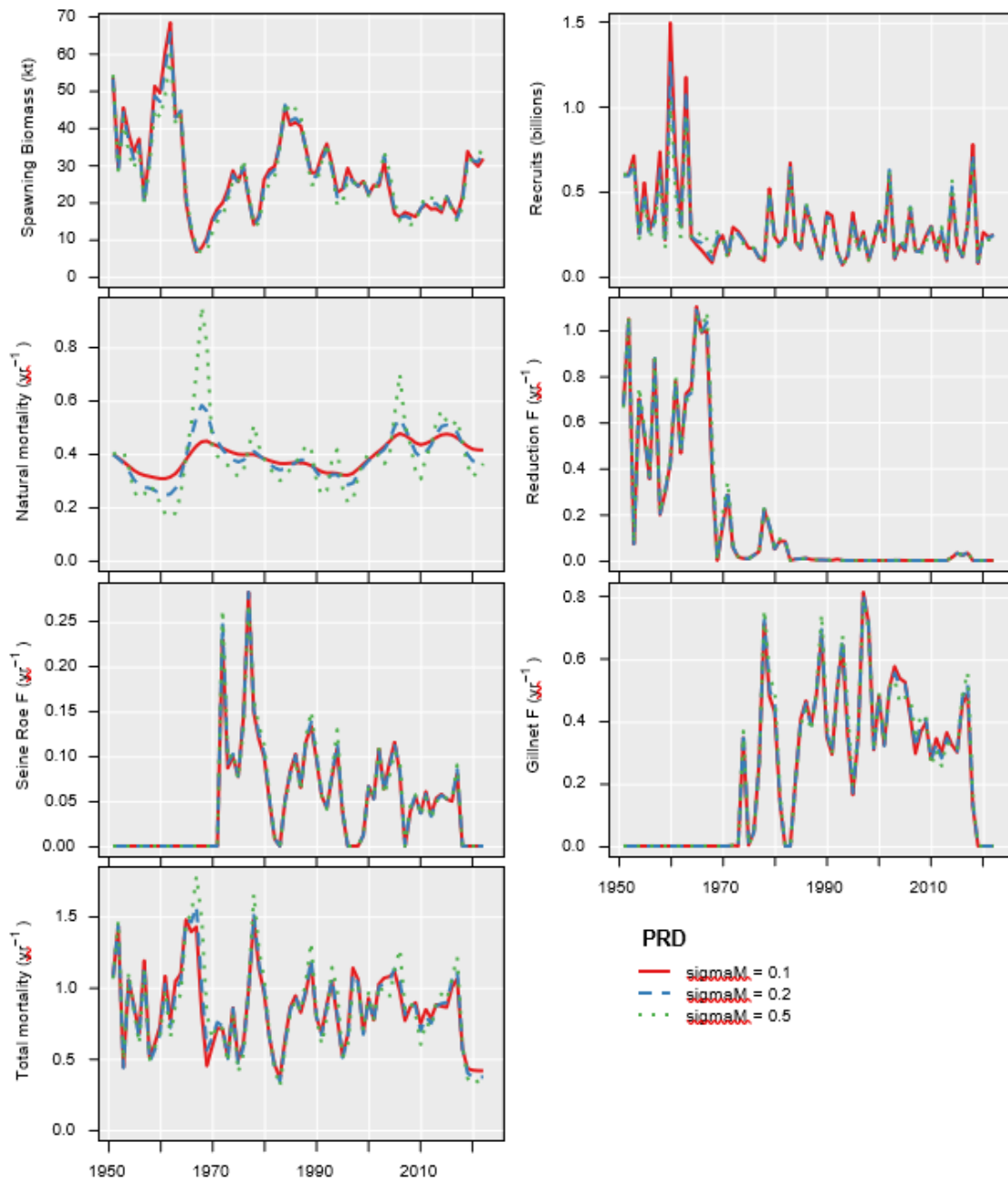


Figure B.7. Prince Rupert District: Comparison of biomass, recruitment, and mortality estimates between SISCAN with three fixed values (0.1, 0.2, 0.5) for the standard error in annual natural mortality log-normal deviations σ_M .

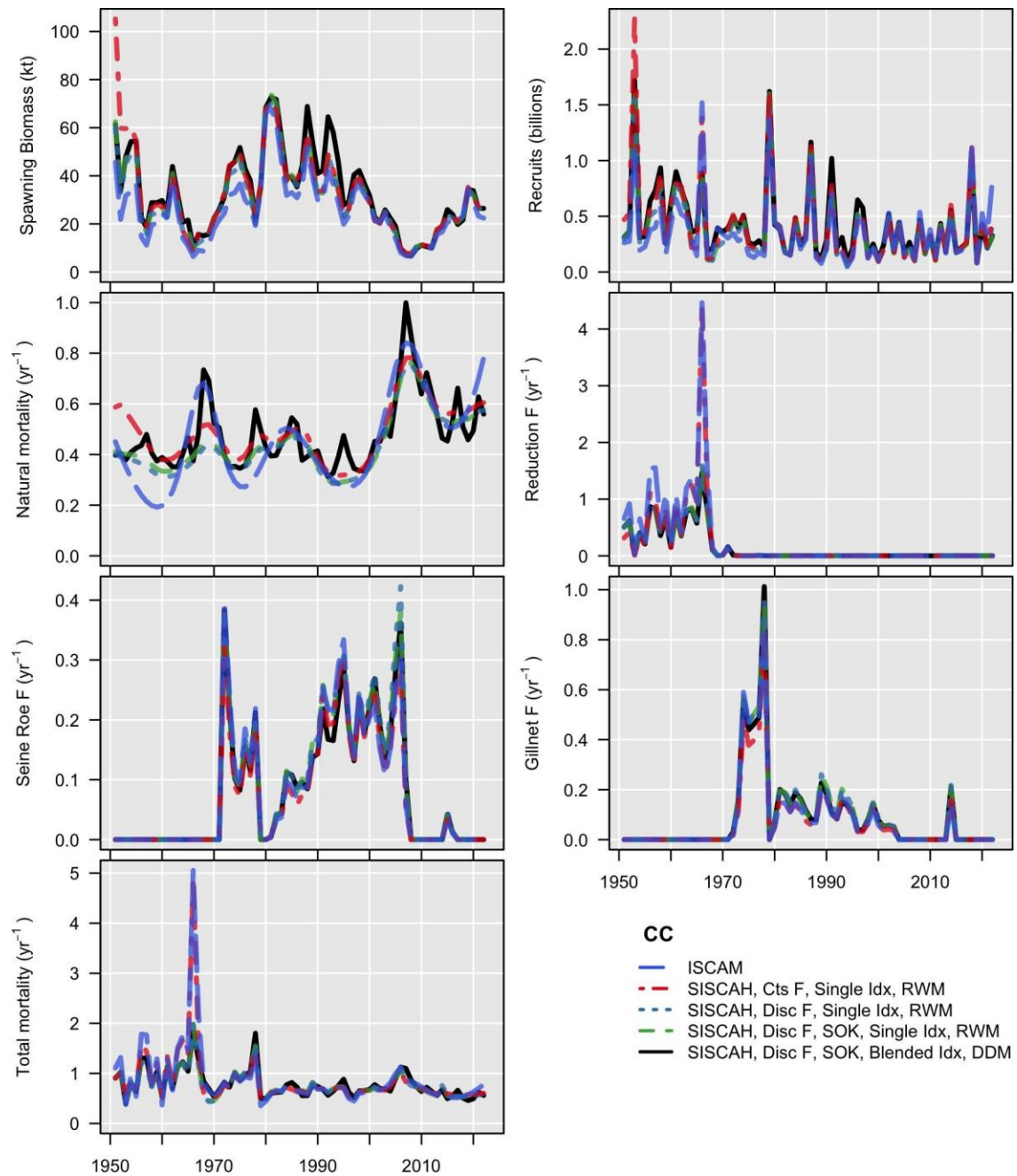


Figure B.8. Central Coast: Comparison of biomass, recruitment, and mortality estimates between ISCAM with continuous F , single index (Idx), random walk mortality (RWM), and SISCAH models with step-wise implementations of discrete F (Disc F), spawn-on-kelp removals (SOK), the blended index (Idx), and density dependent mortality (DDM).

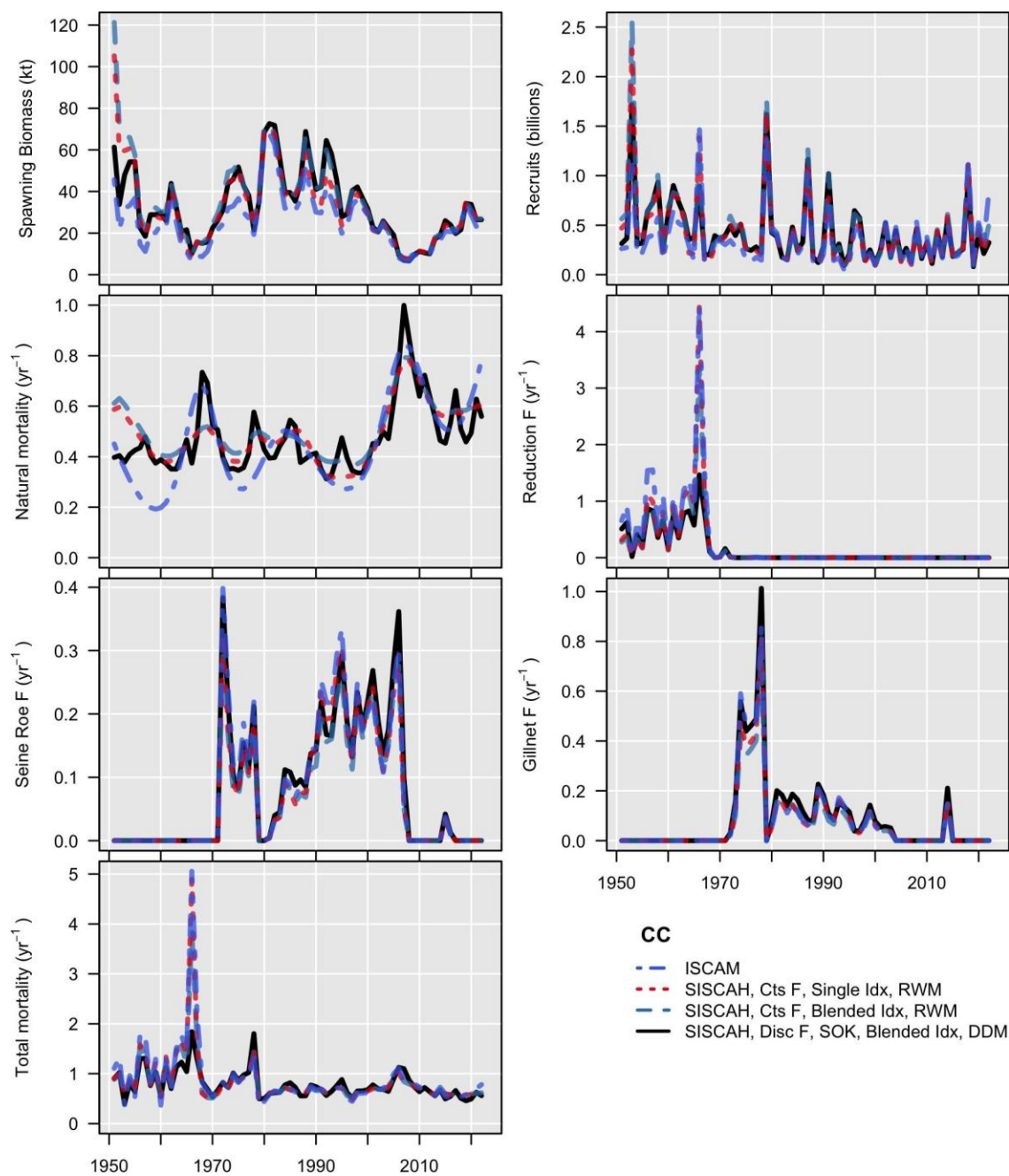


Figure B.9. Central Coast: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAH, base SISCAH with blended index, and a fully implemented SISCAH model.

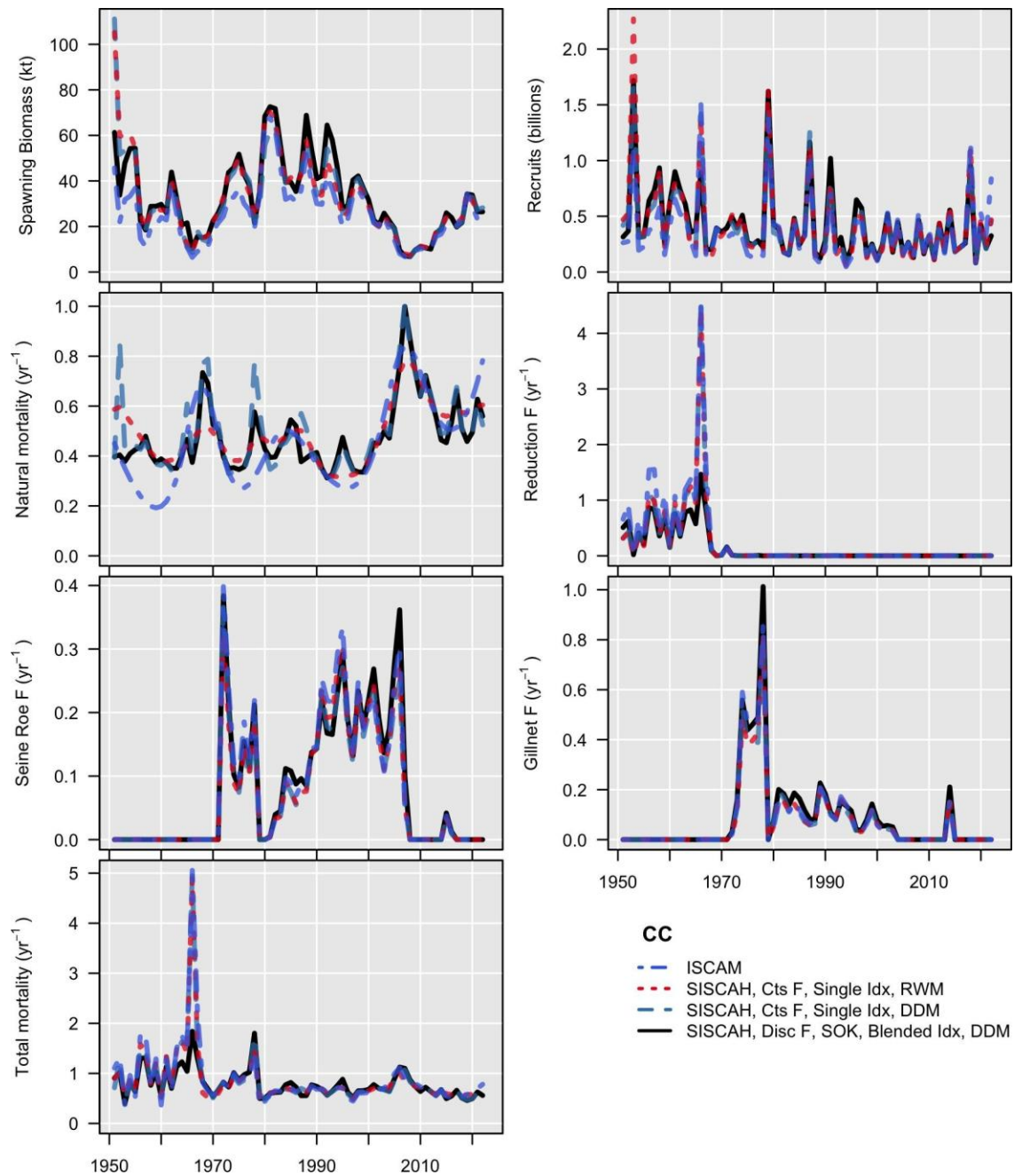


Figure B.10. Central Coast: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAH, base SISCAH with density dependent mortality, and a fully implemented SISCAH model.

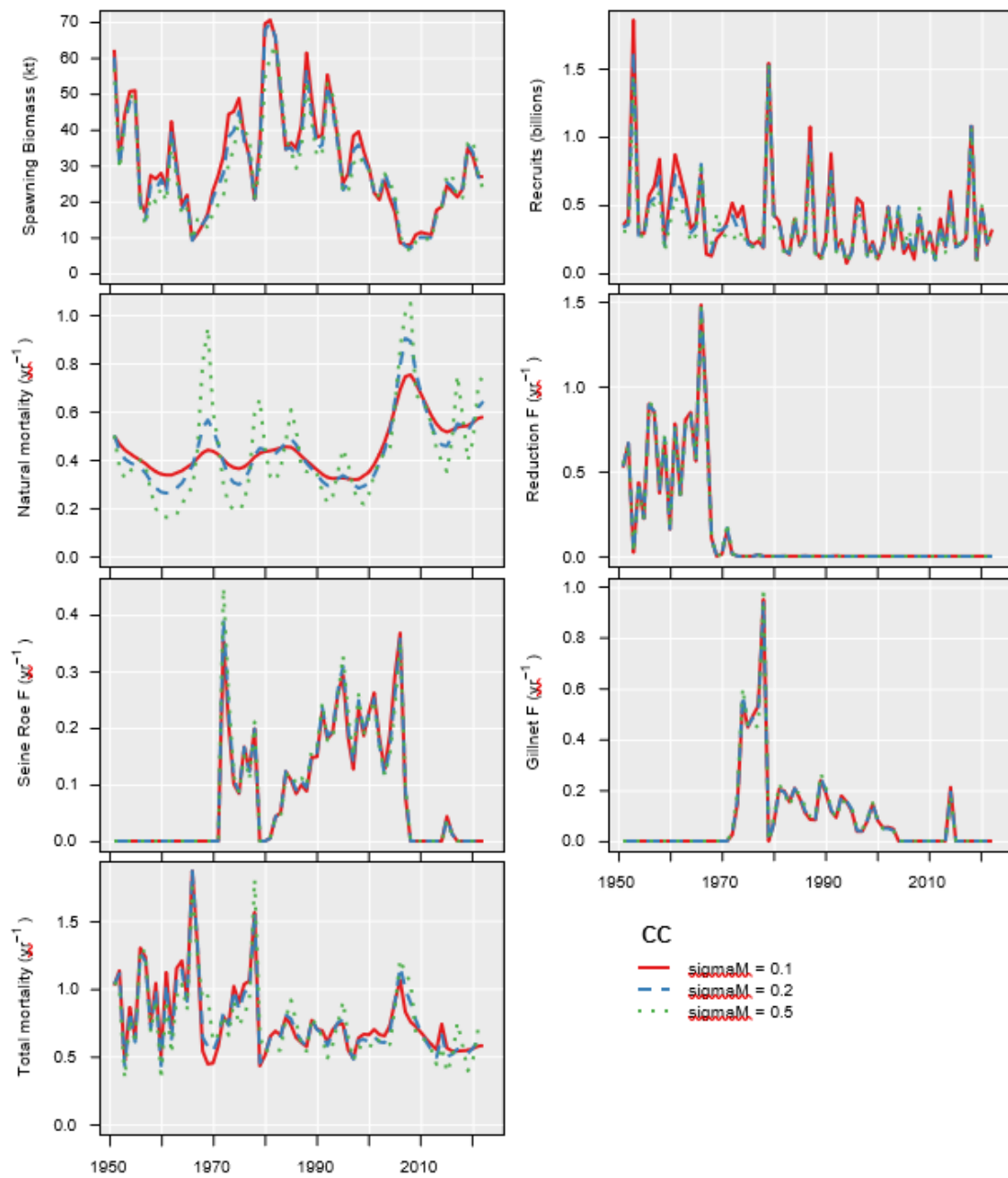


Figure B.11. Central Coast: Comparison of biomass, recruitment, and mortality estimates between SISCAH with three fixed values (0.1, 0.2, 0.5) for the standard error in annual natural mortality log-normal deviations σ_M .

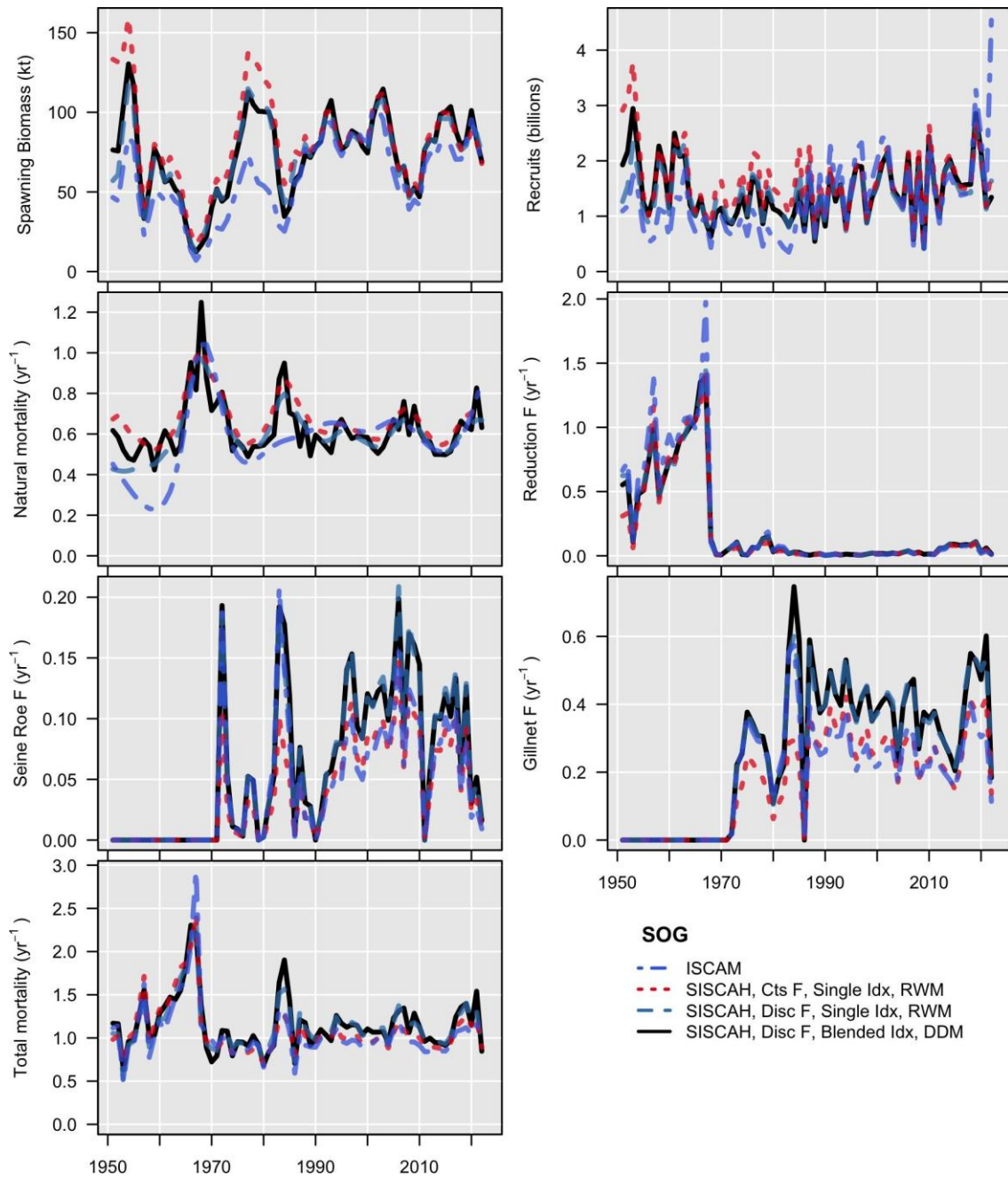


Figure B.12. Strait of Georgia: Comparison of biomass, recruitment, and mortality estimates between ISCAM with continuous F , single index (Idx), random walk mortality (RWM), and SISCAH models with step-wise implementations of discrete F (Disc F), spawn-on-kelp removals (SOK), the blended index (Idx), and density dependent mortality (DDM)

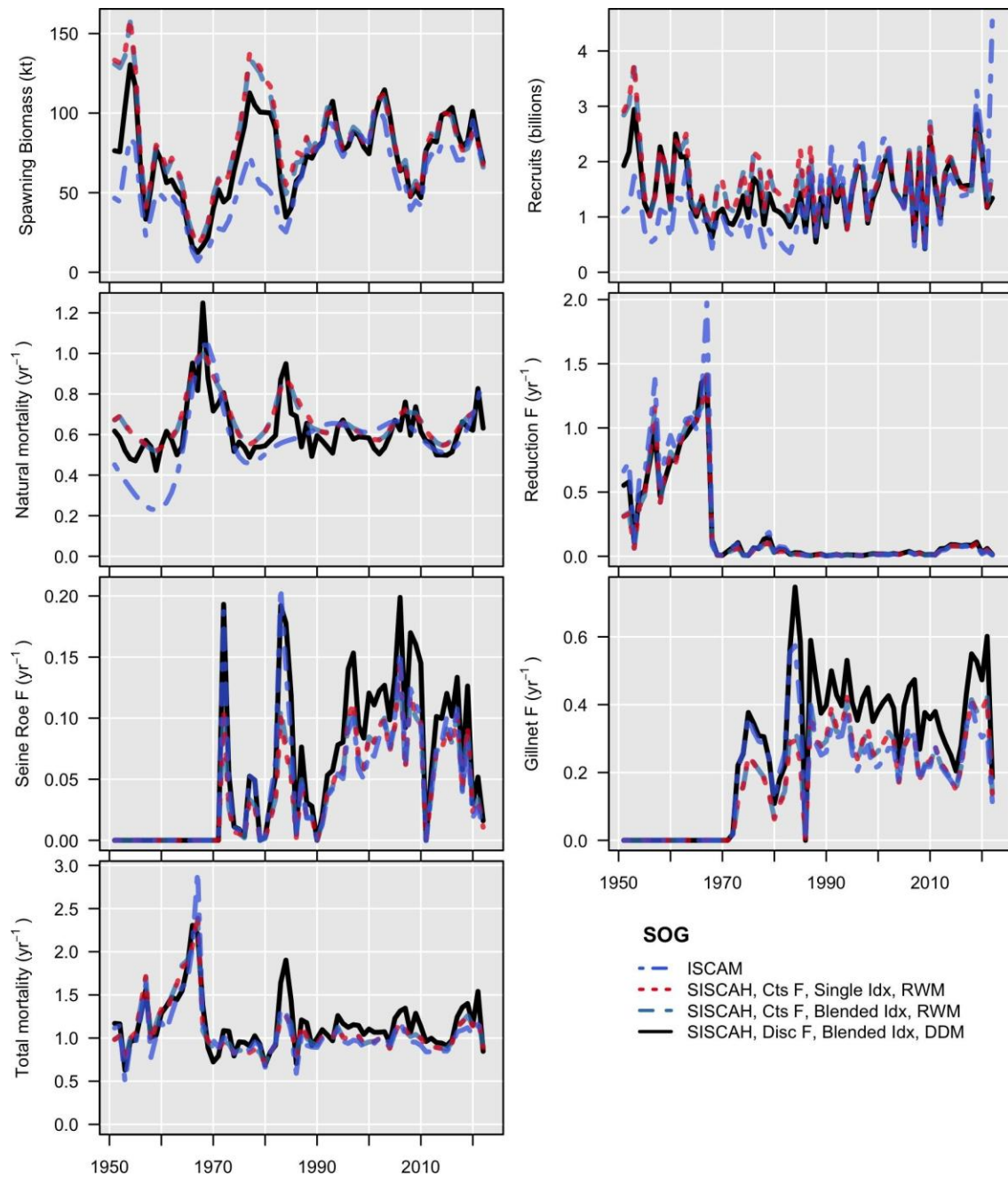


Figure B.13. Strait of Georgia: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAH, base SISCAH with blended index, and a fully implemented SISCAH model.

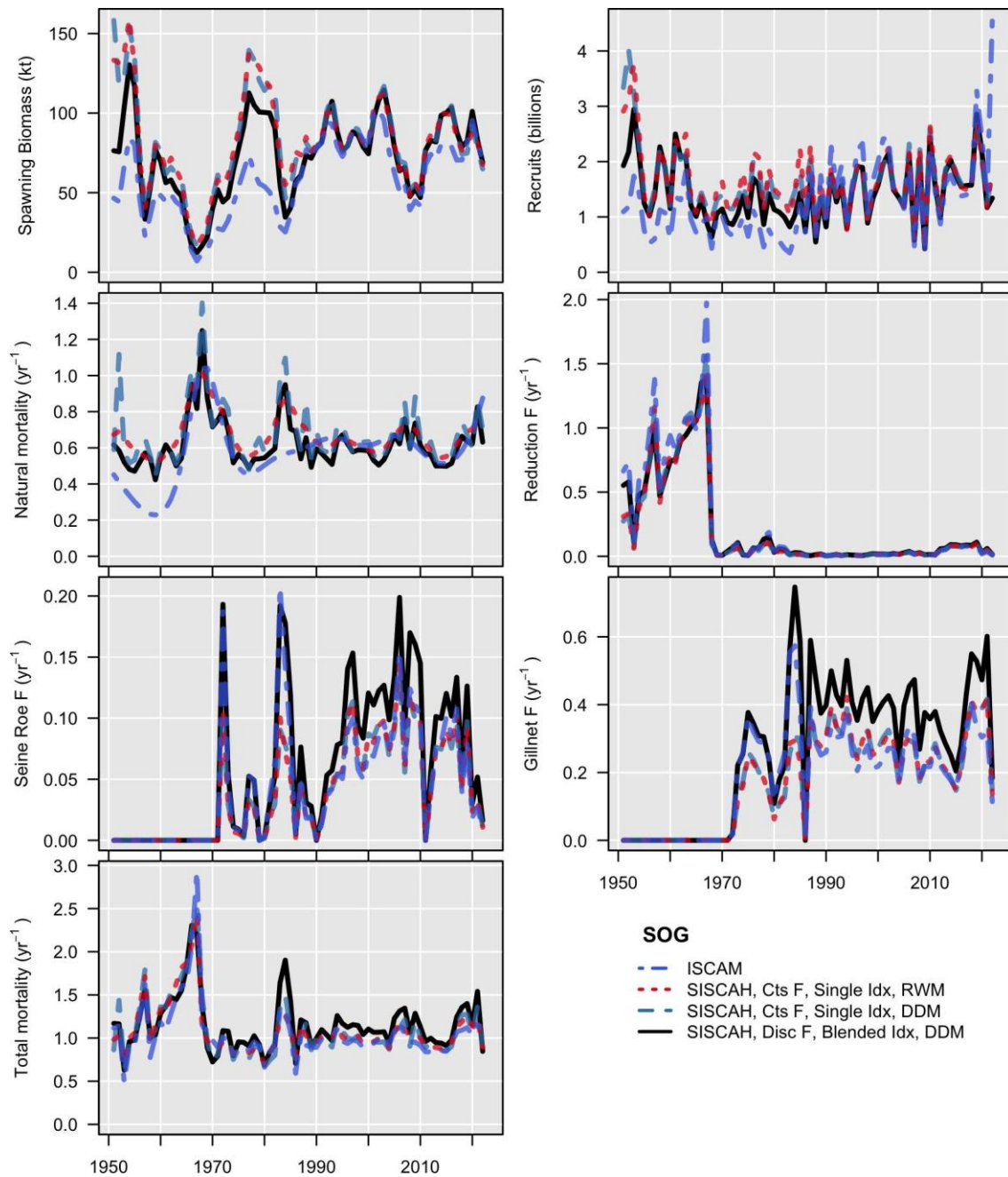


Figure B.14. Strait of Georgia: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAH, base SISCAH with density dependent mortality, and a fully implemented SISCAH model.

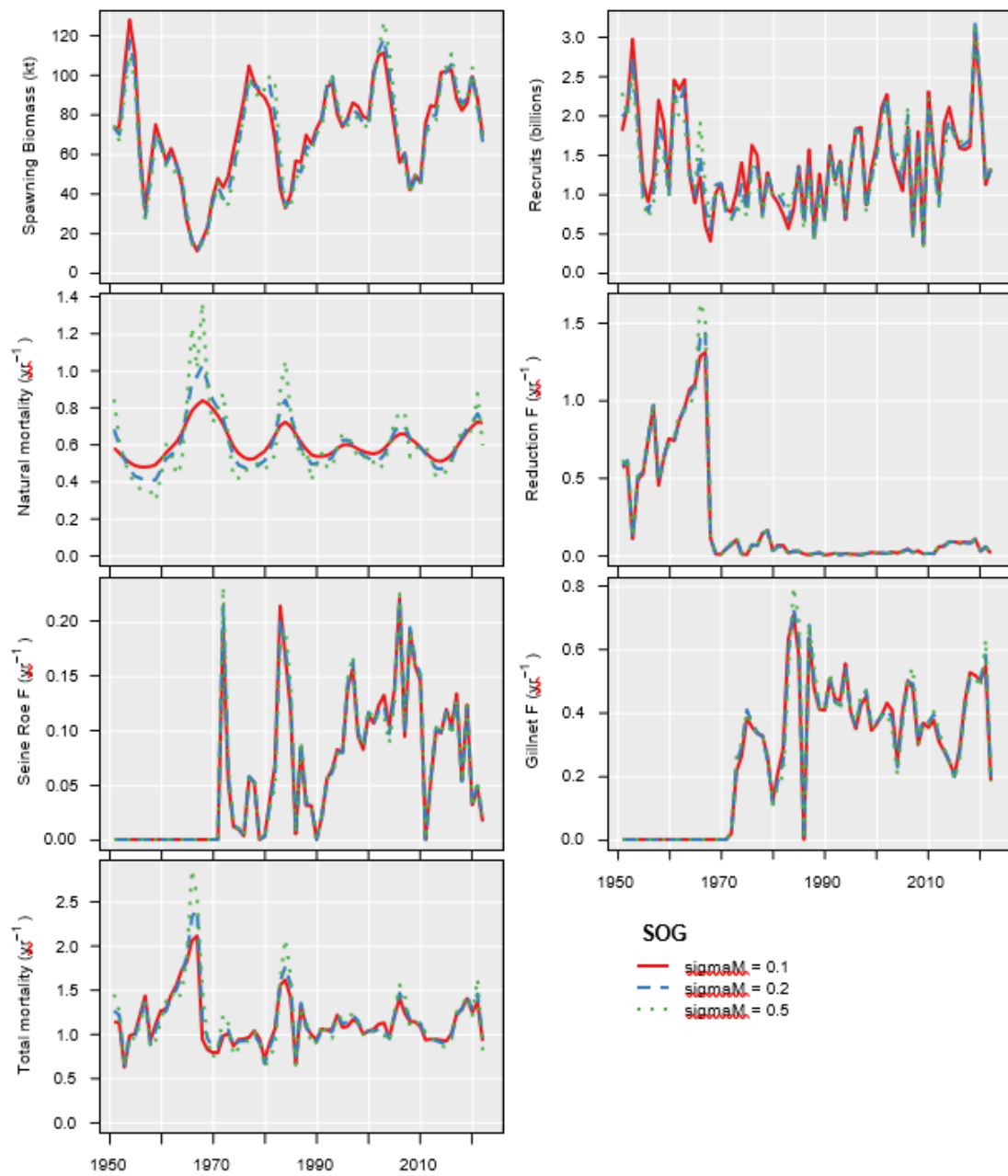


Figure B.15. Strait of Georgia: Comparison of biomass, recruitment, and mortality estimates between SISCARH with three fixed values (0.1, 0.2, 0.5) for the standard error in annual natural mortality log-normal deviations σ_M .

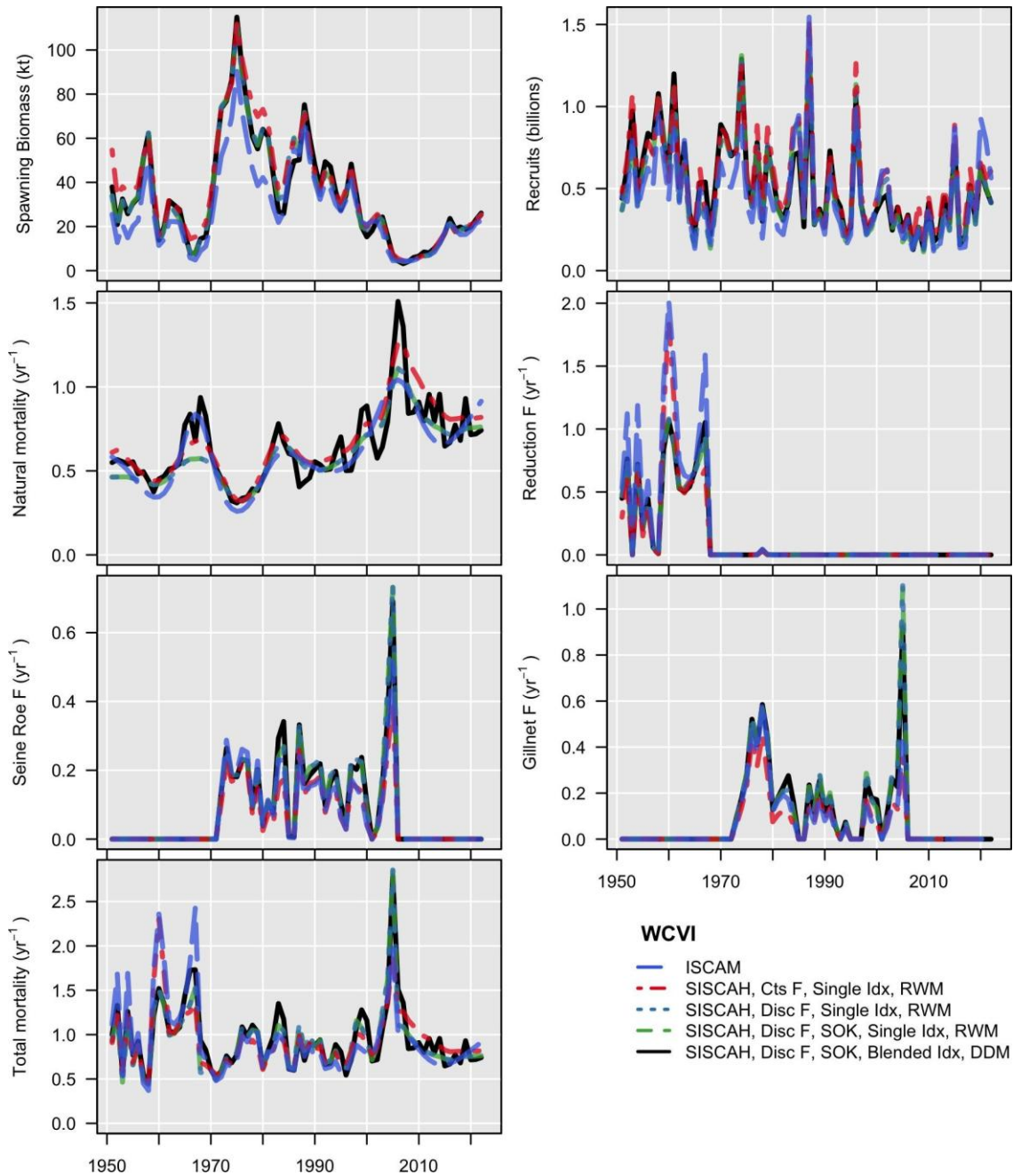


Figure B.16. West Coast of Vancouver Island: Comparison of biomass, recruitment, and mortality estimates between ISCAM with continuous F , single index (Idx), random walk mortality (RWM), and SISCAH models with step-wise implementations of discrete F (Disc F), spawn-on-kelp removals (SOK), the blended index (Idx), and density dependent mortality (DDM).

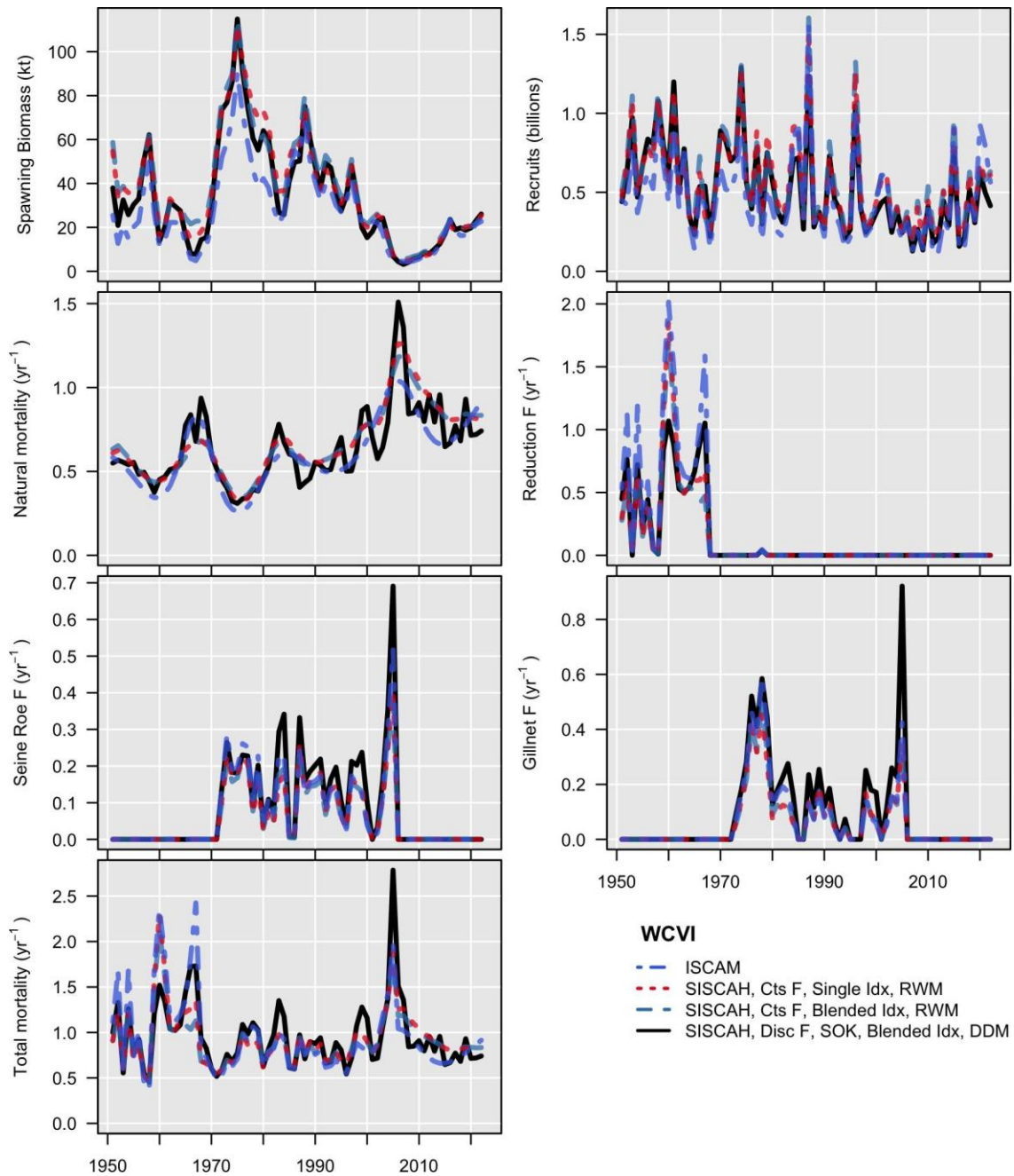


Figure B.17. West Coast of Vancouver Island: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAL, base SISCAL with blended index, and a fully implemented SISCAL model.

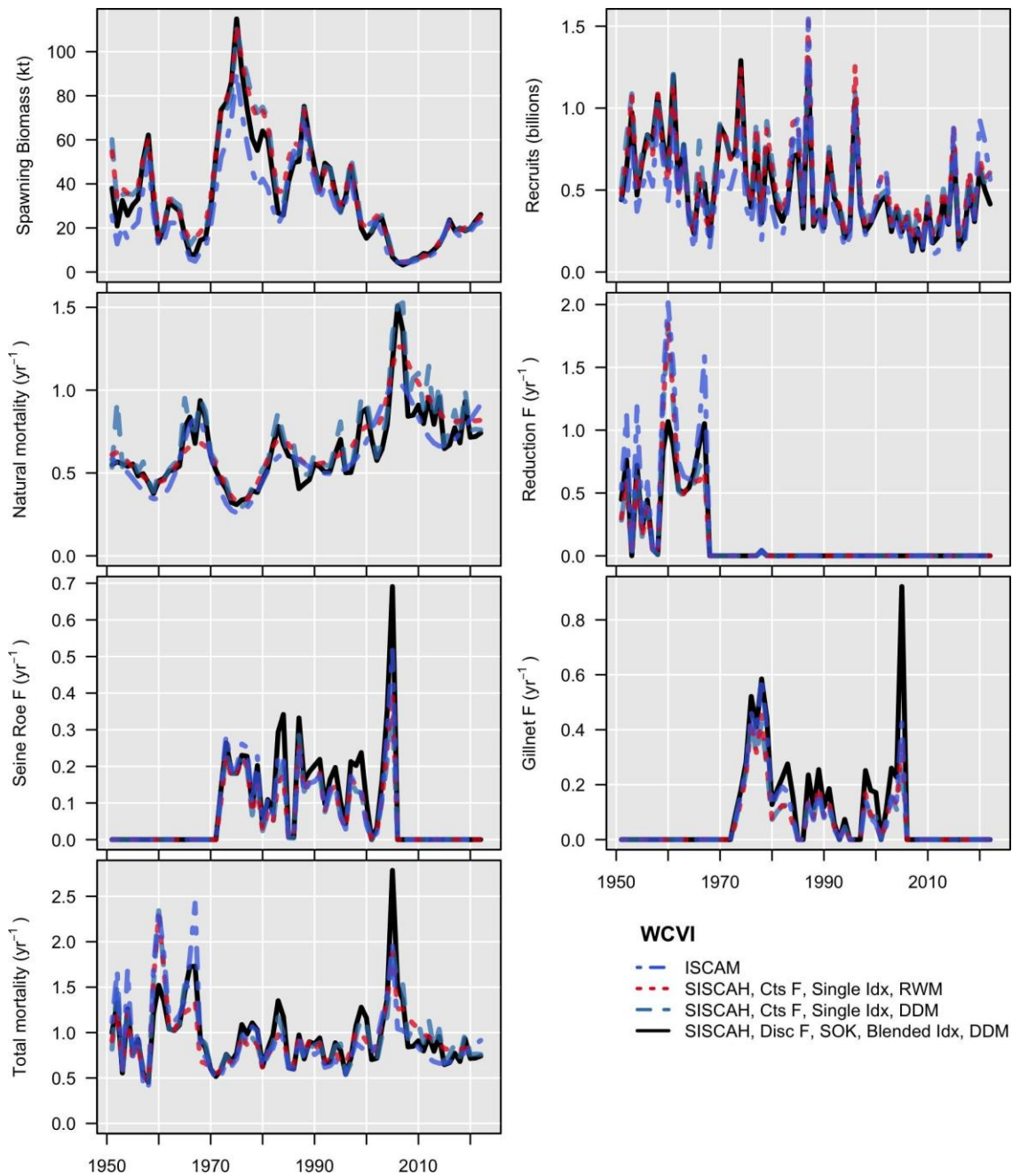


Figure B.18. West Coast of Vancouver Island: Comparison of biomass, recruitment, and mortality estimates between ISCAM, base SISCAN, base SISCAN with density dependent mortality, and a fully implemented SISCAN model.

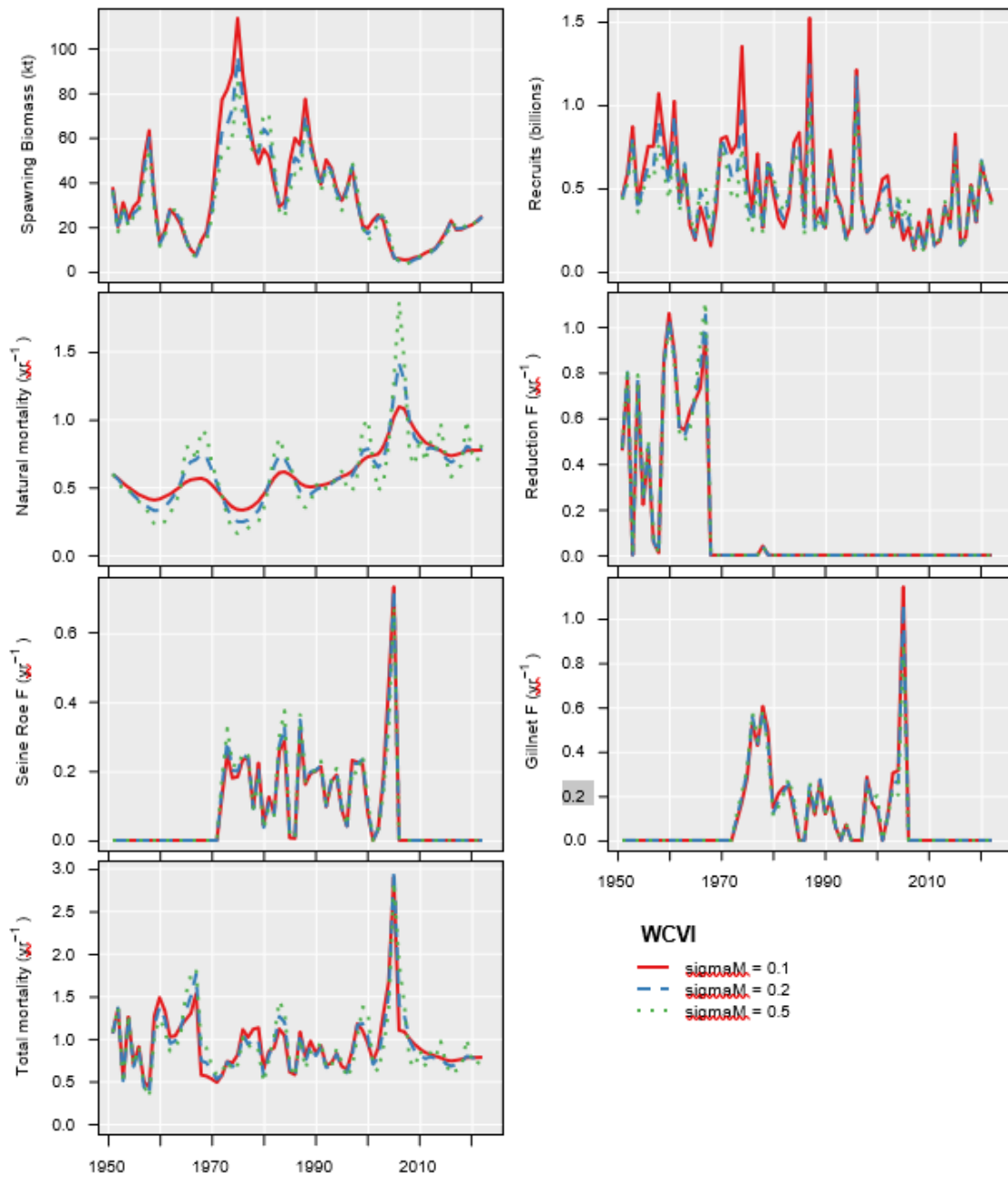


Figure B.19. West Coast of Vancouver Island: Comparison of biomass, recruitment, and mortality estimates between SISCAN with three fixed values (0.1, 0.2, 0.5) for the standard error in annual natural mortality log-normal deviations σ_M .

APPENDIX C. ADDITIONAL SIMULATION-ESTIMATION PLOTS

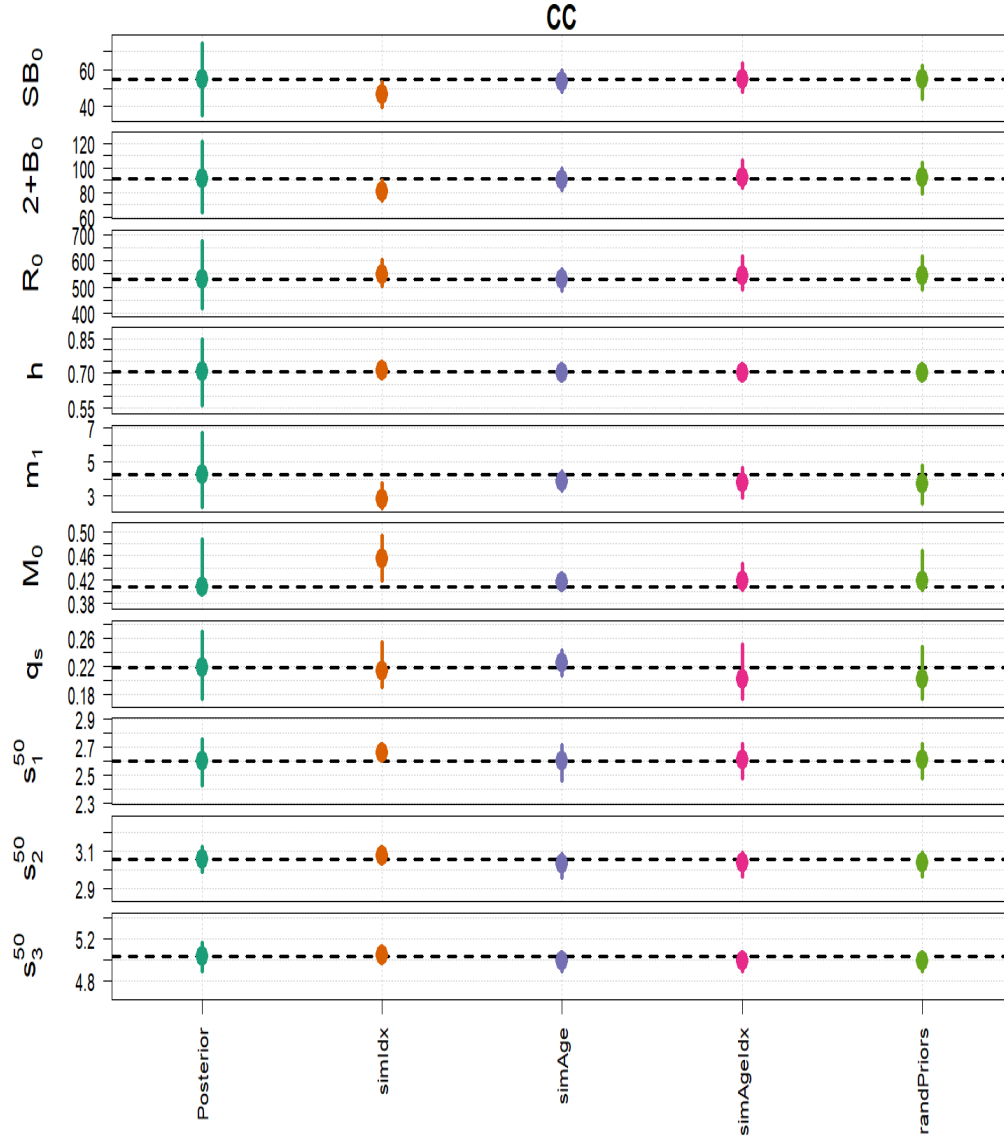


Figure C.1. Central Coast: Comparisons of leading parameter maximum posterior density estimates to SISCAL model posteriors across the four simulation self test scenarios. Parameter estimates include: life-history parameters (SB_0 , $2+B_0$, R_0 , h , M_b , m_1 , M_0), selectivity parameters (s_1^{50} , s_2^{50} , s_3^{50}), and survey observation model parameters (q_s , τ_s , τ_d). Points represent 50th percentile and the line segments extend to the 2.5th and 97.5th percentiles of posterior and relative error distributions.

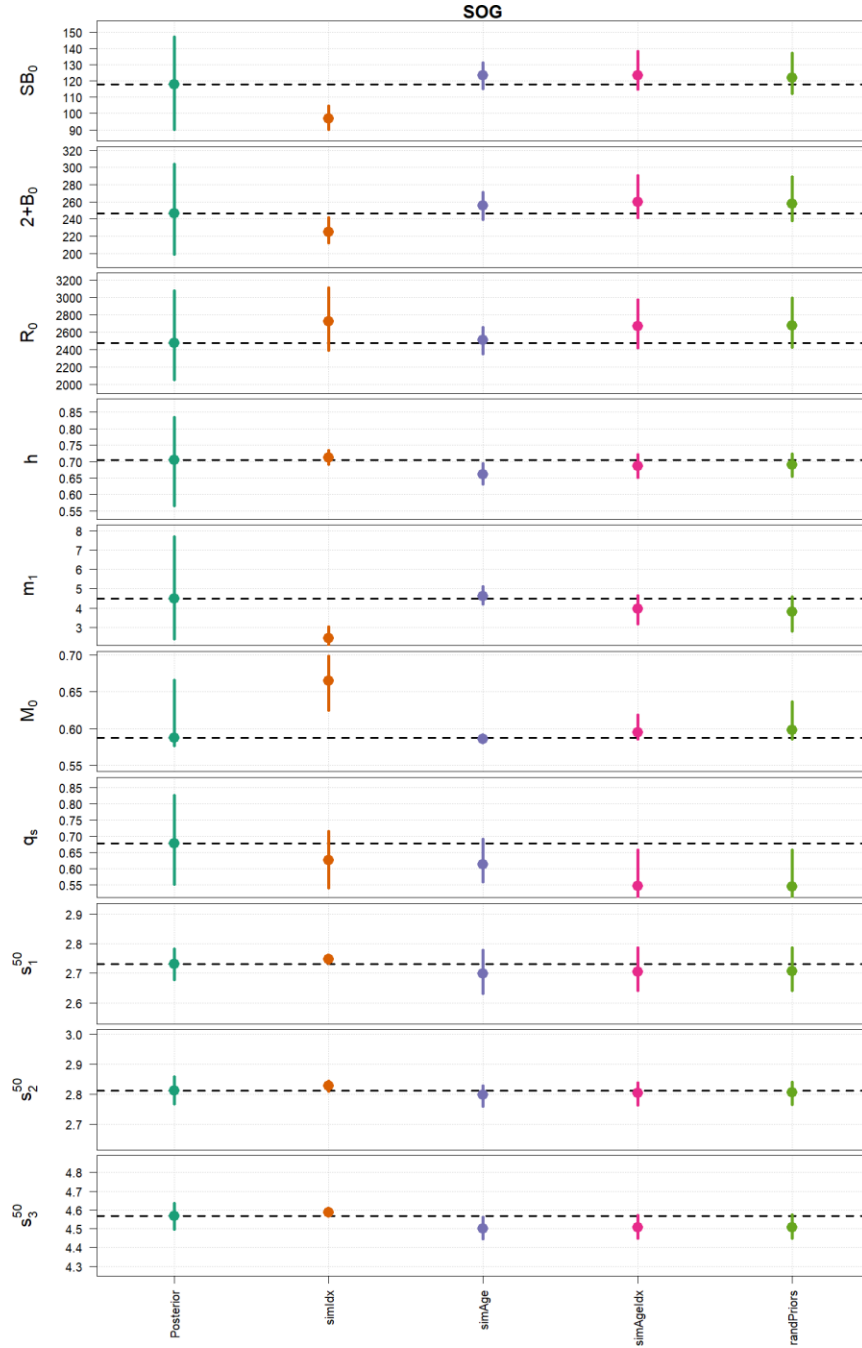


Figure C.2. Strait of Georgia: Comparisons of leading parameter maximum posterior density estimates to SISCAL model posteriors across the four simulation self test scenarios. Parameter estimates include: life-history parameters (SB_0 , $2 + B_0$, R_0 , h , M_b , m_1 , M_0), selectivity parameters (s_1^{50} , s_2^{50} , s_3^{50}), and survey observation model parameters (q_{sr} , τ_{sr} , τ_d). Points represent 50th percentile and the line segments extend to the 2.5th and 97.5th percentiles of posterior and relative error distributions.

APPENDIX D. DETAILED SISCAH MODEL ESTIMATES FOR THE 5 MAJOR STOCK ASSESSMENT REGIONS

D.1. HAIDA GWAIL

D.1.1. Goodness of fit

SISCAH model goodness of fit to Haida Gwaii herring data was well within acceptable limits. Based on SISCAH model standard errors (Table D.1), all data series are consistent with the estimated population dynamics. Age composition data standard errors for reduction and seine roe fisheries were below 0.5, which is generally considered a good fit to the data, while the gillnet fishery had an age-composition standard error of 0.645, which although higher is still within acceptable limits. SISCAH estimated standard errors for individual spawn survey designs were slightly larger than those assumed under ISCAM, and also were not in the same ratio that was assumed in ISCAM. Indeed, SISCAH estimates the surface survey design residuals are about 1.36 times as variable as the dive survey design.

Spawn index observation residuals over time showed no significant indication of poor fits (Figure D.2). In addition to reasonable standard errors, the time series of blended spawn index residuals had no real bias, with a mean residual of -0.15 standard errors. Time trends in residuals were also not of concern, as indicated by a very low lag-1 auto-correlation factor estimate of -0.03 and a non-significant residual trend with $p = 0.71$.

Estimates of age compositions show that SISCAH generally captures the year-class trends over time. SISCAH captures the shape, trend, and modal age-class of reduction fishery catch-at-age data for most years (Figure D.3). In some years, SISCAH over-estimates age-2 and age-3 proportions (e.g., 1951, 1962–65), however this is usually in order to estimate the modal age class correctly in the following year (e.g., compare 1962 and 1963). Such large residuals associated with model predictions of a larger year class may indicate that estimated selectivity is too high for those ages. On the other hand, some higher residuals in the reduction fishery are to be expected, given that the sampling design for data from that time period is hard to determine.

SISCAH captures the shape, trend, and modal age-class of the combined seine roe and test fishery catch-at-age data well (Figure D.4). Estimated catch-at-age tracks large cohorts through the years very well; however, as in the reduction fishery data, there are some years where age-2 proportions are over-estimated, which occurs to reduce residuals for the modal class in the following year (e.g., 1979 and 1987, Figure D.4).

The gillnet fishery had the highest age-composition sampling standard error (Table D.1), but SISCAH still visually fits the data well (Figure D.5). The main source of residual error is the inability to match the size of the modal age class, with age-class proportions coming in consistently below the observations of the 1977 year class as it passed through the gillnet fishery (1981–1984). Despite those higher residuals for the 1977 year class, SISCAH has no trouble matching the shape of the age compositions for gillnet fisheries, with the modal age classes identified in every year.

As with the spawn index residuals, the time series of recruitment process errors does not indicate poor model fits (Figure D.6). The mean recruitment process error deviation is around +0.04 standard deviations, indicating that there is no systemic bias in stochastic recruitments as compared to the underlying deterministic stock-recruitment model. Similarly, there are no long runs of positive or negative recruitment deviations, and auto-correlation is low (0.034). There is evidence of a significant residual trend over the 72 year history ($p = 0.01$), but this is of lower

concern as residuals after 1980, when ageing data are more consistently sampled, are well balanced, while earlier residuals when data were not consistently sampled are not. Moreover, the trend in recruitment residuals is consistent with the shifts in estimated recruitment dynamics, with SISCANH estimating larger cohorts pre-1975, and then smaller cohorts after that time leading into the more recent low biomass regime where HG herring is not recovering in the absence of fishing since 2005. Finally, there are also no indications of poor model fits when viewing recruitments relative to biomass around the stock-recruitment curve (Figure D.7).

D.1.2. Bayes posteriors

Standard Bayes posterior convergence metrics indicate that inferences can be drawn from the Bayes posteriors for the Haida Gwaii SAR SISCANH model. Effective sample sizes for the bulk and tail sections of all marginal distributions are above 100 samples per chain, and most Gelman-Rubin potential scale reduction factors $\hat{R}$ are below the nominated threshold of 1.01 for all estimated model parameters and random effects (Figure D.8). Sampled posterior points include 51 divergent transitions, or 1.3%, which is fewer than the 2% threshold.

Visual inspection of joint marginal posteriors for leading life-history and selectivity parameters indicates no concerning posterior geometry (Figure D.9). Most distributions are very symmetrical and have low skew and low correlation. There is a high degree of correlation in the joint m_1 and SB_0 marginal distribution, which is not surprising given the relationship between mortality and production in stock assessment models in general. Moreover, for SISCANH there is an added link between stock depletion with respect to unfished and the m_1 parameter via the density dependent M model and the definition of unfished equilibrium mortality M_0 . Future revisions may consider a re-parameterisation of the DDM model to reduce this correlation.

SISCANH implements a prior for steepness h with a mean value of 0.67, the same prior mean as implemented in ISCAM (See Table 4), but with a tighter prior variance of 0.01. The posterior distribution for HG shows a slight translation away from the prior mean, with posterior mean estimate of $h = 0.69$ but no change in variance, with the posterior returning 0.01 (Figure D.10).

The prior for the derived unfished mortality rate M_0 shows that there was influence of the data over the prior (Figure D.11). The prior mean is 0.45 and prior variance is 0.04, while the SISCANH marginal posterior of unfished mortality showed a translation away from the prior, with a posterior mean of 0.58 and posterior variance of 0.01.

Finally, SISCANH marginal posteriors for the spawn survey residual standard error for both designs (dive τ_d^2 and surface τ_s^2) show an influence of data over the prior (Figure D.12). For the surface survey component, while the posterior mean of 0.294 is similar to the prior mean of 0.27, the posterior variance of 0.007 is much lower than the prior variance estimate of 0.12 (estimated via random sampling). For the dive survey component, the drop in posterior variance of τ_d^2 from 0.12 to 0.014 is similar to the surface survey, however there is an increase in posterior mean τ_d^2 to 0.354 over the prior mean of 0.27.

The similarity of the prior and posterior distributions for stock-recruitment steepness h is somewhat ambiguous, either indicating that there is either limited information in the data to inform the estimation of h , or that the prior is well aligned with the data. While the latter case is fairly improbable, it may be the case here since there is higher than usual proportion of years with observations derived unfished mortality M_0 estimate and the spawn survey residual standard error components τ_d^2 , τ_s^2 , which all have much lower posterior variance than the prior variance.

D.1.3. Historical dynamics

Estimated biomass time series obtained from SISCAH indicate multiple boom-bust periods for the Haida Gwaii SAR. Prior to the 1970s, each bust is largely driven by extremely high exploitation rates (i.e., > 80%, Figure D.13). During the 1970s and 1980s, Haida Gwaii herring experienced much lower harvest rates than the 50s and 60s, remaining in the 10%–30% range. Booms in spawning biomass were at least as high in the 70s and 80s as occurred earlier, and busts did not go as low. The two peaks in spawning biomass occurring between 1970–1985 are around 2–3 times the unfished level, with troughs close to the SB_0 . Those high peaks are largely driven by above average recruitments (1971–73, and 1978), as well as lower harvest rates during that period. Spawning biomass eventually declines to around the unfished level by the early 1990s, and further declines to historic lows in the mid 1990s. Spawning biomass increased slightly in 1998, and then declined back down to a similar historic low in the early 2000s. Since that time, the biomass has been slowly climbing towards the unfished estimate of around 10 kt, with natural mortality rates remaining elevated above unfished levels since that time.

Given that spawning biomass in the 1980s was several times the unfished biomass level, the estimated decline in the late 1980s and early 1990s is unsurprising. First, while harvest rates and catches both declined over the same time period, large recruitments were much closer to the ‘average’ deterministic level of the Beverton-Holt stock recruit curve, and often separated by multiple years of well below average recruitments (Figure D.13, 2nd panel). As a result, the total biomass of age-1 fish added to the SAR was much lower, and spread over a longer time-interval. As biomass declined, mortality increased via the density dependent model to reach a maximum in the early 2000s (Figure D.13, 3rd panel).

High density dependent natural mortality rates coupled with a low unfished biomass of around 10 kt appear to create a reinforcing feedback loop on elevated mortality rates, slowing recovery of Haida Gwaii herring in the absence of fishing and capping the biomass around recent levels. Mortality has remained elevated since its peak in the early 2000s, likely because as biomass declines, the survival rate of all age classes of herring declines, reducing the size of large year classes more quickly as they age. That erosion of year class strength slows stock growth, leading to longer recovery times. Additionally, the low SB_0 value means that the deterministic average recruitment, even at unfished, is quite low, further limiting stock growth.

Spawning biomass in 2022 is estimated to be around 113% of unfished (Table 11). The median estimate of natural mortality rates briefly dropped below to the unfished equilibrium level of $M_0 = 0.58$ in 2018, which although it coincides with a high biomass at that time, the lower recruitments in 2018 and 2019 brought spawning biomass back down to just below unfished in 2020–2022 (Figure D.13). The tendency of Haida Gwaii M values to have such a sawtooth pattern is driven, in part, by the low depensation rate of $m_1 = 1.39$, which is much lower than estimated for other areas (described below). Lower m_1 values create shallower depensatory M curves, so changes in mortality rates occur at a higher range of depletion levels (Figure D.14). For Haida Gwaii, because the curve is shallow, depensatory M occurs over a wider range of biomass depletion up to $1.5SB_0$. Therefore, as observed in the history, a small run of low recruitments can spike mortality rates and create high variability in spawning biomass, even when there are no fisheries.

D.1.4. Biological reference points

SISCAH model equilibria, or biological reference points (BRPs) estimates show a maximum sustainable yield (MSY) of approximately 330 t, including biomass of herring from Gillnet and Seine fisheries and landings of SOK product. MSY is achieved at an equilibrium spawning biomass is around 3.39 kt, and via the usual calculation of harvest rates as $U = C/(SB + C)$, the

optimal harvest rate is $U_{MSY} = MSY/(B_{MSY} + MSY) = 0.12$ (Figure D.15). The harvest rate accounts for a high allocation of TAC to SOK fisheries, which have a lower mortality rate than the Seine or Gillnet fishing gears.

SISCAH model equilibrium yield and biomass curves show an extirpation of the Haida Gwaii population, but it is not as abrupt as in other areas described below. Yield drops fastest as sustained harvest rates approach 50%, following which the equilibrium biomass, yield, and recruitment all decline to zero. This extirpation is a result of increasing fishing pressure, which lowers biomass and increases the associated equilibrium natural mortality rate M (Figure D.15, 3rd panel), with mortality reaching the maximum level of around 1.3 above $U = 0.38$ (Figure D.15). Unlike other areas the decline in yield and biomass appears to be quite smooth, as biomass drops faster than yield and creating an inflection point on the yield curve as harvest rates shoot up and biomass declines.

Joint marginal posteriors of life-history quantities and biological reference points indicate that the DDM model affects biomass scale more than productivity (Figure D.16). As indicated in the joint marginal posteriors of estimated parameters, there is a correlation between m_1 and SB_0 (Figure D.9, and correlation is also present between m_1 and B_{MSY} , which is unsurprising given that size of B_{MSY} is strongly influenced by the stock size SB_0). Similarly, there is the usual strong correlation between stock-recruit steepness h and optimal harvest rate U_{MSY} , given the influence of steepness over density dependence in recruitment. However, there is only a weak negative correlation between m_1 and U_{MSY} , with a large spread across the entire joint marginal distribution.

Per-capita demographic rates shed more light on the equilibrium properties of SISCAH at low biomass levels (Figure D.17). As harvest rates increase, a component Allee effect is observable. As in all compensatory recruitment models, per-capita recruitment (i.e., recruits-per-spawner) increases towards a maximum rate defined by the stock-recruitment model parameters. At the same time, the density dependence in natural mortality drives survival rates for age-2+ fish down, dropping to a minimum rate of about 25%. While the stochastic equilibrium per-capita surplus production for Haida Gwaii is already around zero at higher stock sizes, the effect of declining survival is to make per-capita surplus production negative. Because surplus production affects equilibrium yield and the equilibrium biomass, the negative production drives biomass down faster than yield and creates the smooth pattern in the yield curve (Figure D.15).

D.1.5. Retrospective analyses

Results of the retrospective analysis suggests that SISCAH estimates of Haida Gwaii herring biomass and life history parameters have low sensitivity to additional years of data. Spawning biomass (both absolute and depletion) are consistent over the ten years of the retrospective peels (Figure D.18), with the exception of the 2020 peel. From the 2020 to 2021 peel, the MPDE of spawning biomass roughly doubles for 2018 and 2019, which is related to a mis-assignment of a large incoming cohort to the 2017 year class (Figure D.19). In 2021 and 2022, that year class is revised downwards, and the 2016 year class is instead assigned the large positive recruitment deviation. As a result, the biomass is revised upwards for 2018/19 as the large 2016 year class recruits to the spawning biomass (Figure D.18).

Year class strength is somewhat variable for Haida Gwaii herring. About half of the year classes in the retrospective analysis resolve by age-4 while the others take until age-6 (or longer).

SISCAH retrospective estimates of natural mortality are very consistent over time (Figure D.18), with the exception of the 2020 peel. As with most retrospective analyses, there are end effects

where a lack of age data and deterministic recruitments mean that SISCAN misses changes in trend for the final years of each peel, but those effects are relatively minor. From the 2020 peel to the 2021 peel, the revision of 2018/19 biomass to a higher has a corresponding revision downwards in natural mortality, because the biomass went from below unfished levels to above unfished levels, driving the deterministic component of density dependent mortality below M_0 for those years.

In contrast to the stability of mortality and biomass estimates over the retrospective years, leading parameters and unfished equilibrium quantities generally declined over the retrospective peels (Table D.2). Unfished spawning biomass SB_0 , unfished recruitment R_0 , and initial recruitment R_{init} all reduced by 13%–17% over the ten years. Changes in the density dependent mortality model parameters were much smaller, with m_1 changing from year to year, with a low of 1.287 and high of 1.330, which drove small changes in M_0 ranging from 0.595–0.606.

D.1.6. Sensitivity analyses

SISCAN estimates of Haida Gwaii herring biomass and life history parameters were somewhat sensitive to specific choices of priors (Table D.3). Unfished biomass SB_0 ranged between 15 kt and 22.2 kt, with the highest values observed for lower values of M_0 , which were associated with more informative priors on M_0 (sdMHi) or lower prior mean M_0 values (meanMLow). Similarly, the lower values of SB_0 were associated with higher M_0 values, influenced by higher prior mean M_0 (meanMHi) or less informative priors (sdMLow); lower SB_0 values were also influenced by lower steepness values (steepMeanLo), and higher magnitude penalties (jeffHi). The stock-recruitment steepness parameter h was fairly insensitive to changes in most priors aside from alternative steepness prior hyperparameters, under which steepness ranged from 0.534 (steepMeanLo) to 0.895 (steepMeanHi); the steepness prior standard deviation was less influential.

Six out of seven SISCAN initial condition configurations successfully converged for the Haida Gwaii SAR. As anticipated, the primary impact of adjusting the fished initialization settings was observed in the first-year age-1 recruitment, represented by either R_0 or R_{init} , and in the unfished biomass SB_0 (see Table D.4). The effects on M_0 , due to its correlation with SB_0 , and the stock-recruitment steepness h were relatively smaller.

The influence of initial conditions on biomass and recruitment estimates in each year was minimal (not displayed, although the low sensitivity of q_s indicates stability). Other model parameters, including recruitment and mortality process errors, exhibited the ability to adapt and compensate for variations arising from the initial conditions within the model.

D.1.7. Tables

Table D.1. Estimated residual standard errors and lag-1 age residual correlations for Haida Gwaii herring data. The first six columns show age data sampling standard errors τ_g^{age} and correlation coefficients ρ_g from the LN1 age composition likelihood function the Reduction and Food & Bait ($g = 1$), Seine-rope ($g = 2$), and gillnet fisheries ($g = 3$), and the last two columns show spawn survey index standard deviations for the surface (τ_s) and dive (τ_d) surveys.

SAR	τ_1^{age}	ρ_1	τ_2^{age}	ρ_2	τ_3^{age}	ρ_3	τ_s	τ_d
HG	0.428	0	0.438	0.269	0.645	0.298	0.485	0.515

Table D.2. Haida Gwaii retrospective estimates of selected SISCAL model leading and derived life-history quantities over data peels from 2012–2022. Selected quantities are SB_0 = estimated unfished equilibrium spawning biomass(kt), R_0 = estimated unfished equilibrium recruitment (1e6), R_{init} = estimated initial recruitment (1e6), m_1 = depensation rate (unitless), M_b = asymptotic lower bound on age-2+ natural mortality (yr), M_0 = equilibrium unfished age-2+ natural mortality (yr), q_s = surface survey catchability (unitless).

Peel	SB_0	R_0	m_1	M_0	h	q_s
2013	20.213	442.071	1.287	0.606	0.708	0.300
2014	19.275	414.081	1.304	0.601	0.699	0.310
2015	18.632	396.131	1.314	0.599	0.700	0.316
2016	18.860	403.548	1.311	0.600	0.699	0.314
2017	18.452	396.782	1.308	0.600	0.694	0.315
2018	18.181	382.316	1.330	0.595	0.682	0.319
2019	18.632	405.203	1.302	0.602	0.706	0.313
2020	18.355	397.897	1.307	0.601	0.703	0.316
2021	17.945	381.251	1.327	0.595	0.702	0.322
2022	17.209	368.121	1.324	0.596	0.698	0.325

Table D.3. Haida Gwaii SISCAH model estimates of life-history and observation model quantities under sensitivity analyses.

Sensitivity	SB_0	R_0	R_{init}	m_1	M_0	h	q_s
base	17.209	368.121	–	1.324	0.596	0.698	0.325
jeffHi	15.210	359.373	–	1.239	0.620	0.694	0.330
jeffLo	17.209	368.121	–	1.324	0.596	0.698	0.325
meanMHi	15.034	381.542	–	1.181	0.637	0.693	0.323
meanMLow	21.428	349.040	–	1.590	0.534	0.707	0.328
qSurfSDHi	17.315	371.116	–	1.322	0.597	0.698	0.322
qSurfSDLo	16.828	357.346	–	1.330	0.594	0.699	0.340
sdMHi	15.251	380.062	–	1.195	0.633	0.693	0.323
sdMLow	22.150	346.461	–	1.635	0.525	0.709	0.329
sigmaMhi	17.028	359.422	–	1.336	0.593	0.694	0.328
sigmaMlo	17.588	379.380	–	1.316	0.598	0.699	0.320
steepMeanHi	17.466	364.202	–	1.347	0.590	0.895	0.329
steepMeanLo	15.779	367.867	–	1.250	0.617	0.534	0.322
steepSDHi	17.306	367.722	–	1.330	0.595	0.721	0.326
steepSDLo	17.144	368.326	–	1.320	0.597	0.685	0.325

Table D.4. Haida Gwaii SISCAH model estimates of life-history and observation model quantities under the initial conditions sensitivity analyses.

Initial Conditions			SB_0	R_0	R_{init}	F_{init}	m_1	M_b	M_0	h	q_s
initR	initF	initDevs									
R_0	TRUE	TRUE	22.215	363.064	–	0.147	1.587	0.33	0.535	0.708	0.326
R_0	FALSE	TRUE	17.209	368.121	–	0.000	1.324	0.33	0.596	0.698	0.325
R_{init}	FALSE	FALSE	16.243	361.660	458.115	0.000	1.289	0.33	0.606	0.696	0.327
R_{init}	TRUE	FALSE	23.313	348.985	431.606	0.199	1.686	0.33	0.515	0.712	0.330
R_{init}	TRUE	TRUE	21.339	352.179	392.733	0.167	1.576	0.33	0.537	0.708	0.329
R_{init}	FALSE	TRUE	17.338	359.302	346.538	0.000	1.352	0.33	0.589	0.699	0.328

D.1.8. Figures

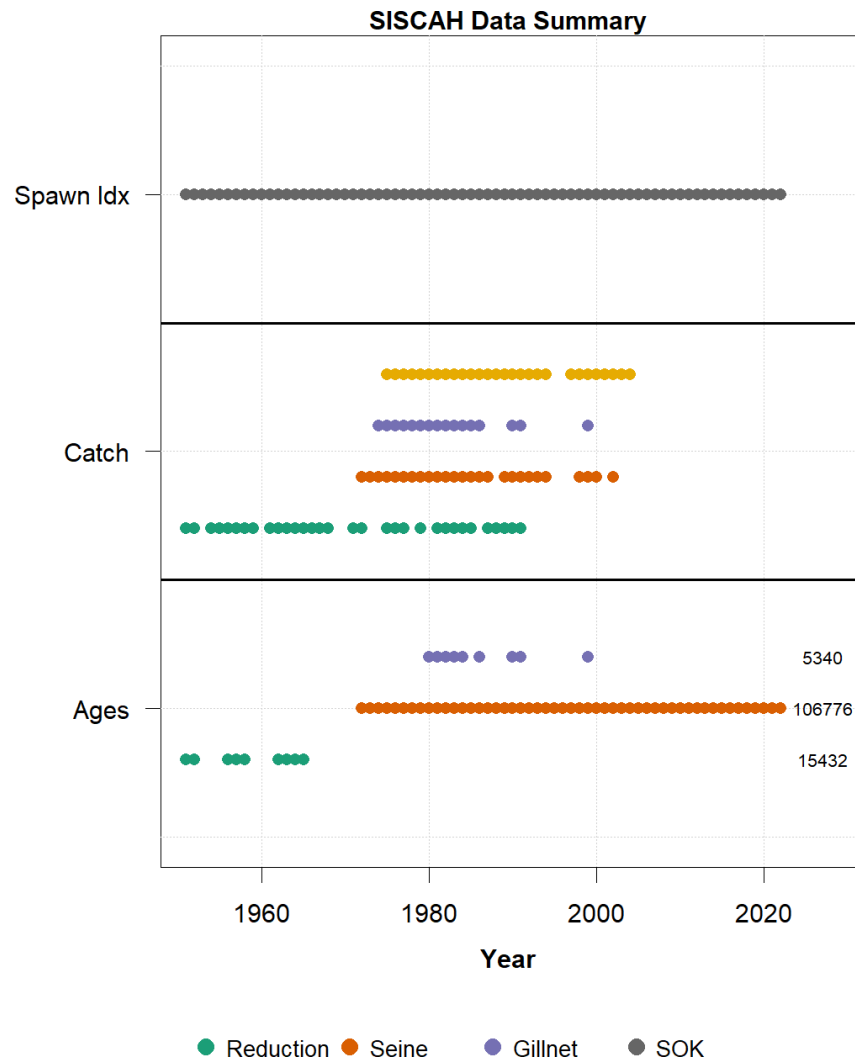


Figure D.1. Time series of Haida Gwaii herring stock assessment data. Each dot shows the existence of data, and age data shows total number of samples over all years at the right hand end.

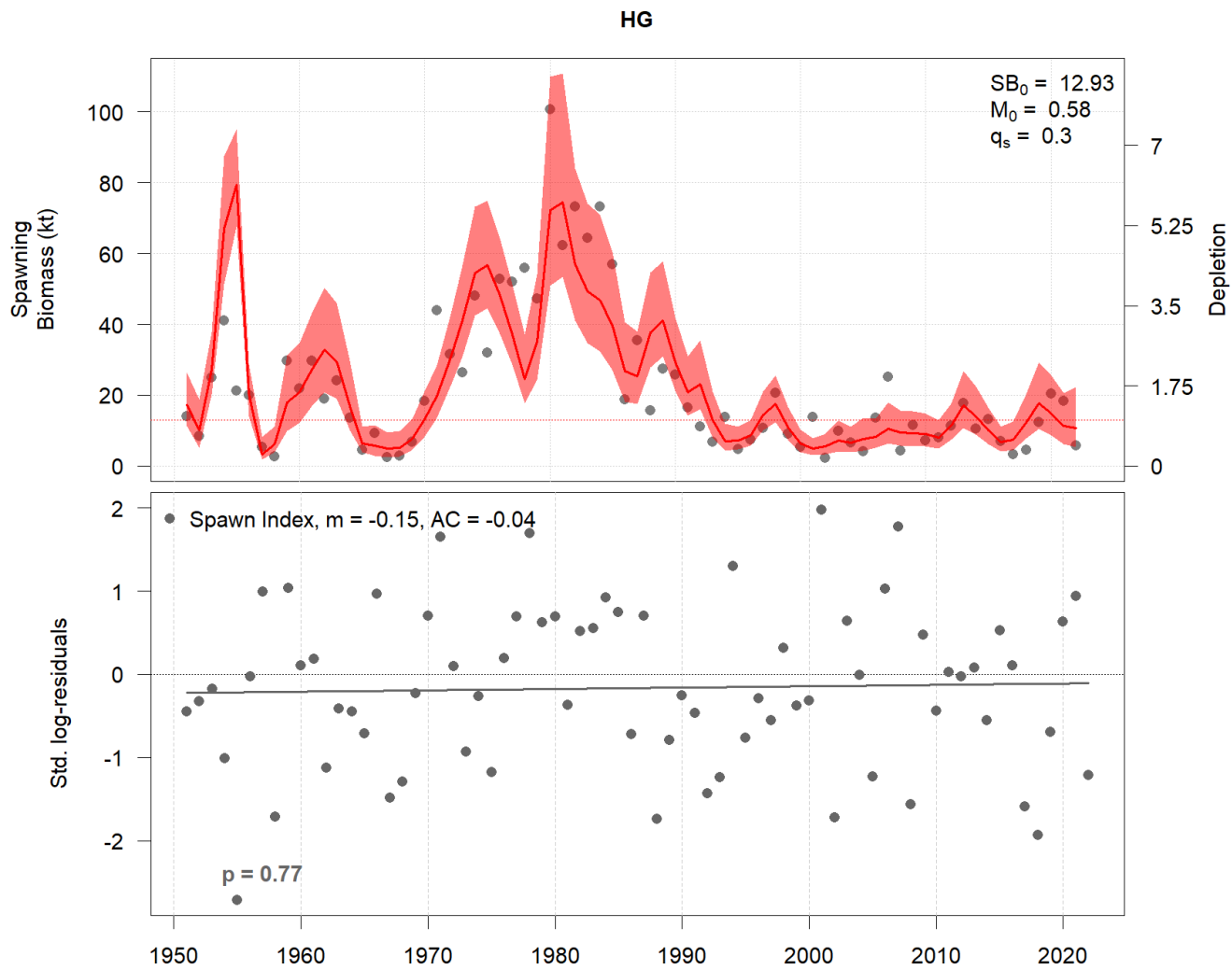


Figure D.2. Haida Gwaii blended spawn index and SISCAN spawning biomass estimates (top) and standardised observation residuals (bottom). SB_0 and M_0 are the unfished equilibrium spawning stock biomass and the natural mortality respectively, q_s is the catchability coefficient for the surface surveys, m is the mean log residual of the spawning index, and AC is the autocorrelation.

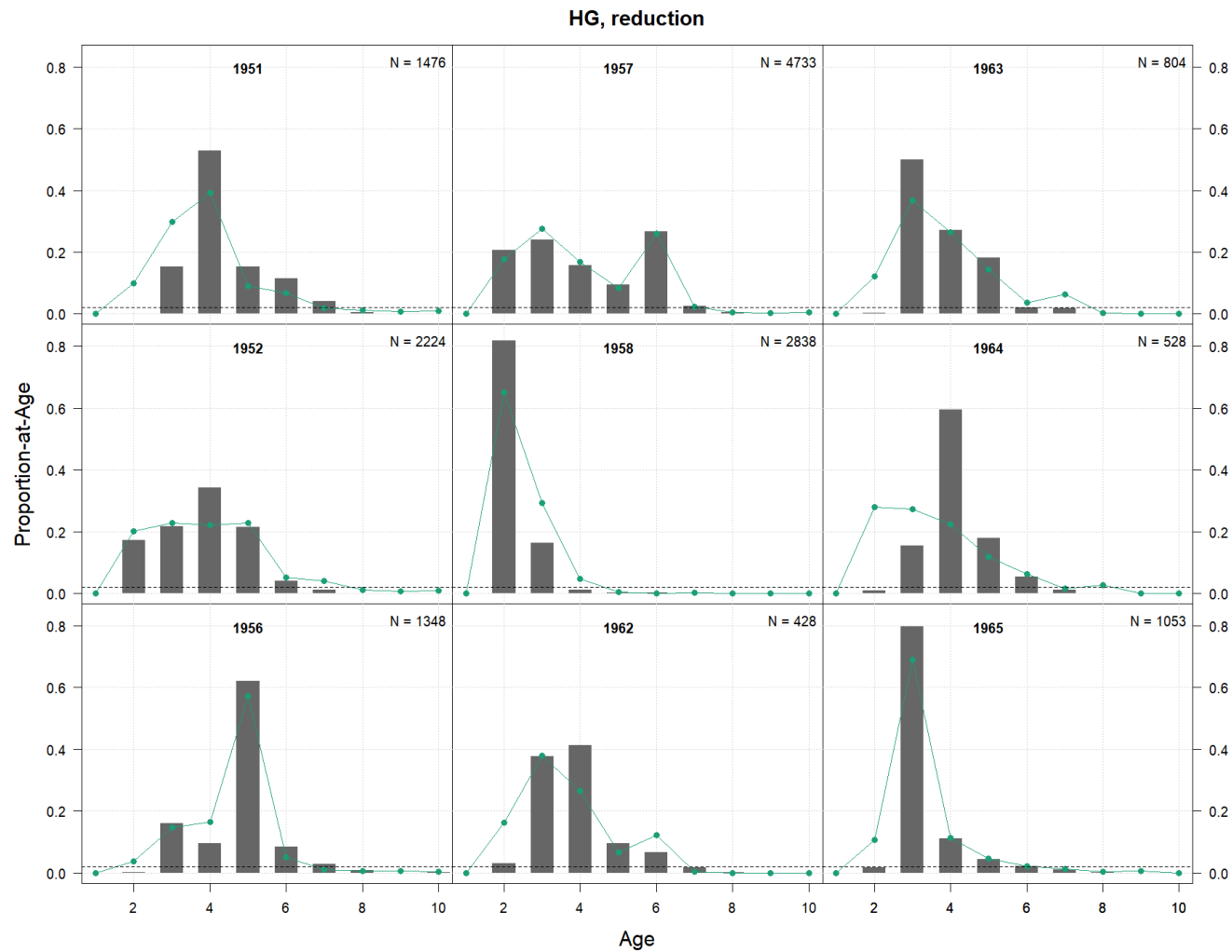


Figure D.3. SISCAH model fits to reduction age compositions collected from the Haida Gwaii region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

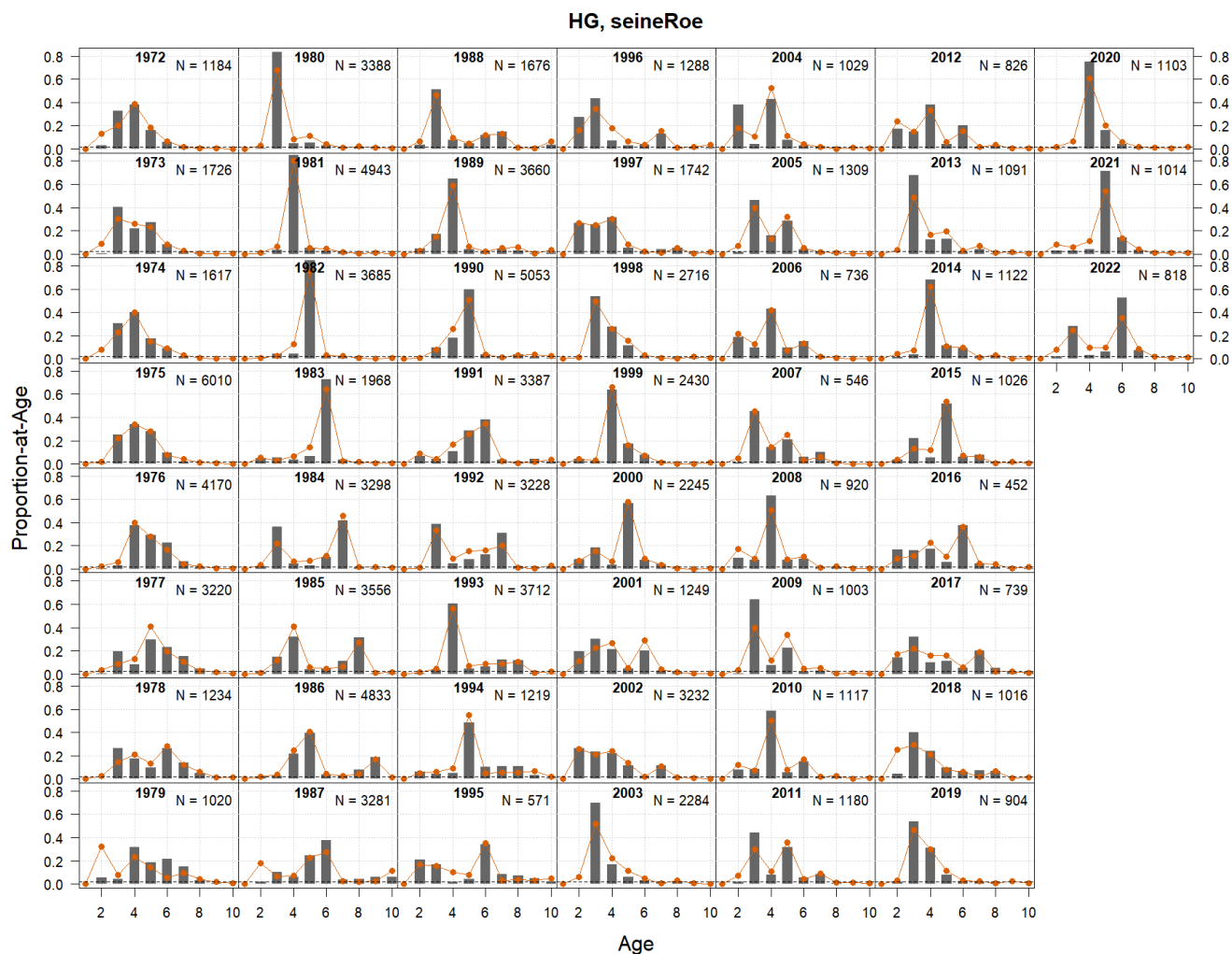


Figure D.4. SISCAH model fits to seine roe age compositions collected from the Haida Gwaii region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

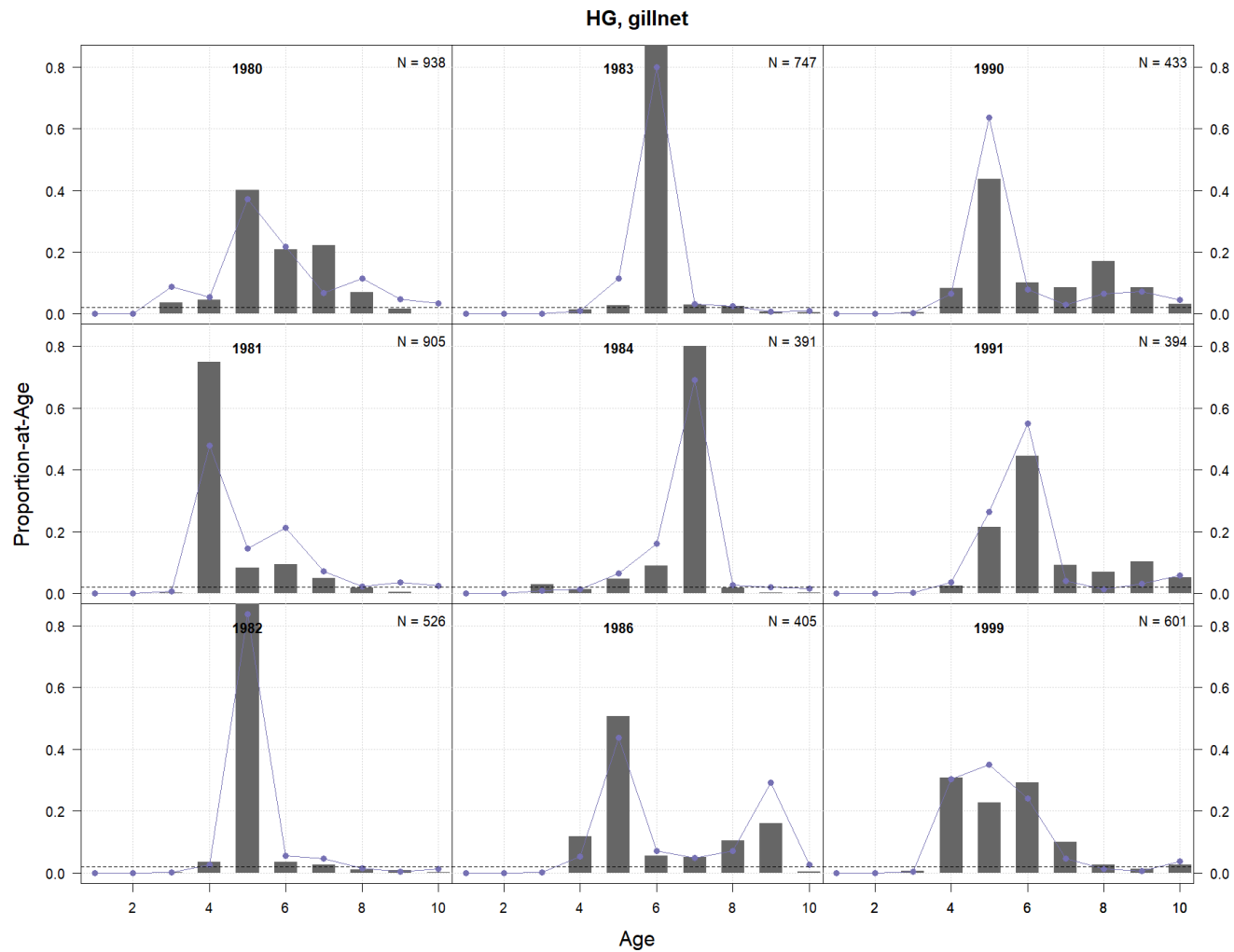


Figure D.5. SISCAN model fits to gillnet age compositions collected from the Haida Gwaii region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. *N* is the sample size.

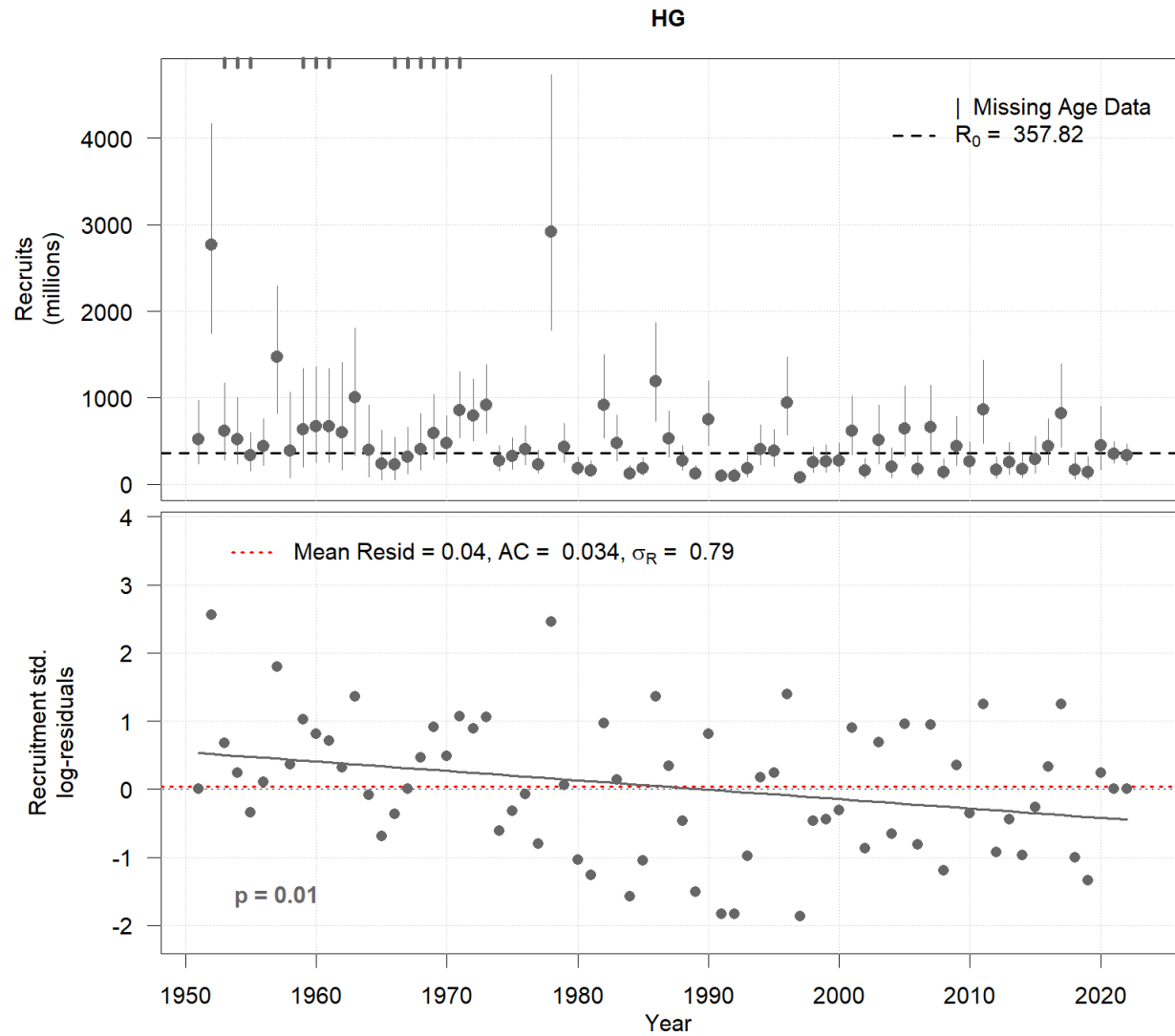


Figure D.6. Haida Gwaii age-1 recruitments (top) and standardised recruitment process errors (bottom). Equilibrium unfished recruitment R_0 is indicated by the horizontal dashed line in the top panel, and the mean process error (Mean Resid) is shown by the horizontal red dashed line in the bottom panel. AC is auto correlation and σ_R is the standard error in the log residuals.

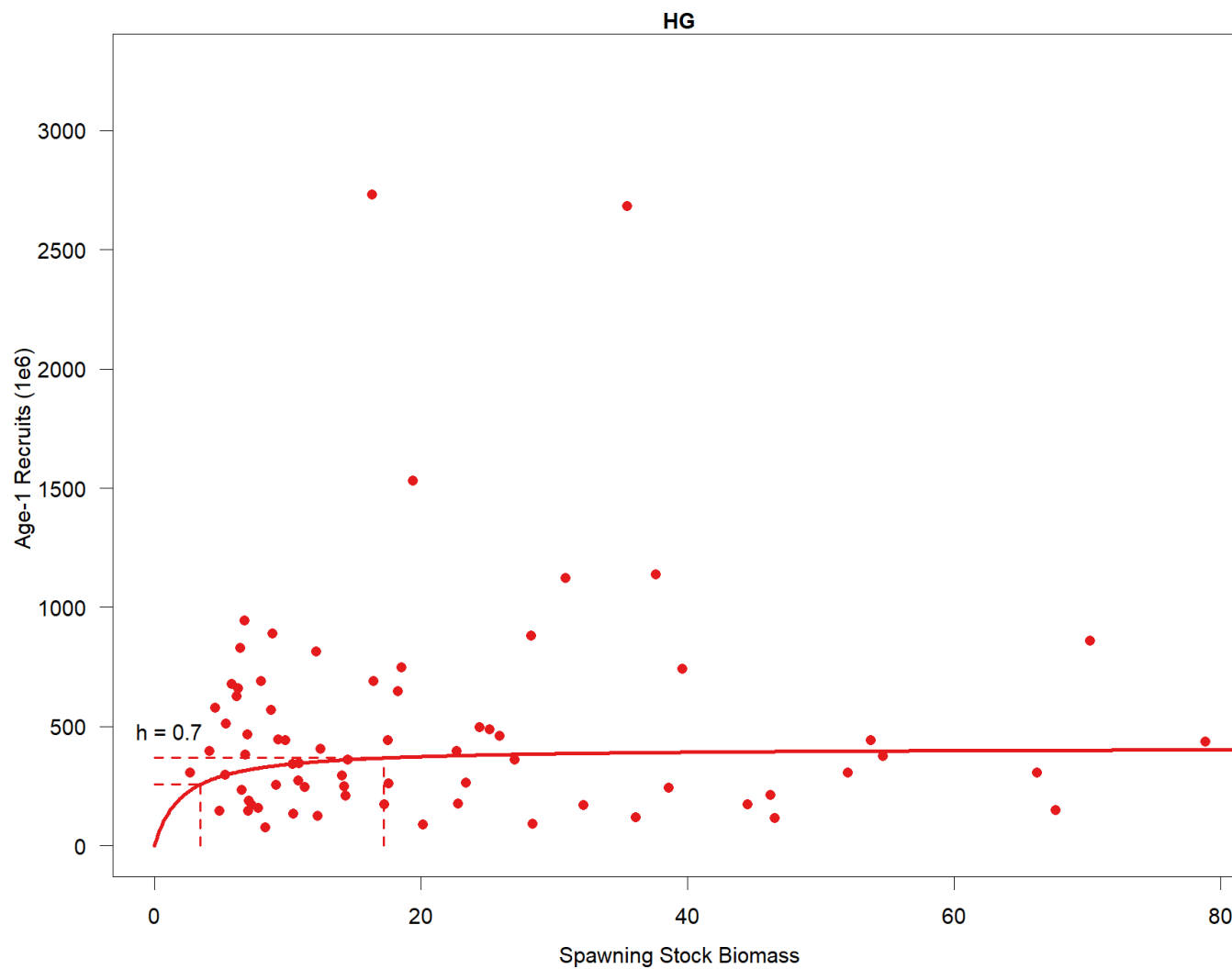


Figure D.7. Haida Gwaii stock-recruitment curves (solid lines) and age-1 estimated recruitments (points), with unfished and 20% of unfished biomass and recruitment shown as dashed lines. h is the estimated stock recruit steepness.

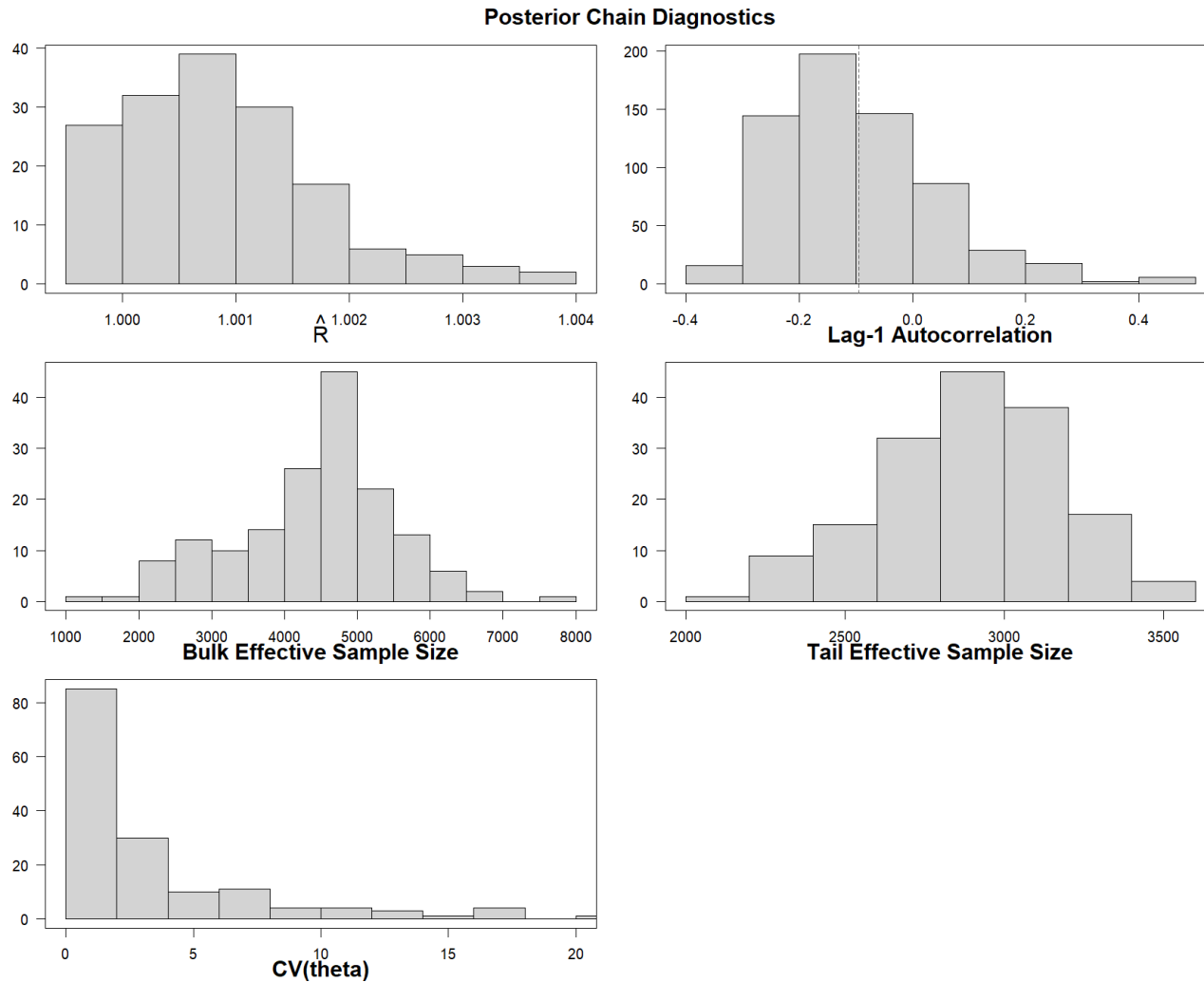


Figure D.8. Histograms of Haida Gwaii SISCAH model Bayes posterior convergence diagnostics for each leading model parameter, showing the distribution of values of each metric across all parameters. From left-to-right, starting in the top row, metrics are Gelman-Rubin scale reduction factors ($\hat{R}$), lag-1 autocorrelation factors, (bulk) effective sample size of draws in the central quantiles, (tail) effective sample size in the outer quantiles, and coefficient of variation (CV) of each parameter. Vertical red dashed lines indicate convergence thresholds, and the vertical dashed grey line indicates the median lag-1 autocorrelation.

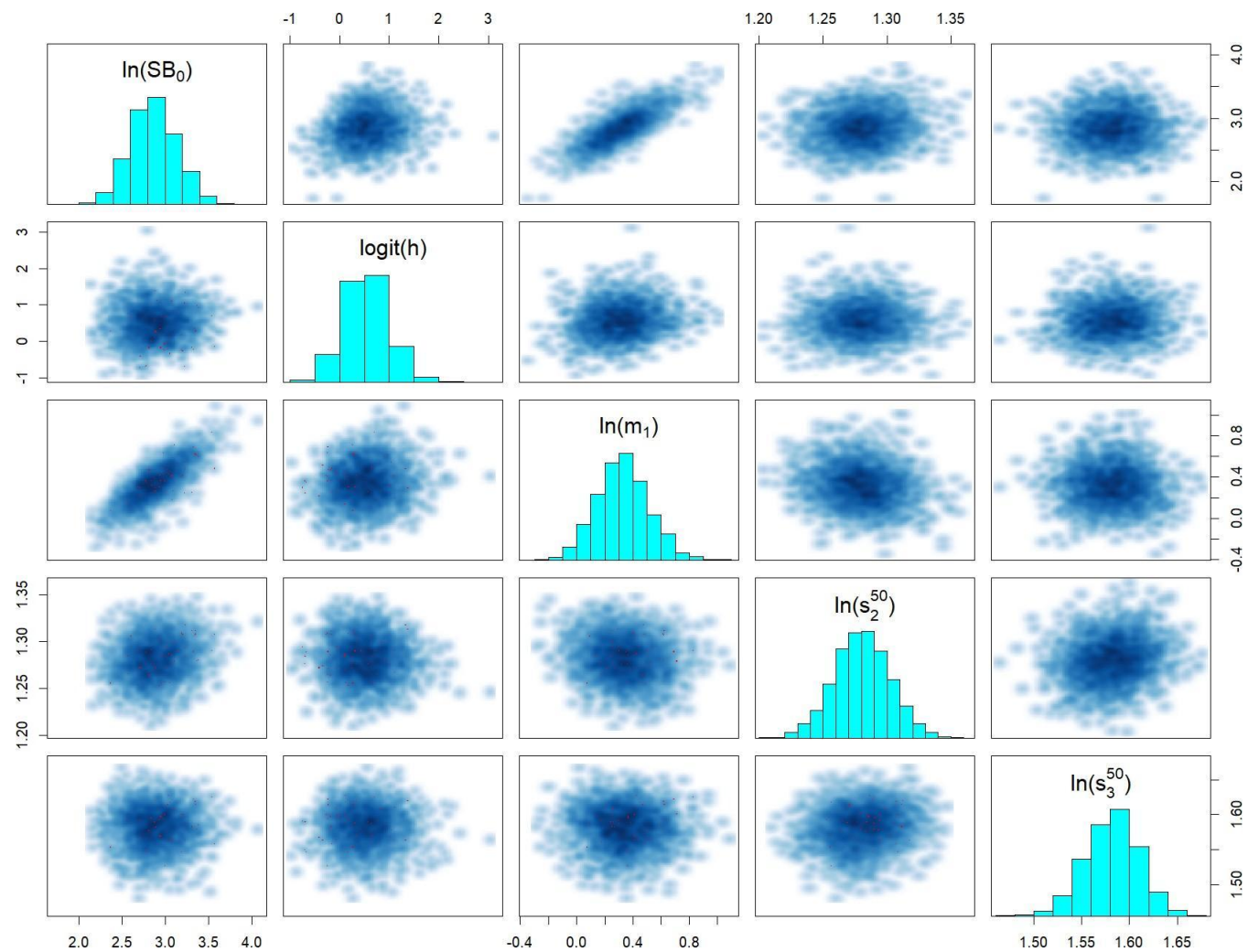


Figure D.9. Haida Gwaii SISCAH model marginal Bayes posteriors (main diagonal) and pair-wise joint-marginal Bayes posteriors (off-diagonal) for selected life-history and selectivity parameters. Red points indicate samples associated with divergent transitions.

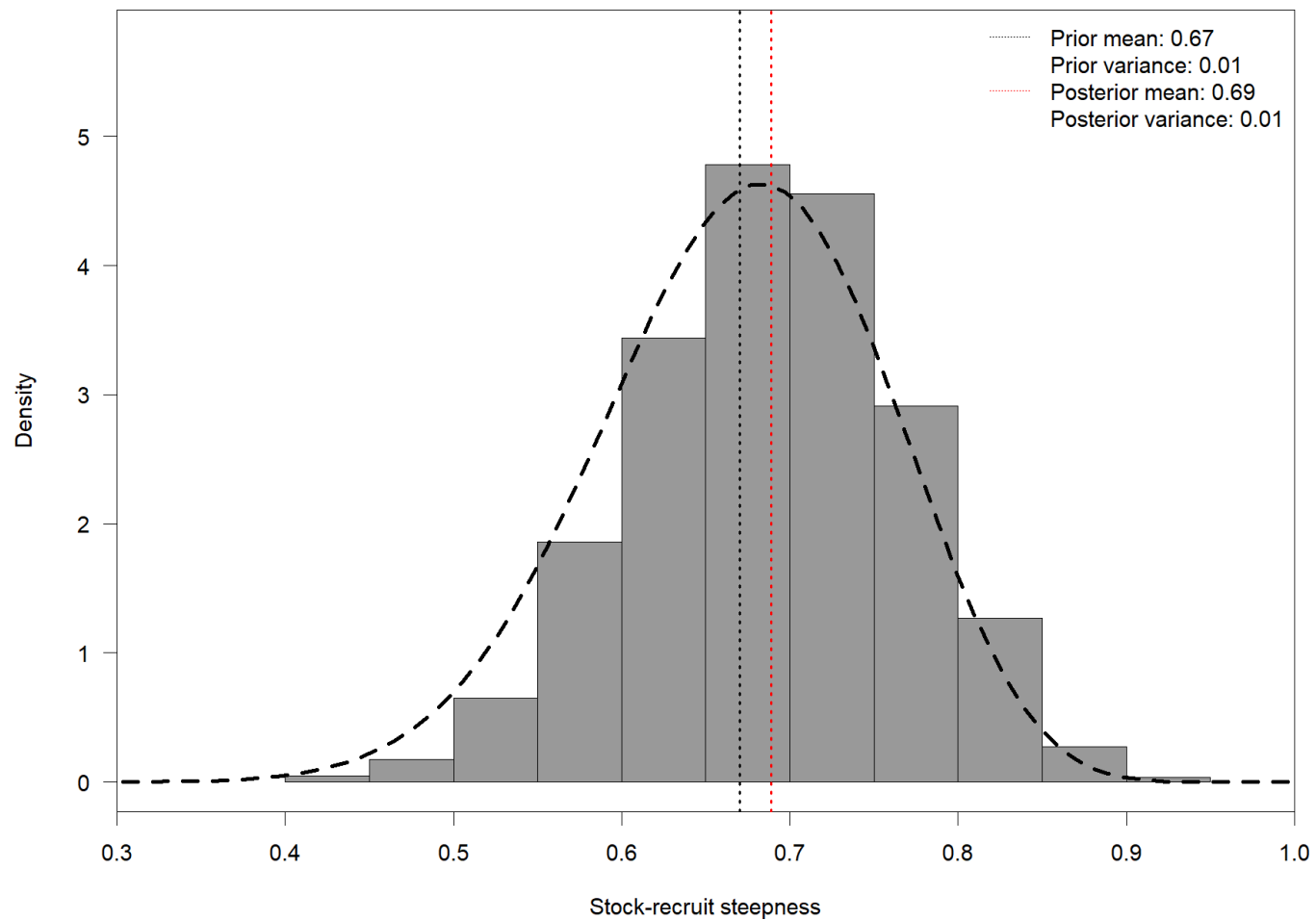


Figure D.10. Haida Gwaii SISCAL model marginal Bayes posterior (rectangles) and prior (line) distributions for stock-recruitment steepness.

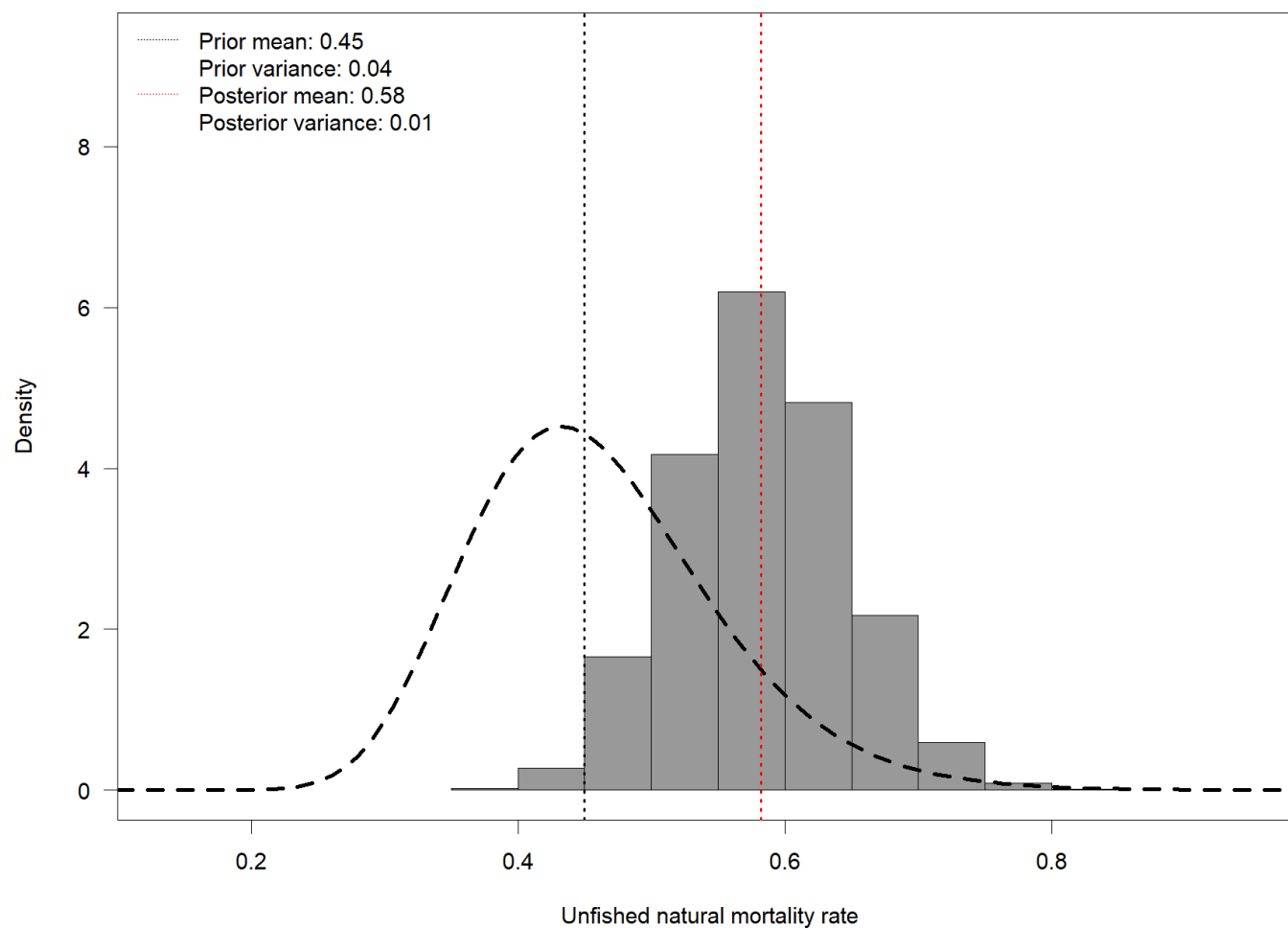


Figure D.11. Haida Gwaii SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for the unfished natural mortality rate M_0 .

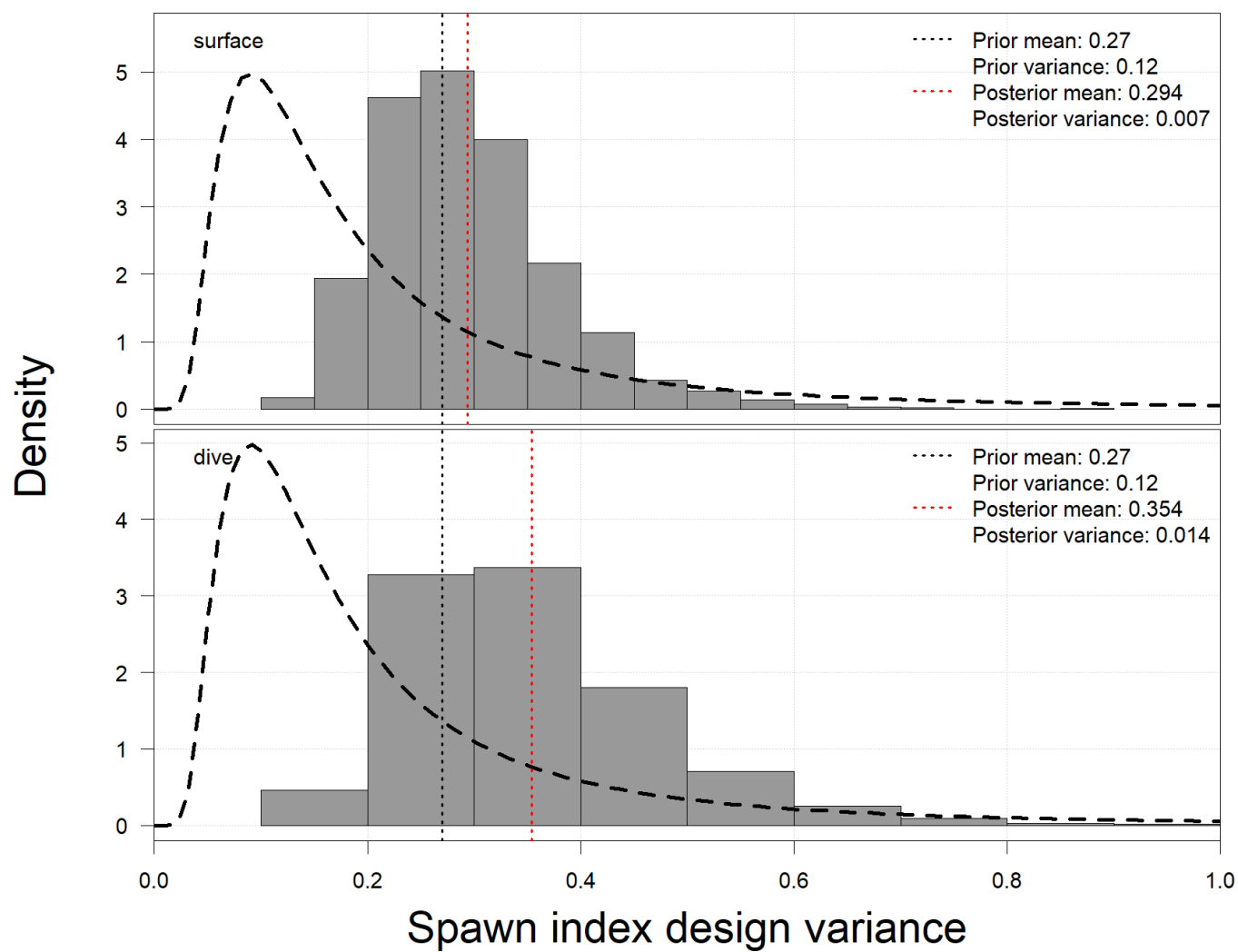


Figure D.12. Haida Gwaii SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for spawn index observation residual standard error components from the Dive survey design (top) and surface survey design (bottom).

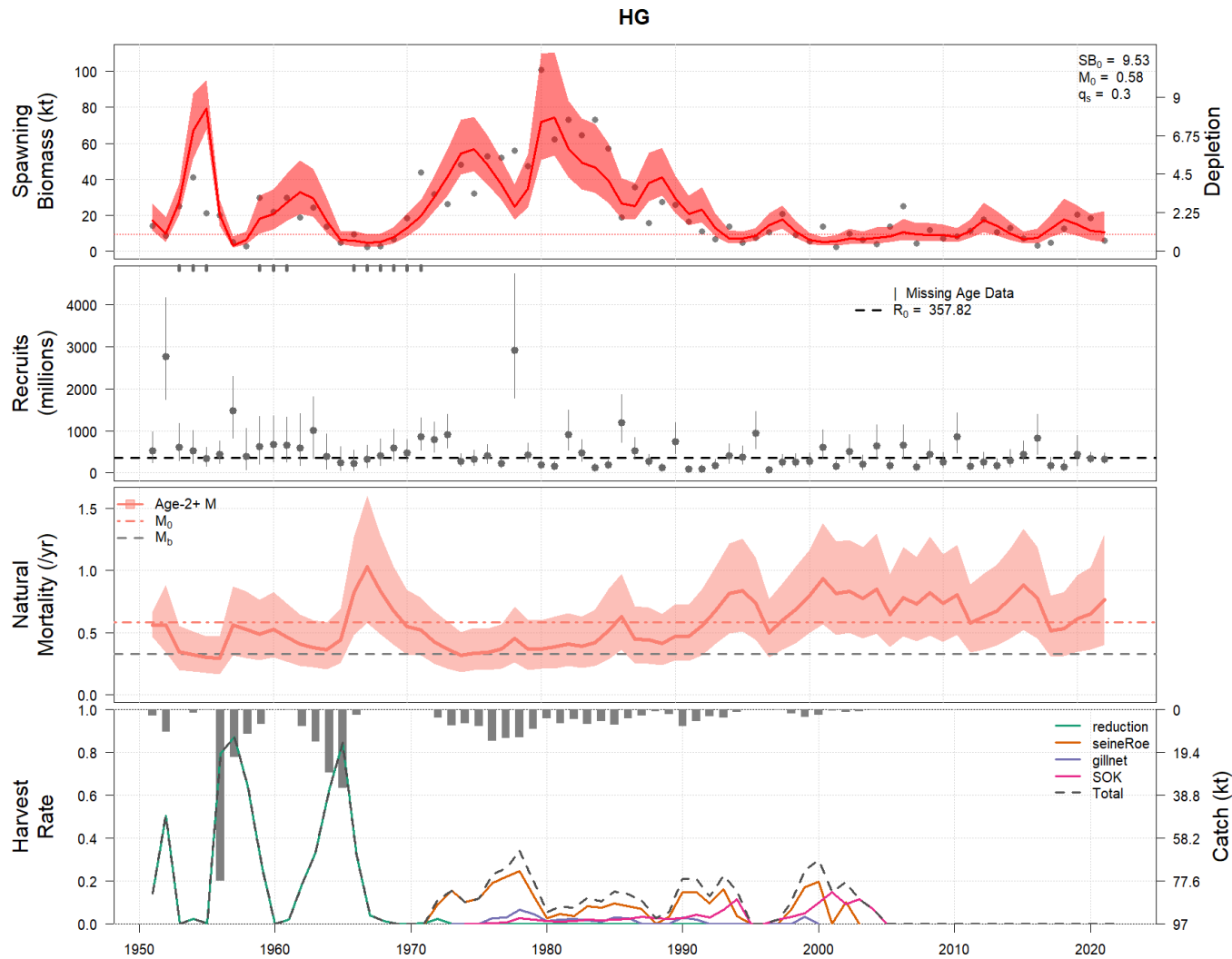


Figure D.13. Time series of Haida Gwaii herring spawning biomass with scaled spawn indices (top), recruitments (second row), natural mortality (third row), and harvest rates (bottom row). SB_0 , M_0 , and R_0 are unfished equilibrium spawning stock biomass, natural mortality, and recruitment respectively. q_s is the catchability coefficient for the surface surveys. SOK is spawn-on-kelp. In the recruitment panel, years with missing age data are indicated with a tick along the top axis, denoted by a 'I' in the figure legend.

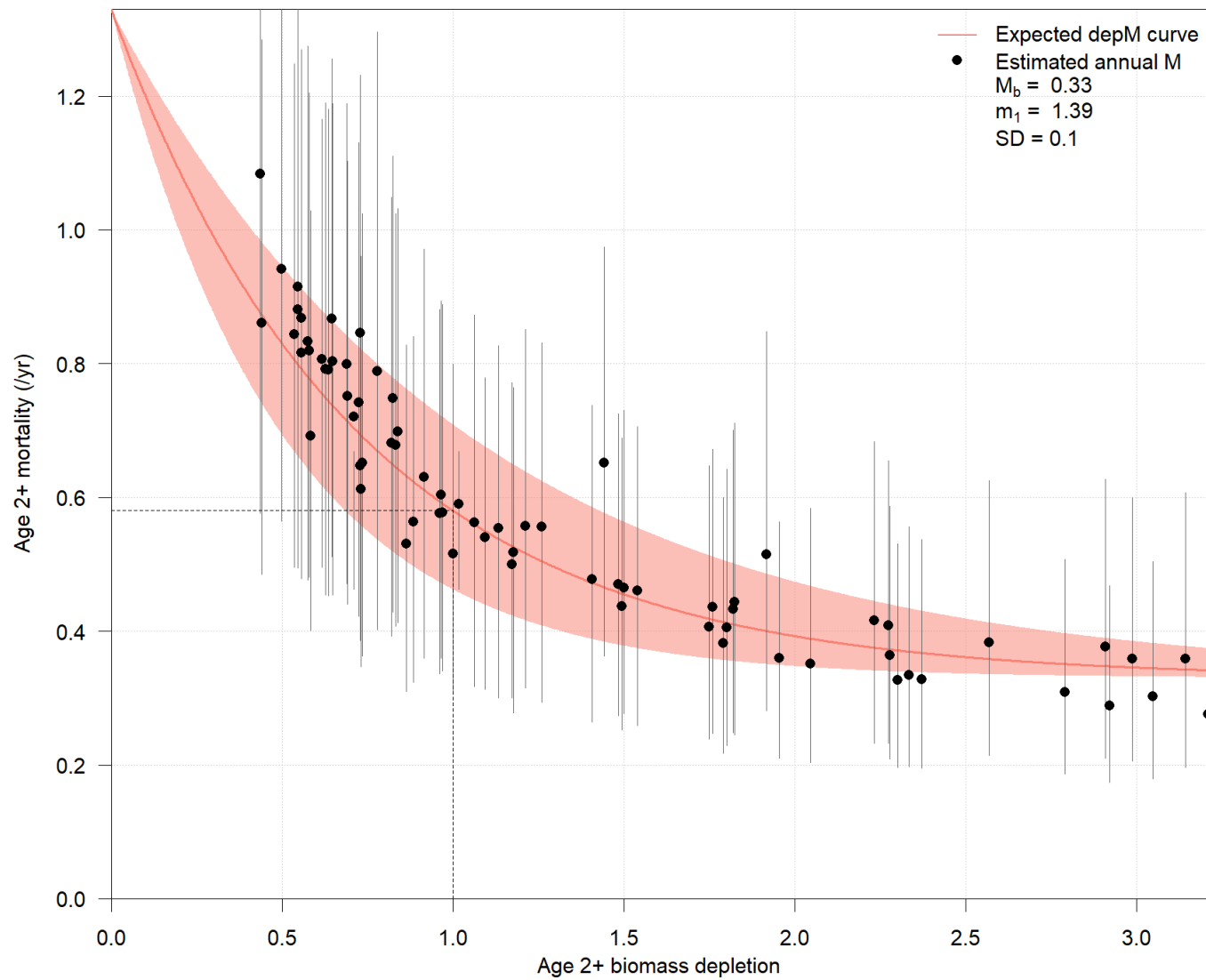


Figure D.14. Haida Gwaii SISCAH model posterior estimate of the density dependent relationship between age-2+ biomass and age-2+ natural mortality. The median relationship is shown by a thick line, with the posterior 95% credibility range shown by the shaded region. Individual points show the annual posterior median natural mortality estimates. The parameters shown are: m_1 = depensation rate; and M_b = asymptotic lower limit of density dependent mortality.

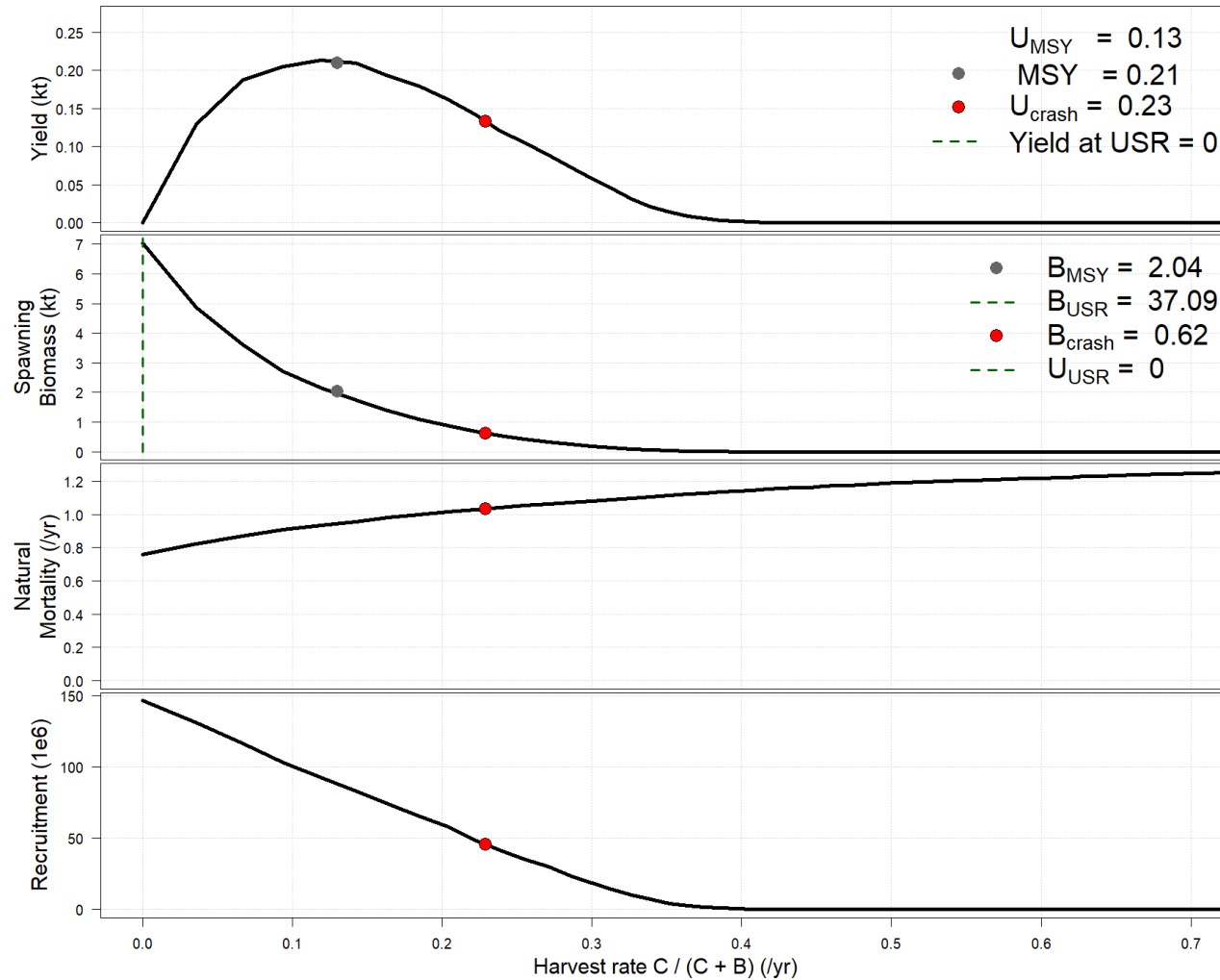


Figure D.15. Haida Gwaii reference points derived via median model equilibria of 200 year fishing mortality simulations, using the SISCAH model, with panels for yield, spawning biomass, natural mortality and recruitment. Grey points show values associated with the maximum sustainable yield (MSY). Red points show values associated with the steepest decline in yield. Green dashed lines show values associated with the upper stock reference (USR). Harvest rates are calculated as catch divided by catch plus spawning biomass.

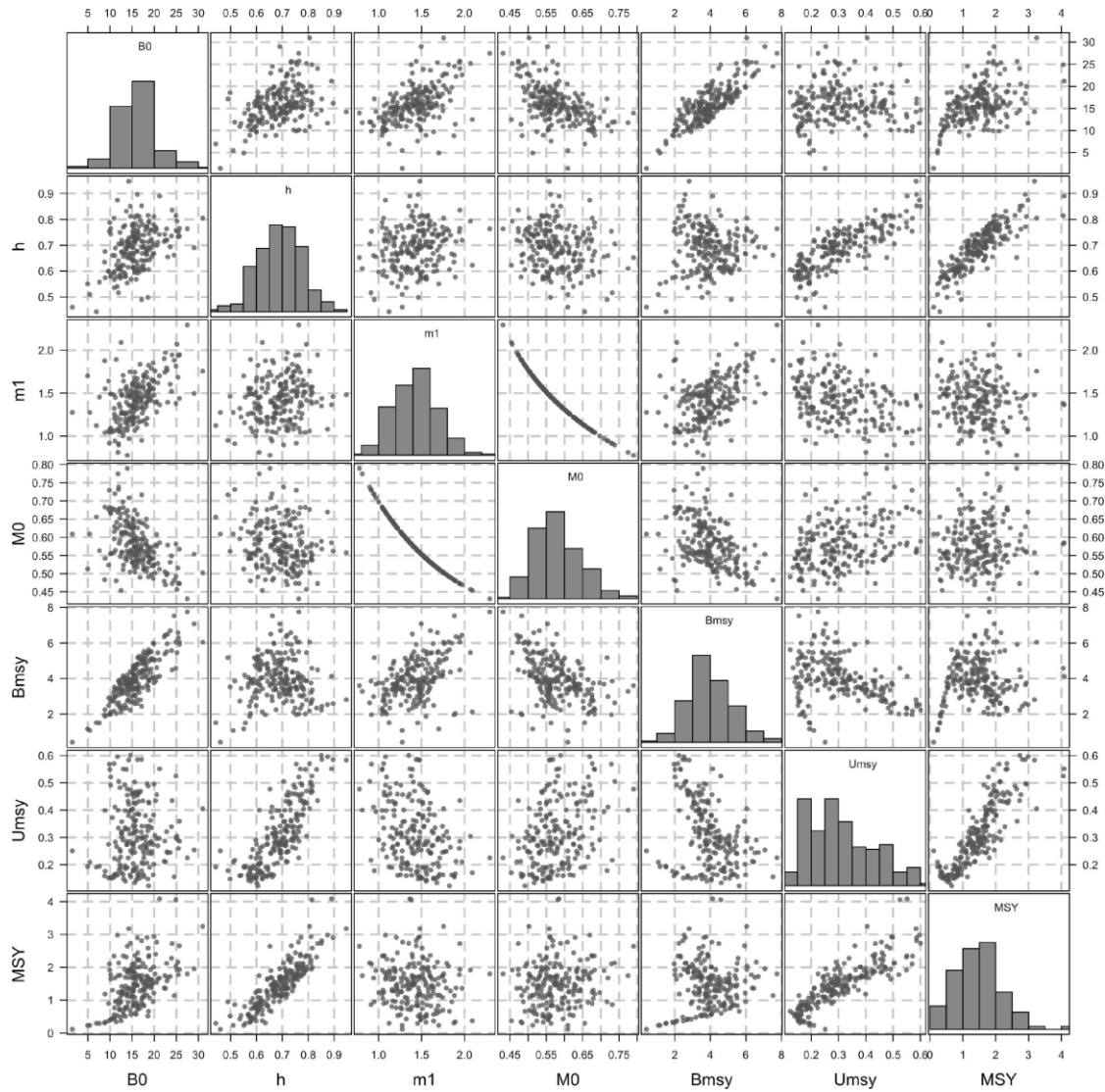


Figure D.16. Haida Gwaii: 500 random draws from joint marginal posterior distributions of selected life-history quantities and deterministic biological reference points, namely SB_0 = deterministic unfished equilibrium spawning biomass, h = stock-recruitment steepness, m_1 = depensation in density dependent mortality (if estimated), M_0 = deterministic unfished equilibrium mortality rate, B_{MSY} = deterministic optimal biomass, U_{MSY} = deterministic optimal harvest rate, MSY = deterministic maximum sustainable yield.

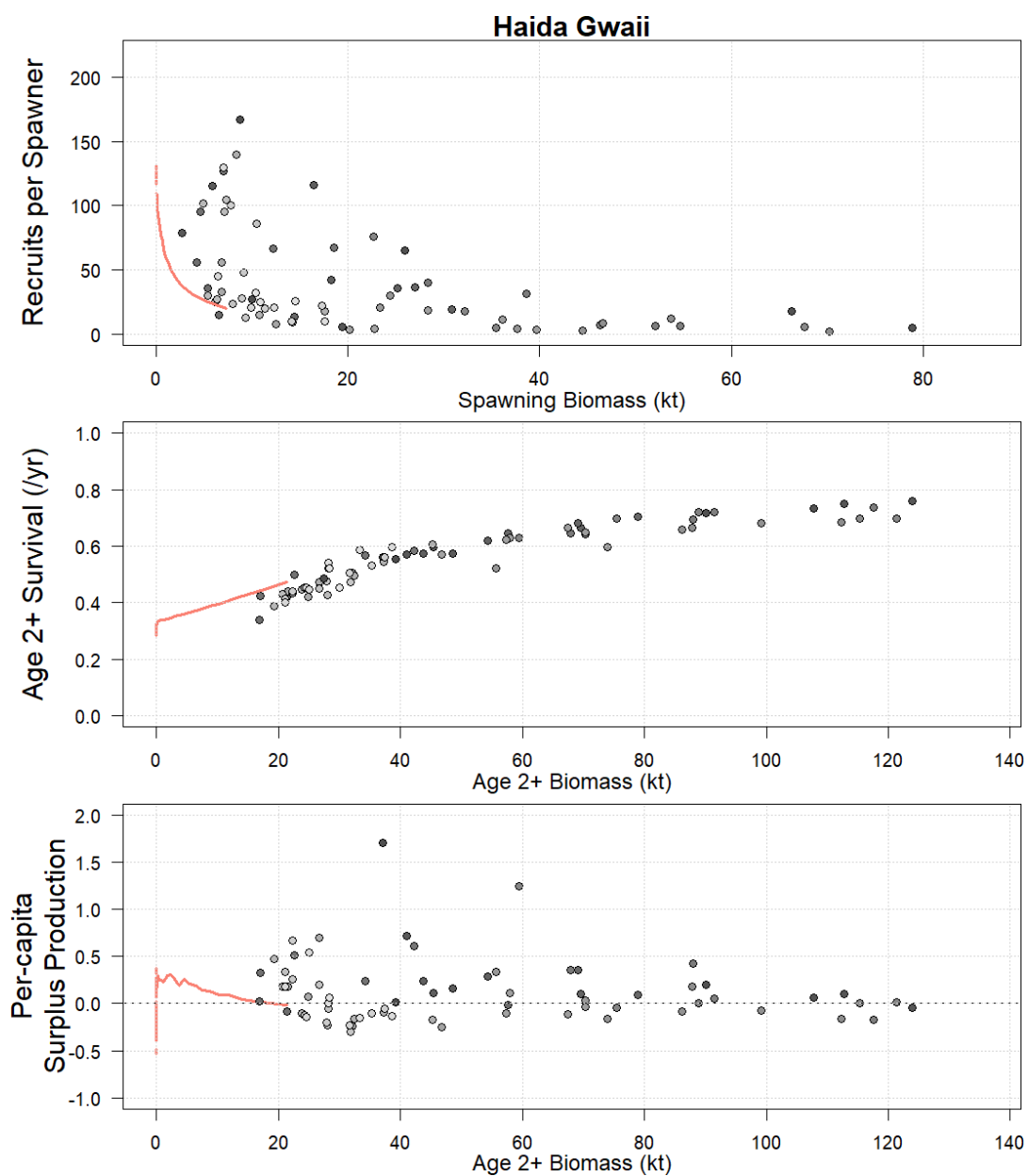


Figure D.17. Haida Gwaii SISCAH model estimates (points) and deterministic equilibria (lines) of recruits-per-spawner vs spawning biomass (top), density dependent age-2+ mortality as a function of age-2+ biomass (middle), and per-capita surplus production as a function of age-2+ biomass (bottom). Points are coloured to show phase, with light points for later years.

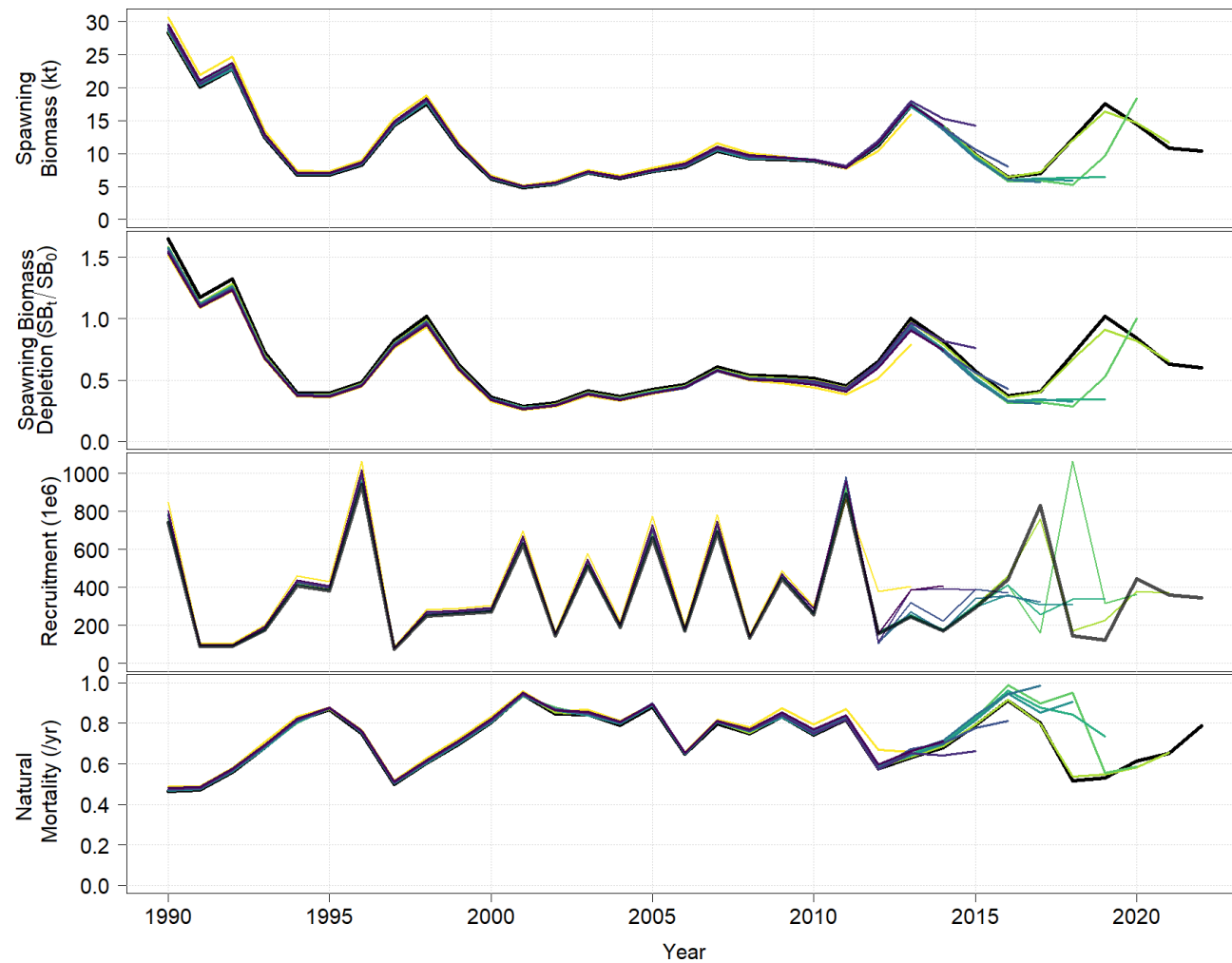


Figure D.18. Haida Gwaii SISCAN model retrospective estimates of spawning biomass (top) and spawning biomass depletion (second row), age-1 recruitment (3rd row), and natural mortality (bottom row), showing SISCAN model fits to successive data 'peels', which are truncated data sets with terminal years 2013–2022. The reference model is the largest data set in the 2022 peel, shown in black.

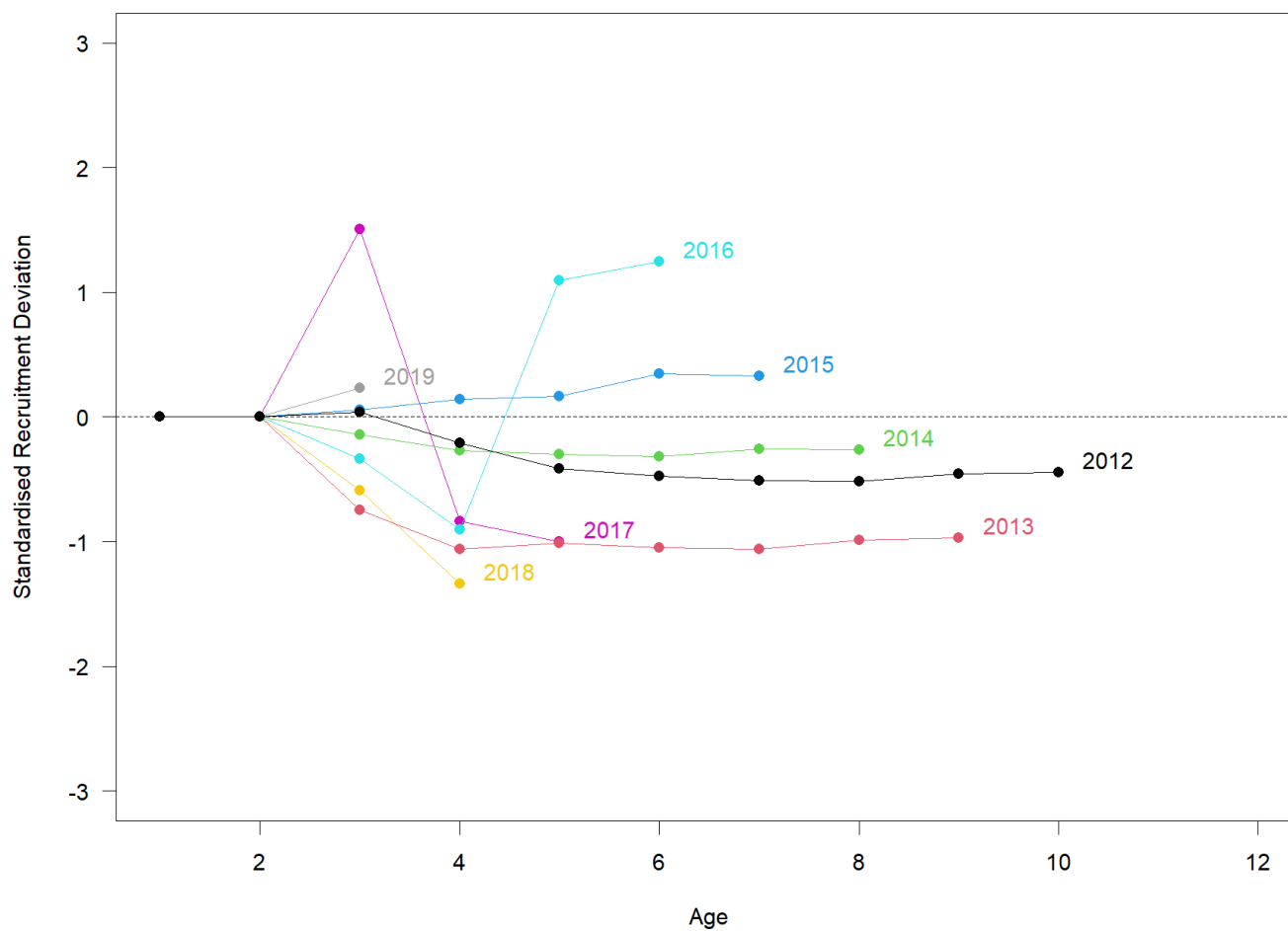


Figure D.19. Haida Gwaii SISCAN model retrospective estimates of standardised recruitment residuals, representing year class strength relative to the deterministic stock-recruitment relationship for models fit to successive data 'peels', which are truncated data sets with terminal years 2013–2022.

D.2. PRINCE RUPERT DISTRICT

Prince Rupert District (PRD) is the only herring SAR where the DDM model was unable to meet the HMC convergence criteria. As a result, this section describes the results of fitting the density independent Random Walk M (RWM) model to PRD herring data.

D.2.1. Goodness of fit

SISCAH model goodness of fit to PRD herring data was acceptable. Based on SISCAH model standard errors (Table D.5), index data and age-composition data from the seine roe and gillnet fisheries are consistent with the estimated population dynamics, but age composition data from the reduction fishery was difficult to fit. The residual standard error for individual spawn survey designs had slight differences, with surface survey residuals ($\tau_s = 0.485$) higher in standard deviation than the dive survey design ($\tau_d = 0.292$). Statistically, there is no significant indication of poor fits (Figure D.21), with practically no bias (mean residual of 0.02 standard errors) and no significant time-trends (lag-1 auto-correlation factor estimate of 0.02 and a non-significant residual trend with $p = 0.87$). However, there is roughly decadal repeating pattern of spawn index residuals, where residuals have runs of mostly negative values in the 1970s, mostly positive (and increasing) values in the 1980s, and then mostly negative values again in the 1990s. The reason for these runs is not entirely obvious, but in the 1980s and 1990s are probably related to blending of the two survey designs, and some non-standardised data collection as the two surveys overlapped. In any case we do not consider these residual runs a large issue, because the absolute residuals are within 2 standard deviations, and therefore are not outliers. Additionally, despite these runs there is still very low auto-correlation and no residual trend.

Age-composition data from two of the three fisheries was fit to very well, with the third, reduction and food and bait, being of marginal quality. The reduction and food and bait fishery age-composition data have a much higher standard error of 0.701, indicating a marginally acceptable fit. Visual inspection of the annual fits to age-composition data for the reduction fishery show that the higher residuals come from a small number of years (Figure D.22). Notably, 1953 has a large positive residual for age-2 fish, which is partially compensating for a large age-4 class in 1955.

Other notable years are the 1963, 1966, and 1979, where SISCAH over-estimates one or more year classes. For 1963 and 1966 the reason is unclear, but in 1979 the over-estimated age-2 class appears to be in anticipation of a large age-3 group in 1980. Standard errors for seine roe and gillnet and fisheries are both below 0.5, which is considered a good fit to the data. While fits are not perfect, SISCAH is able to track the cohort signals in the data from both roe fisheries with high fidelity (Figures D.23 and D.24).

The time-series of recruitments indicates that there may have been two phases to PRD recruitment (Figure D.25), roughly corresponding to the collapse induced by the reduction fishery. In years up to and including 1962, there are generally very high recruitments and large positive recruitment deviations. Then, recruitments decline steadily to 1968, and post-collapse the mean and variation in recruitments is much closer to the current-day ranges. Pre-collapse, recruitment appears to be much higher, with posterior median age-1 recruitment regularly above the unfished recruitment estimate of $R_0 = 269.9$ billion, with almost exclusively positive recruitment deviations up to 1962, then exclusively negative recruitment deviations from 1963–1967. Outside of the pre-collapse recruitment phase that appears to have different dynamics than the post-collapse years, there are no long runs of positive or negative recruitment deviations, and auto-correlation is low.

The residual trend is non-significant ($p = 0.22$), although it is negative consistent with the early large recruitments. Finally, there are no indications of poor model fits when viewing recruitments relative to the stock-recruitment curve (Figure D.26).

D.2.2. Bayes posteriors

Standard Bayes posterior convergence metrics indicate that reasonable inferences may be drawn from SISCAH for the Prince Rupert District SAR. Effective sample sizes for the bulk and tail sections of all marginal distributions are above 100 samples per chain, and all Gelman-Rubin potential scale reduction factors $\hat{R}$ are at or below the nominated threshold of 1.01 for all estimated model parameters and random effects (Figure D.27). There were no divergent transitions in the Hamiltonian Monte Carlo sampling procedure.

Visual inspection of joint marginal posteriors for leading life-history and selectivity parameters indicates that posterior geometry is of low concern (Figure D.28). All distributions are very symmetrical with low skew and low correlation. Given the density independent model structure, there is no indication of correlation between unfished biomass SB_0 and the initial natural mortality rate M_{1951} .

As with Haida Gwaii, for stock-recruit steepness there is a high level of agreement between the prior and posterior distributions, indicating that there is likely little information in the data for the steepness parameter (Figure D.29). This is unsurprising, as there are a limited number of years where spawning biomass is very low, limiting SISCAH's ability to identify the shape of the stock-recruitment curve in that region.

SISCAH marginal posteriors for the spawn survey residual standard error for both designs is similar to the Haida Gwaii area. There is an obvious influence of the data over the prior (Figure D.31), but it differs between the survey components. For the surface survey component, the posterior mean of 0.279 is similar to the prior mean of 0.27, but the posterior variance of 0.006 is much lower than the prior variance estimate of 0.12 (estimated via random sampling). For the dive survey component, the drop in posterior variance of τ_d^2 from 0.12 to 0.001 is similar in magnitude to the surface survey, however there is a larger drop in posterior mean τ_d^2 to 0.105 in contrast to the prior mean of 0.27.

D.2.3. Historical dynamics

As outlined above, there appear to be two phases to PRD herring dynamics (Figure D.32). The first phase begins in 1951 and extends up to the collapse of the reduction fishery in the mid-to-late 1960s. During that period, the PRD stock consistently produced very large recruitment events, ranging between 1 billion and 3 billion age-1 recruits. These high recruitments, combined with a constant and low natural mortality at the lower limit M_b , sustained a biomass that was above unfished levels on average and provided very high catches to the reduction fishery. The last large recruitment event of the first phase is in 1962, after which there was a prolonged period of lower recruitment events until 1967. Those lower recruitments were unable to sustain the high reduction fishery catches, which ultimately led to a collapse in the spawning biomass, ending the first phase.

The second phase begins with the recovery from the reduction-fishery induced collapse and is characterised by lower average recruitments, largely varying around the R_0 level with occasional spikes close to the 1 billion range.

Natural mortality, estimated via a random walk, for the PRD SAR generally shows fairly smooth behaviour throughout the historical time series. Additionally, the range of mortality rate values is quite a bit lower than the other SARs, with a maximum posterior median value around 0.4.

Mortality begins around 0.2 in 1951 and remains there for most of the pre-collapse phase, ramping up at the same time as harvest rates increase from around 20% at the end of the 1950s to around 60% in the mid-late 1960s. Post-collapse, natural mortality begins to slowly decline towards the unfished level M_0 (which for RWM models is the time-averaged estimate of age-2+ mortality), stopping at around 0.3 in the mid 1990s before climbing again to the record highs around 0.4 in the mid-2000s. That higher mortality rate is maintained until around 2017, after which mortality begins to decline again to the recent level of approximately 0.35.

The spawning biomass trajectory over the 1970–2022 period indicates very stable dynamics. Aside from a short spike in harvest rates in the late 1970s, fishing pressure has remained around 20% for PRD herring from the early 1980s to around 2017. That stable fishing pressure, combined with the relatively stable and low natural mortality, as well as reasonably good recruitments, have created generally favourable conditions in the PRD area. Spawning biomass peaked at around unfished levels in the mid-1980s, and since then has varied between unfished and 50% of unfished.

The stable M trajectory has almost no indication of density dependent behaviour. The lack of density dependence in the M and SB relationship is consistent with the difficulty in fitting a density dependent M model for PRD herring. Indeed, the general relationship with biomass is flat (not shown), so while there is a slight increase in mortality at lower biomass depletion levels, there is not a strong depensatory signal.

D.2.4. Biological reference points

SISCAH estimates a maximum sustainable yield (MSY) of approximately 4.06 kt, which is achieved when spawning biomass at around 13.6 kt. The associated optimal harvest rate is calculated as $U_{MSY} = MSY / (SB_{MSY} + MSY) = 0.229$ (Figure D.33). As with Haida Gwaii, the reference points account for around 20% of TAC being allocated to the SOK fishery, so harvest rates are much higher than total mortality from fishing. For PRD herring, U_{crash} is estimated as the harvest rate where spawning-stock-biomass-per-recruit is equal to the reciprocal of the slope of the stock-recruit curve at the origin, or joint marginal posterior distributions for life history quantities (i.e., SB_0 , h , M_0) and MSY-based reference points show nothing out of the ordinary (Figure D.34).

Biomass quantities like SB_0 , B_{MSY} , and MSY have a high degree of positive correlation, as well as productivity parameters h and U_{MSY} . There is also a stronger negative correlation between h and B_{MSY} , reflecting that as optimal harvest rate (i.e., productivity) increases, the optimal biomass of the stock decreases.

D.2.5. Retrospective analyses

Retrospective analysis of SISCAH model estimates for PRD herring suggest that SISCAH has low sensitivity to additional years of data. Time series of spawning biomass, recruitment, and mortality are very stable over the 10 years of the retrospective peels (Figure D.35), with the large and small year classes all assigned to the same cohorts by all peels, albeit with year class strength revised over successive peels (e.g., 2017). Over successive peels, there is a drop in unfished biomass SB_0 by about 10% and a corresponding small rise in mortality M_0 by about 5%. Recruitment parameters are fairly stable, with unfished recruitment R_0 and initial recruitment R_{init} changing by less than 2%.

Year class strength is also fairly stable in response to additional years of data. Most year classes appear largely resolved by age-4, and any variation after that time is fairly minor. There are two year classes that appear to take longer to resolve than 4 years, namely 2015 and 2016,

which are both revised upwards over time. The 2016 year class is the last major recruitment in the time series, and that appears to have been revised upwards as additional ageing data has become available, which is not uncommon, however the scale and trend are quite noticeable. Future model updates should revisit this year class to ensure it fully resolves in the next couple of years. Revision of the 2015 year class is smaller by comparison to 2016, and appears to just draw the 2016 age-1 recruitment off the deterministic stock-recruit curve, and is revised upwards to match the age-3 modal age class in 2018 that was not visible in 2017 data.

D.2.6. Sensitivity analyses

SISCAH estimates of PRD herring biomass and life history parameters were relatively insensitive to specific choices of priors (Table D.7). The most influential priors on unfished biomass were the Jeffreys prior that placed a penalty on the magnitude of SB_0 , R_0 , and R_{init} . All three of those parameters increased when the Jeffreys prior weighting was reduced, as expected; the most notable increase was in the initial recruitment parameter, which increased to 275 million age-1 fish (jeffLo) from 105 million (base). Adjusting the steepness prior mean lower (steepMeanLo) led to a lower steepness value of 0.539, coupled with a similar increase in unfished spawning biomass as under the jeffWtLo sensitivity.

As with Haida Gwaii, adjustments to the M prior had a noticeable effect. While the prior is applied to initial mortality, rather than unfished mortality, a shift in prior mean or standard deviation had a similar effect on the M_0 value, and through that, other model life history parameters. For example, a higher prior mean M_{1951} value (meanMHi), or lower prior standard deviation (sdMLow) increases the M_0 value, leading to a decrease in SB_0 and a corresponding increase in R_0 and R_{init} values.

Out of the seven SISCAH initial condition configurations tested for the Prince Rupert District SAR, four successfully converged. Similar to the Haida Gwaii case, the primary impact of adjusting the fished initialization settings was observed in the first-year age-1 recruitment, in terms of either R_0 or R_{init} , and the unfished biomass SB_0 (see Table D.4). There were relatively smaller effects on M_0 , considering its correlation with SB_0 , and the stock-recruitment steepness h .

As expected, as discussed in the main body, the inclusion of F_{init} in the initial survivorship calculations could significantly inflate the initial recruitment parameter. Specifically, when F_{init} was included in the initial conditions, R_{init} nearly doubled, and R_0 increased by approximately 26%. The effects on unfished biomass were less pronounced, with SB_0 hovering around 40 kt for three out of four configurations and increasing by about 15% to reach approximately 46 kt in the remaining model.

Despite these variations, there remained a considerable degree of stability in biomass and recruitment estimates for each year after the conclusion of the 1950s (not displayed). Prior to 1960, changes in biomass resulted from variations in initial conditions, which partially contributed to changes in surface survey catchability q_s . After 1960, other model parameters, including recruitment and mortality process errors, proved capable of compensating for variations stemming from the model's initial conditions.

D.2.7. Tables

Table D.5. Estimated residual standard errors and lag-1 age residual correlations for Prince Rupert District herring data. The first six columns show age data sampling standard errors τ_g^{age} and correlation coefficients ρ_g from the LN1 age composition likelihood function the Reduction and Food & Bait ($g = 1$), Seine-rope ($g = 2$), and gillnet fisheries ($g = 3$), and the last two columns show spawn survey index standard deviations for the surface (τ_s) and dive (τ_d) surveys.

SAR	τ_1^{age}	ρ_1	τ_2^{age}	ρ_2	τ_3^{age}	ρ_3	τ_s	τ_d
PRD	0.695	0.752	0.436	0.213	0.394	0.254	0.475	0.292

Table D.6. Prince Rupert District retrospective estimates of selected SISCAN model leading and derived life-history quantities over data peels from 2012–2022. Selected quantities are SB_0 = estimated unfished equilibrium spawning biomass(kt), R_0 = estimated unfished equilibrium recruitment (1e6), R_{init} = estimated initial recruitment (1e6), m_1 = depensation rate (unitless), M_b = asymptotic lower bound on age-2+ natural mortality (yr), M_0 = equilibrium unfished age-2+ natural mortality (yr), q_s = surface survey catchability (unitless).

Peel	B_0	R_0	R_{init}	M_0	h	q_s
2013	49.144	260.366	103.793	0.312	0.694	0.583
2014	48.450	253.642	102.255	0.310	0.692	0.589
2015	47.674	254.882	103.339	0.313	0.692	0.588
2016	46.657	257.549	104.516	0.317	0.692	0.585
2017	46.082	255.029	103.938	0.317	0.690	0.587
2018	45.060	257.155	105.924	0.322	0.689	0.585
2019	45.009	262.433	107.595	0.325	0.690	0.580
2020	44.970	258.238	105.500	0.322	0.687	0.600
2021	44.762	258.470	105.812	0.322	0.684	0.596
2022	44.685	258.806	105.919	0.322	0.685	0.594

Table D.7. Prince Rupert District SISCAH model estimates of life-history and observation model quantities under sensitivity analyses.

Sensitivity	SB_0	R_0	R_{init}	M_0	h	q_s
base	44.685	258.806	105.920	0.322	0.685	0.594
jeffHi	48.570	328.148	221.155	0.348	0.651	0.545
jeffLo	49.982	354.546	275.209	0.356	0.638	0.530
meanMHi	42.377	276.774	138.548	0.342	0.674	0.560
meanMLow	44.158	262.781	111.761	0.327	0.682	0.586
qSurfSDHi	44.650	259.309	106.212	0.323	0.684	0.591
qSurfSDLo	44.824	256.910	104.813	0.321	0.685	0.605
sdMHi	44.685	258.806	105.920	0.322	0.685	0.594
sdMLow	41.943	280.264	147.295	0.346	0.671	0.554
sigmaMhi	43.932	251.264	104.201	0.320	0.697	0.633
sigmaMlo	44.685	258.806	105.920	0.322	0.685	0.594
steepMeanHi	41.255	238.999	105.368	0.322	0.886	0.593
steepMeanLo	48.453	286.832	108.912	0.326	0.539	0.585
steepSDHi	44.452	257.289	105.813	0.322	0.696	0.594
steepSDLo	44.828	259.747	105.989	0.322	0.678	0.594

Table D.8. Prince Rupert District SISCAH model estimates of life-history and observation model quantities under the initial conditions sensitivity analyses.

Initial Conditions			SB_0	R_0	R_{init}	F_{init}	m_1	M_b	M_0	h	q_s
initR	initF	initDevs									
R_0	TRUE	FALSE	46.146	388.657	–	0.390	3	0.413	0.387	0.586	0.462
R_0	FALSE	TRUE	40.980	309.203	–	0.000	3	0.307	0.367	0.656	0.518
R_{init}	FALSE	FALSE	40.599	295.024	670.292	0.000	3	0.294	0.361	0.658	0.529
R_{init}	TRUE	FALSE	39.474	287.198	1,198.744	0.367	3	0.377	0.361	0.643	0.509

D.2.8. Figures

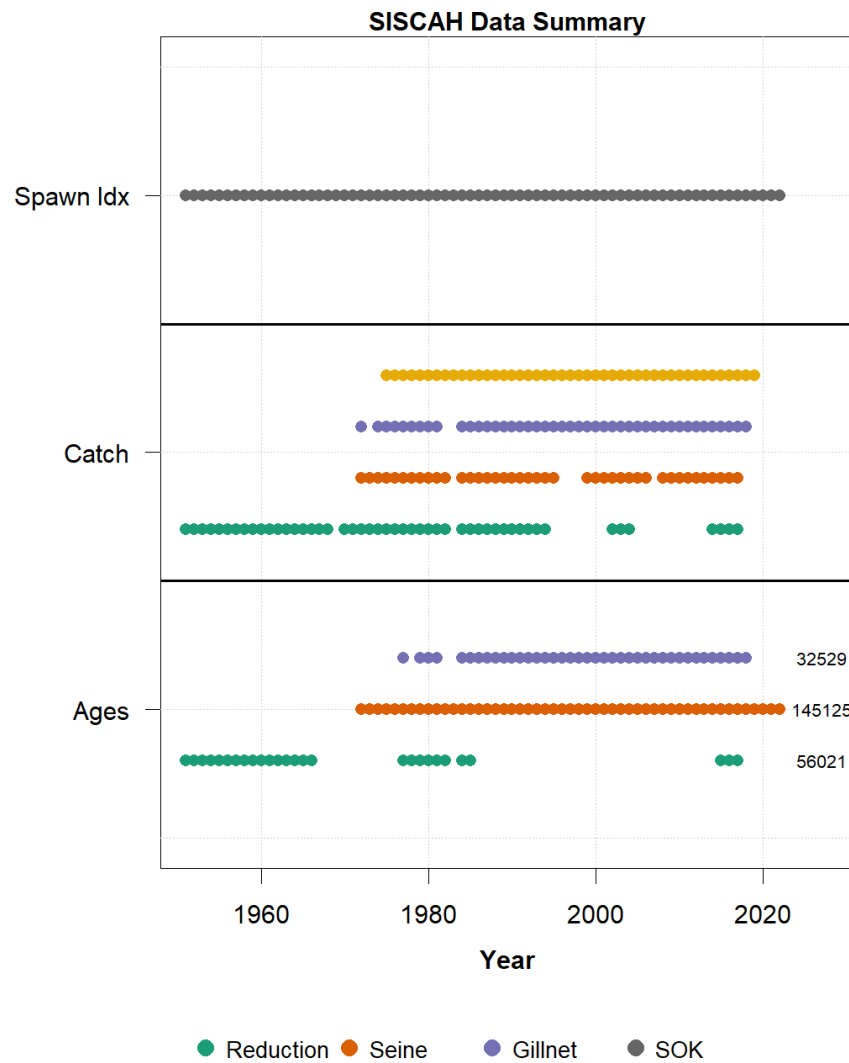


Figure D.20. Time series of Prince Rupert District herring stock assessment data. Each dot shows the existence of data, and age data shows total number of samples over all years at the right hand end.

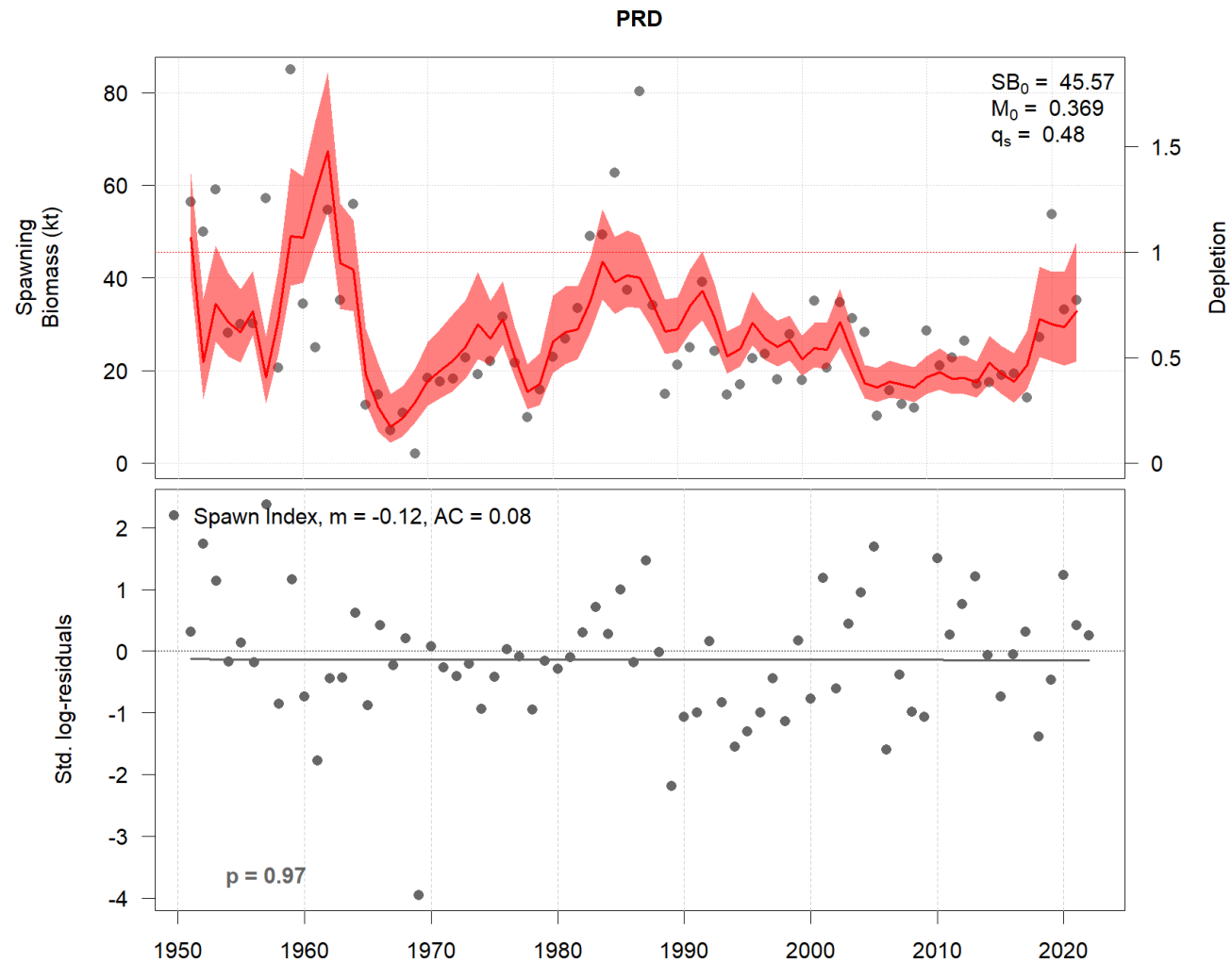


Figure D.21. Prince Rupert District blended spawn index and SISCAN spawning biomass estimates (top) and standardised observation residuals (bottom). SB_0 and M_0 are the unfished equilibrium spawning stock biomass and the natural mortality respectively, q_s is the catchability coefficient for the surface surveys, m is the mean log residual of the spawning index, and AC is the autocorrelation.

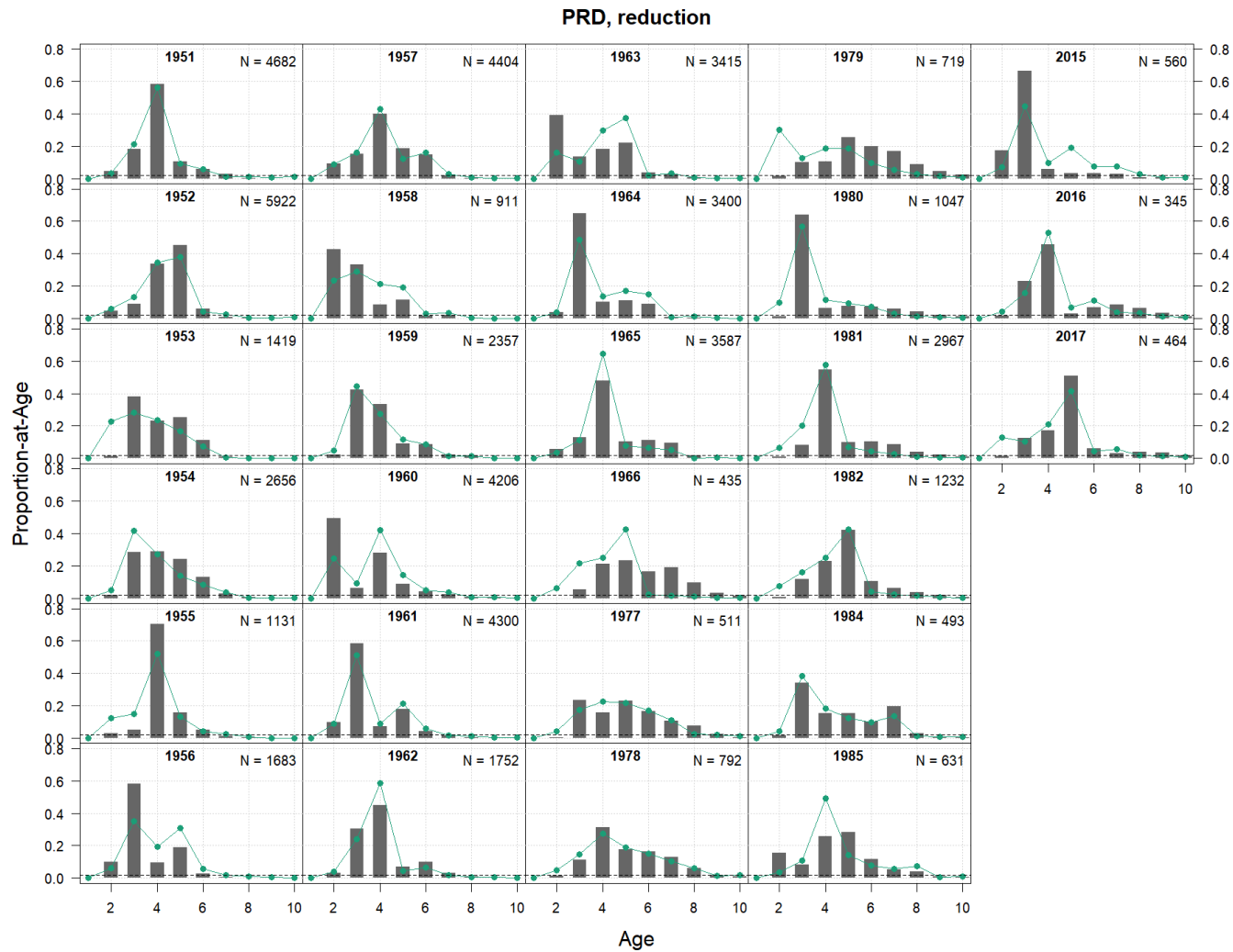


Figure D.22. SISCAH model fits to reduction age compositions collected from the Prince Rupert District region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

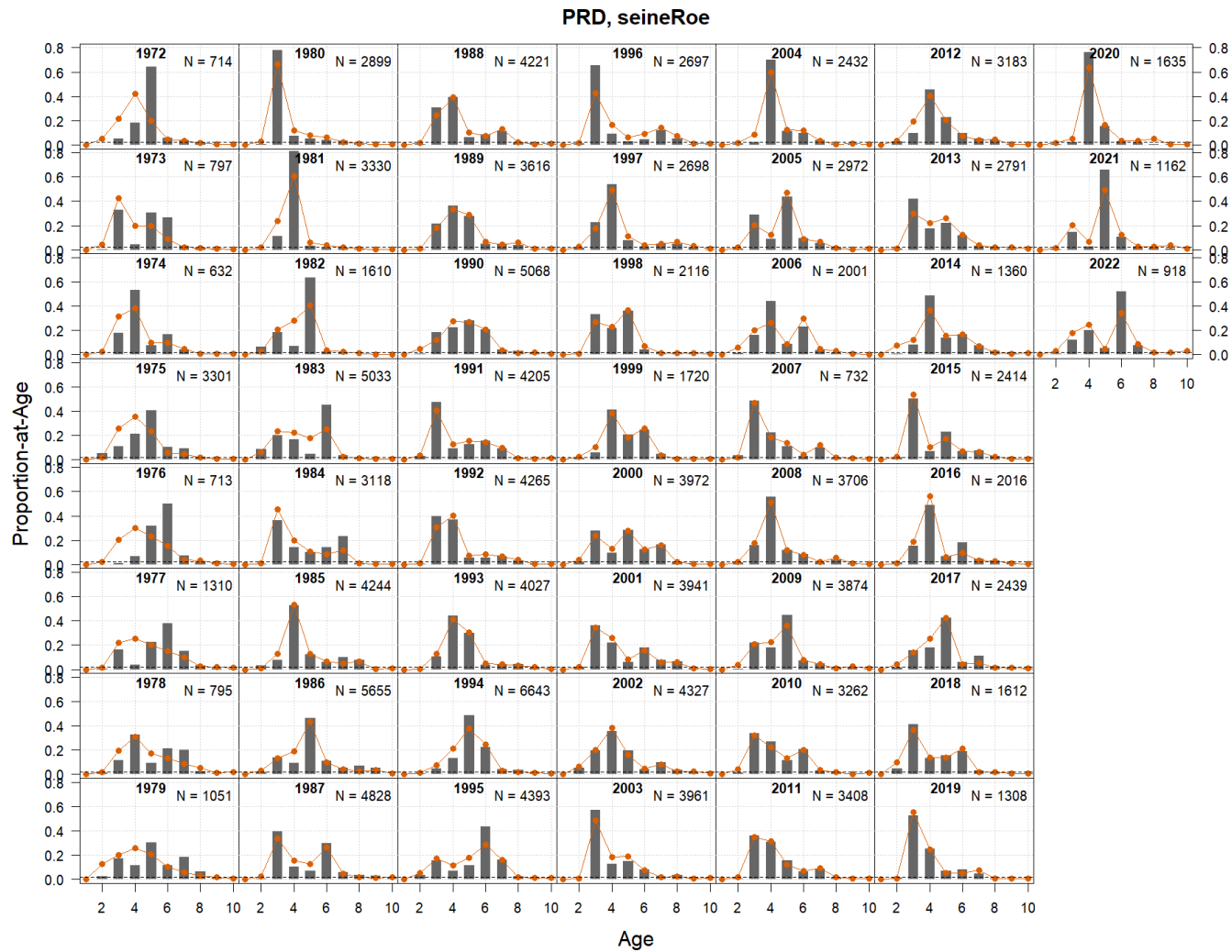


Figure D.23. SISCAH model fits to seine roe age compositions collected from the Prince Rupert District region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

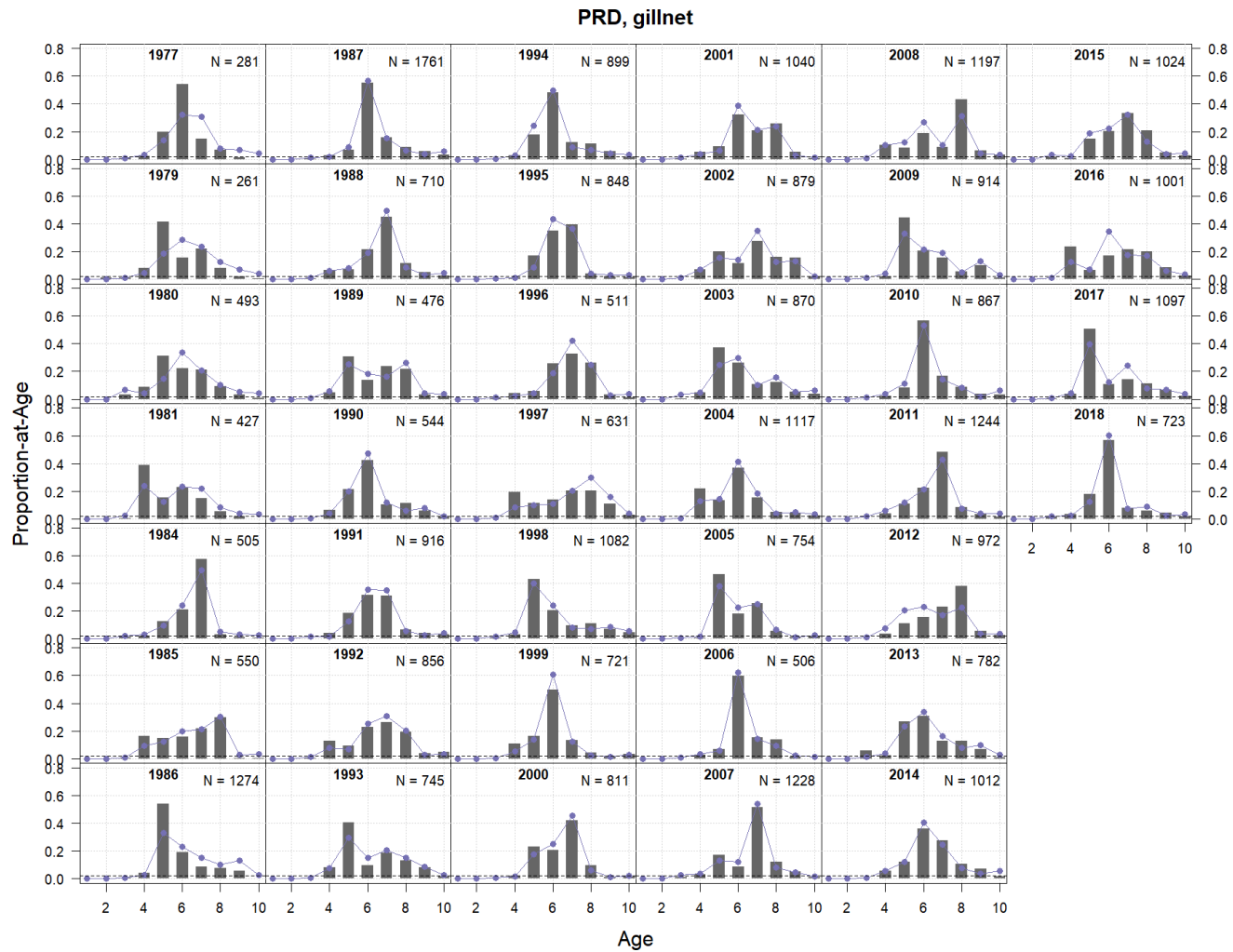


Figure D.24. SISCAH model fits to gillnet age compositions collected from the Prince Rupert District region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

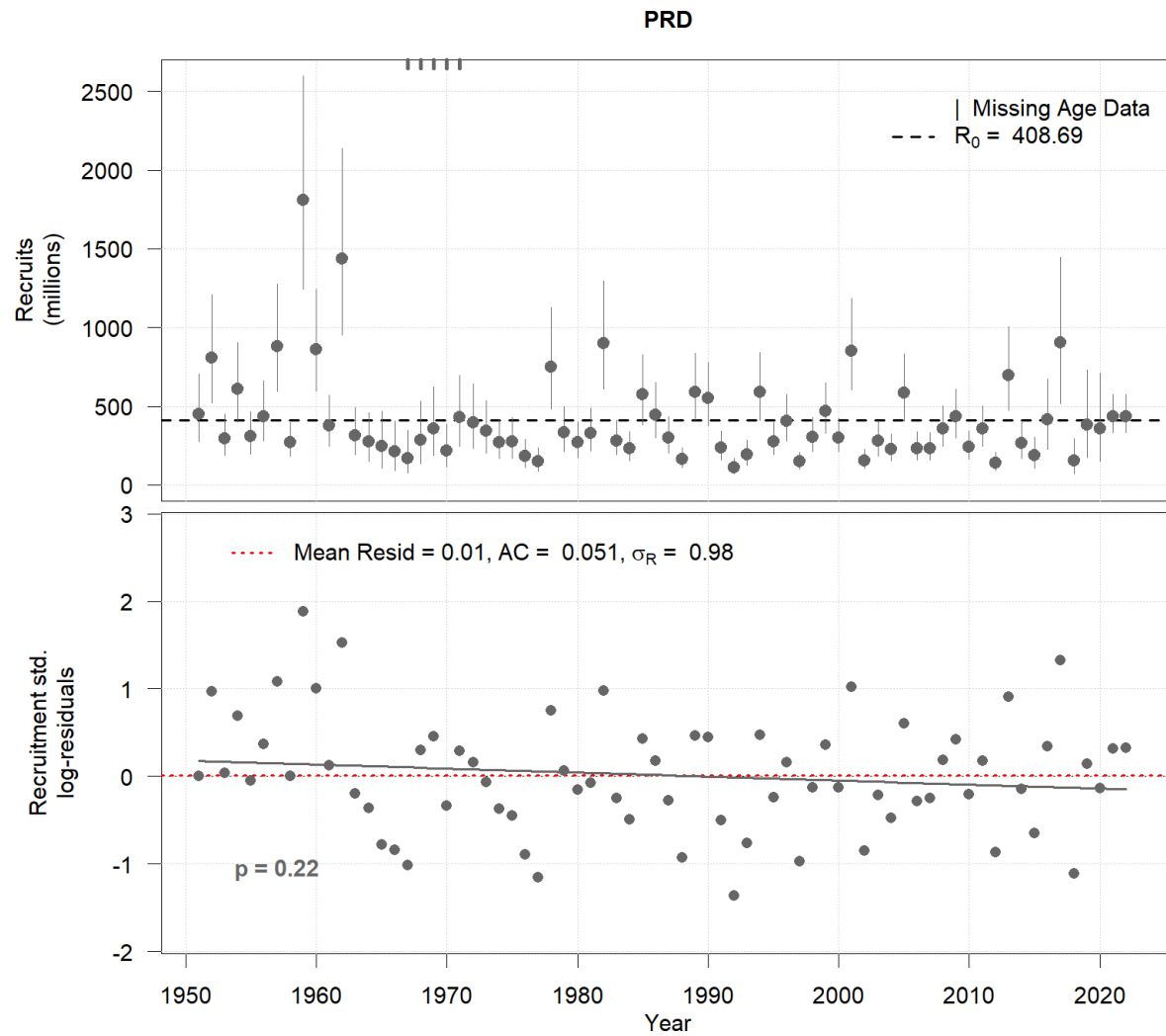


Figure D.25. Prince Rupert District age-1 recruitments (top) and standardised recruitment process errors (bottom). Equilibrium unfished recruitment R_0 is indicated by the horizontal dashed line in the top panel, and the mean process error (Mean Resid) is shown by the horizontal red dashed line in the bottom panel. AC is auto correlation and σ_R is the standard error in the log residuals.

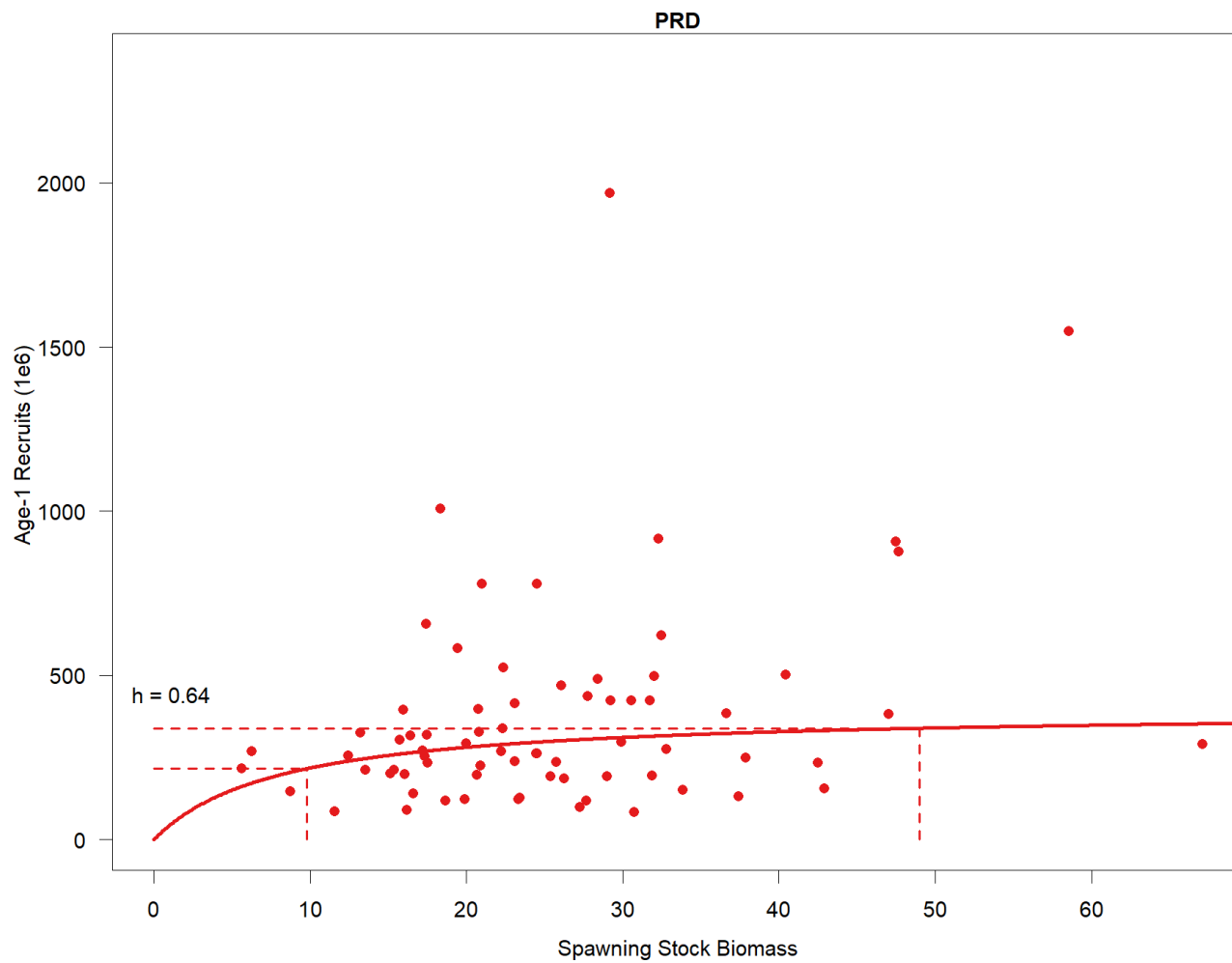


Figure D.26. Prince Rupert District stock-recruitment curves (solid lines) and age-1 estimated recruitments (points), with unfished and 20% of unfished biomass and recruitment shown as dashed lines. h is the estimated stock recruit steepness.

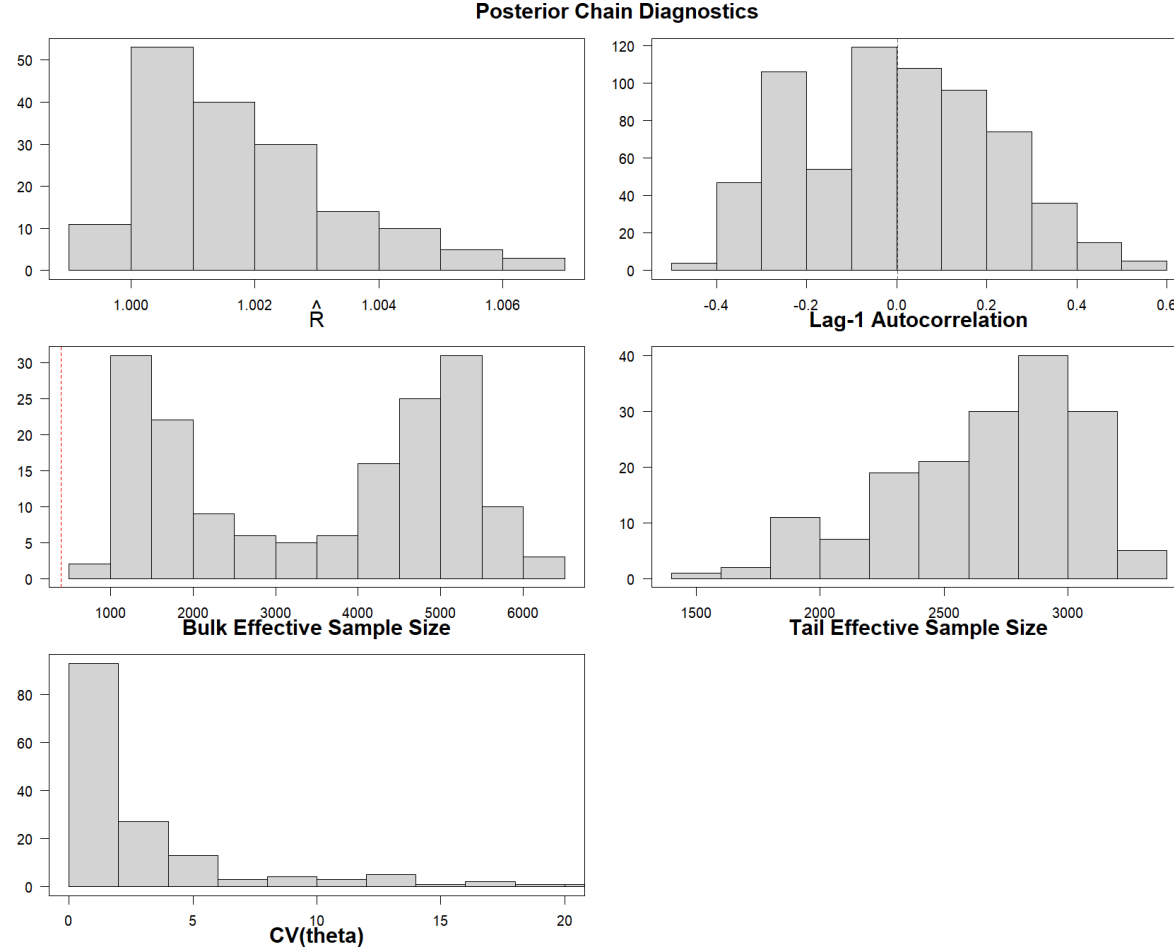


Figure D.27. Histograms of Prince Rupert District SISCAH model Bayes posterior convergence diagnostics for each leading model parameter, showing the distribution of values of each metric across all parameters. From left-to-right, starting in the top row, metrics are Gelman-Rubin scale reduction factors ($\hat{R}$), lag-1 autocorrelation factors, (bulk) effective sample size of draws in the central quantiles, (tail) effective sample size in the outer quantiles, and coefficient of variation (CV) of each parameter. Vertical red dashed lines indicate convergence thresholds, and the vertical dashed grey line indicates the median lag-1 autocorrelation.

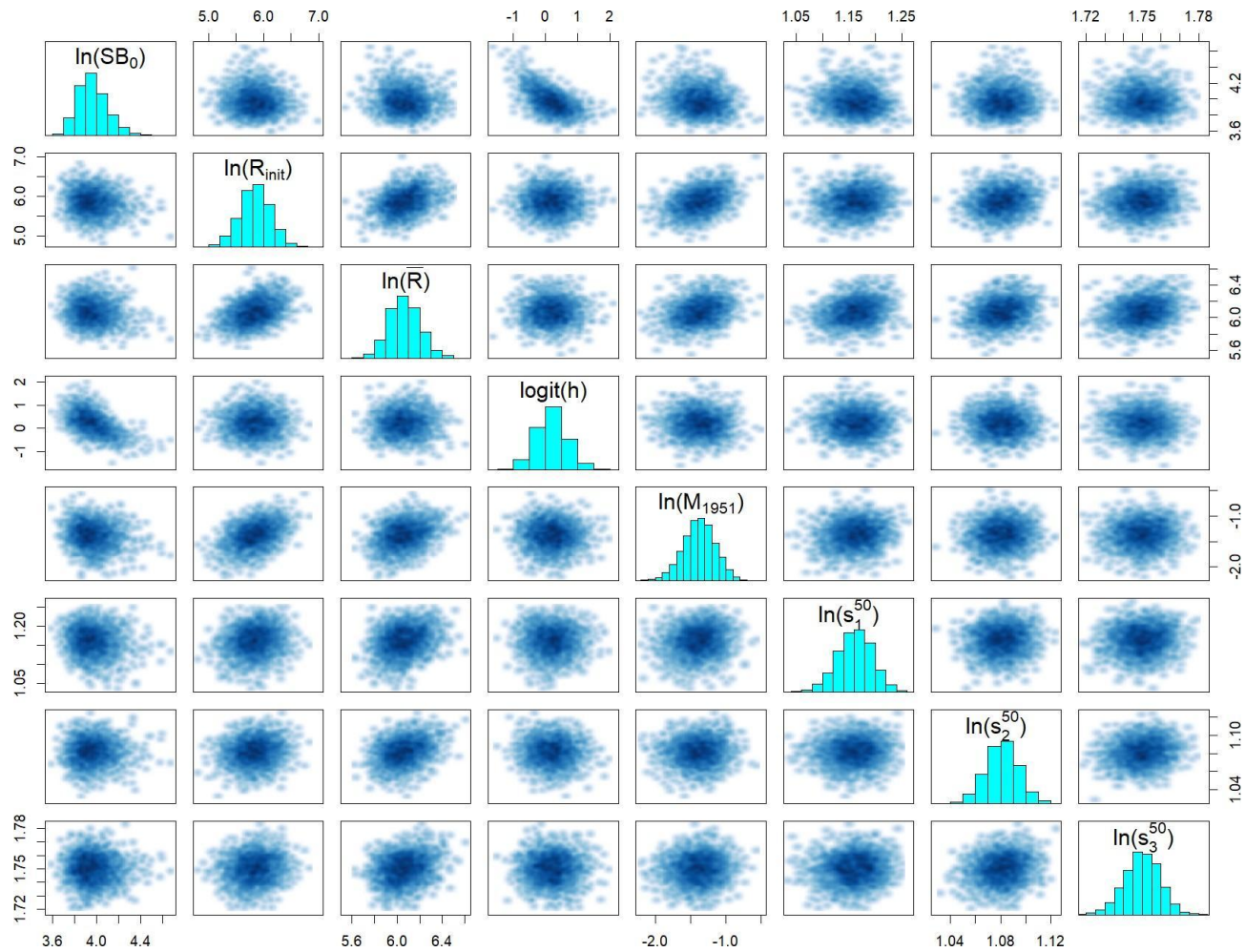


Figure D.28. Prince Rupert District SISCAH model marginal Bayes posteriors (main diagonal) and pair-wise joint-marginal Bayes posteriors (off-diagonal) for selected life-history and selectivity parameters. Red points indicate samples associated with divergent transitions.

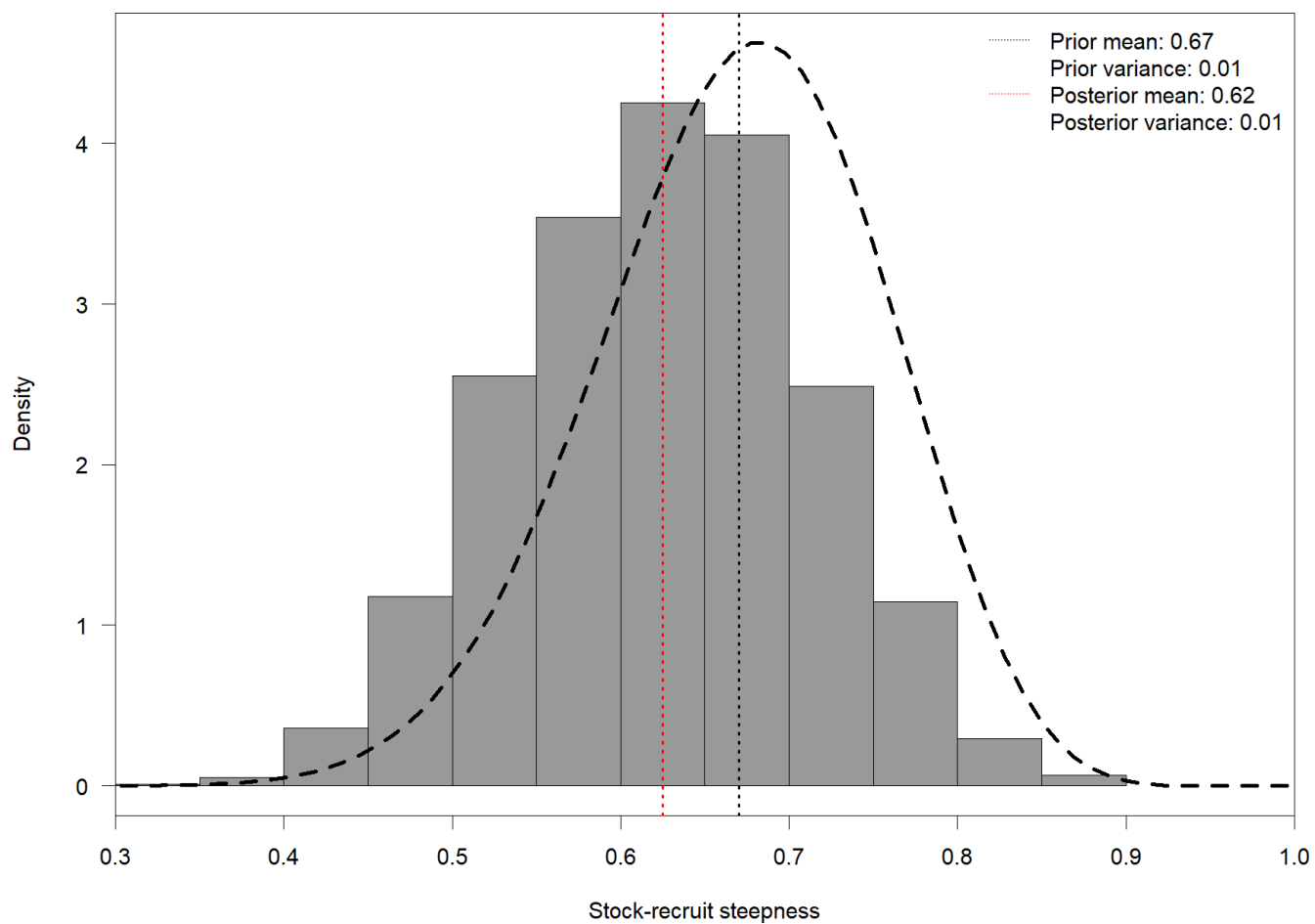


Figure D.29. Prince Rupert District SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for stock-recruitment steepness.

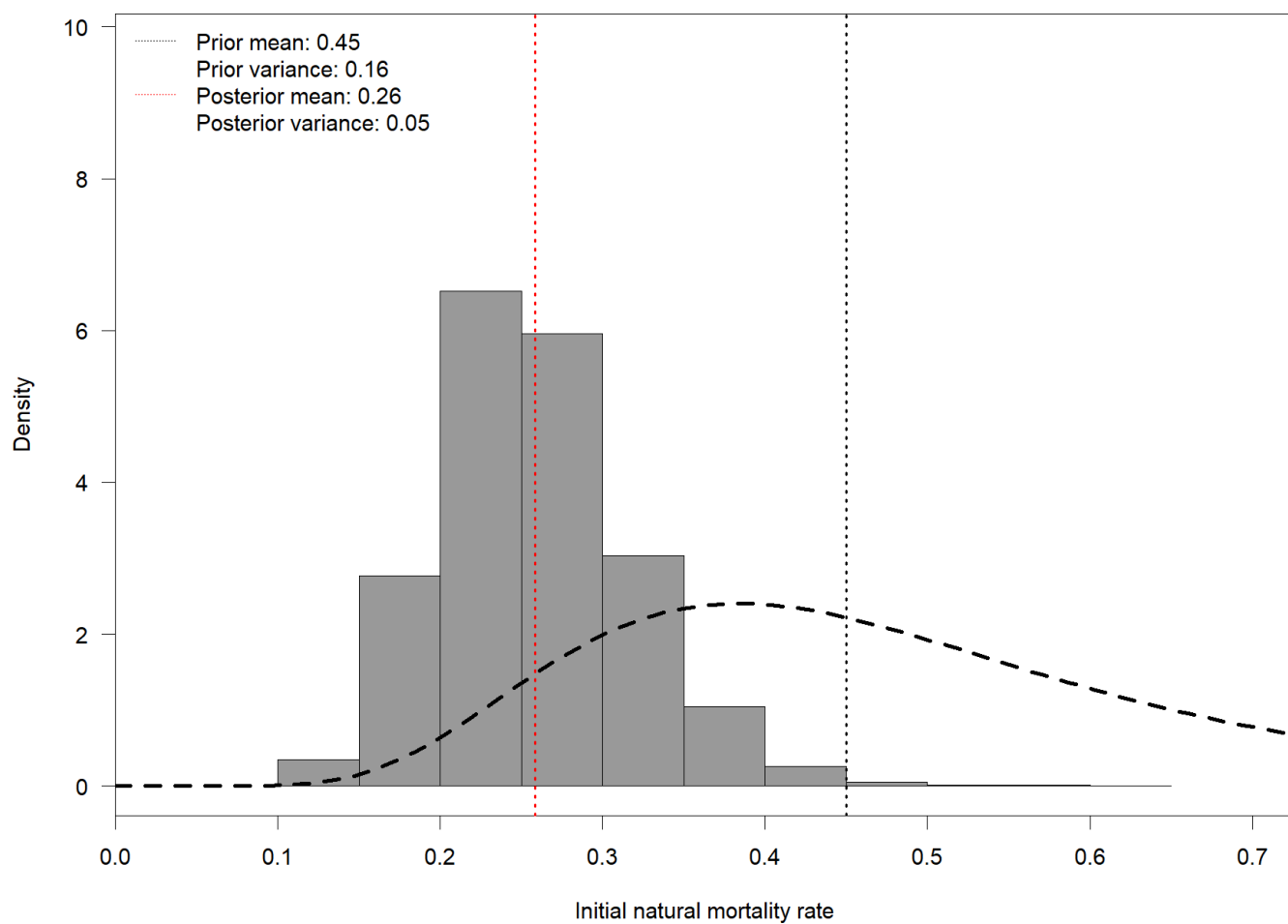


Figure D.30. Prince Rupert District SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for the initial natural mortality rate M_{1951} .

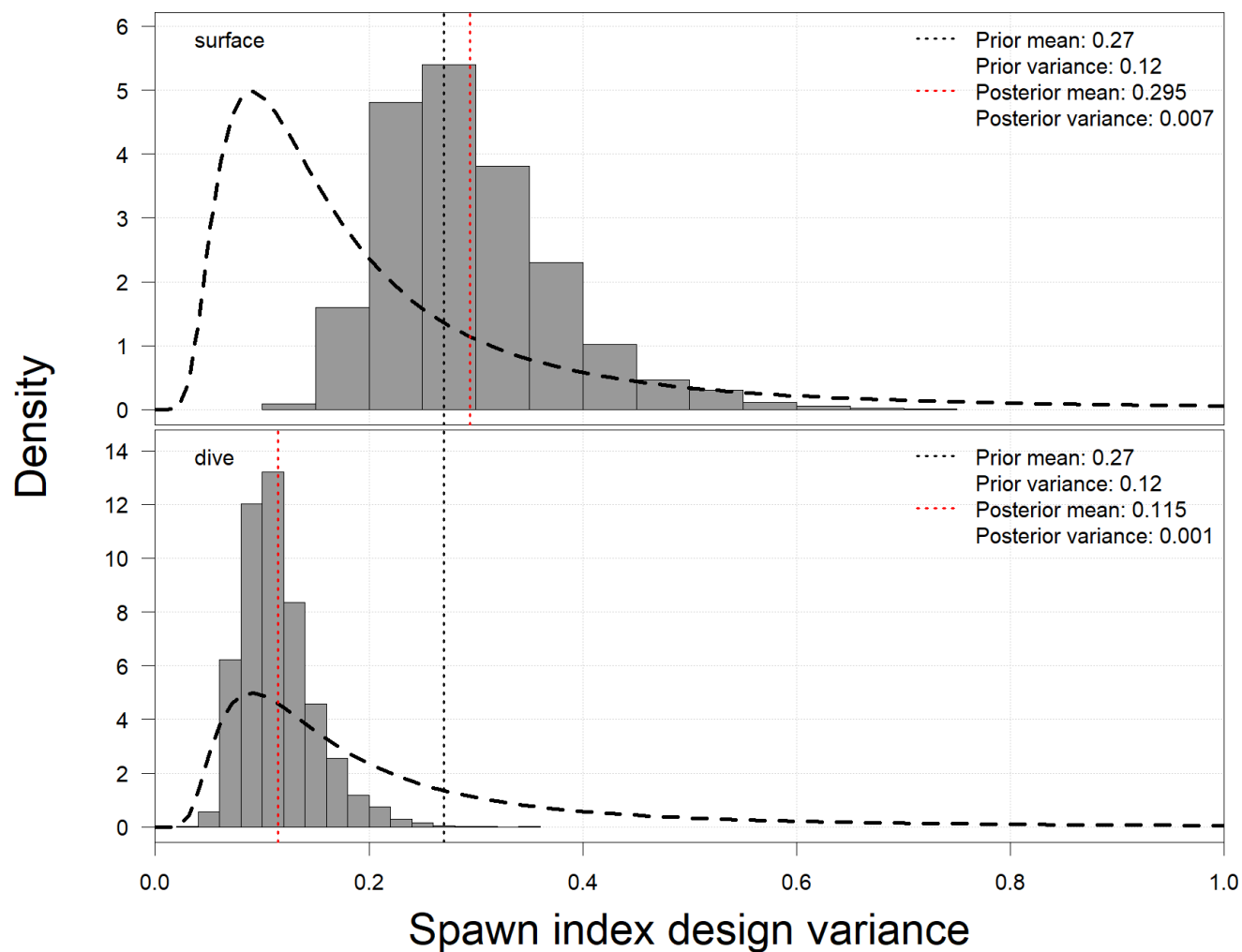


Figure D.31. Prince Rupert District SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for spawn index observation residual standard error components from the Dive survey design (top) and surface survey design (bottom).

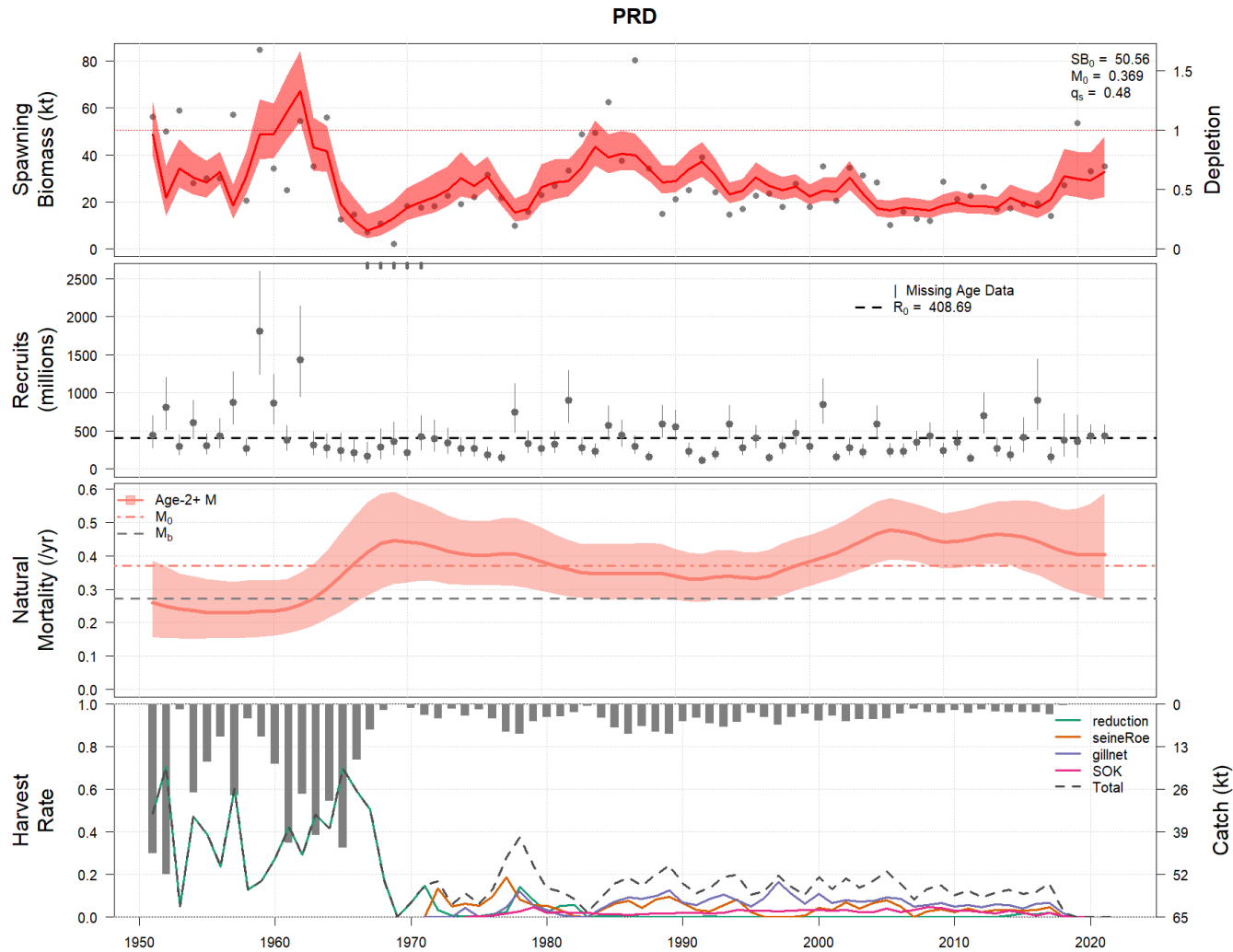


Figure D.32. Time series of Prince Rupert District herring spawning biomass with scaled spawn indices (top), recruitments (second row), natural mortality (third row), and harvest rates (bottom row). SB_0 , M_0 , and R_0 are unfished equilibrium spawning stock biomass, natural mortality, and recruitment respectively. q_s is the catchability coefficient for the surface surveys. SOK is spawn-on-kelp. In the recruitment panel, years with missing age data are indicated with a tick along the top axis, denoted by a 'I' in the figure legend.

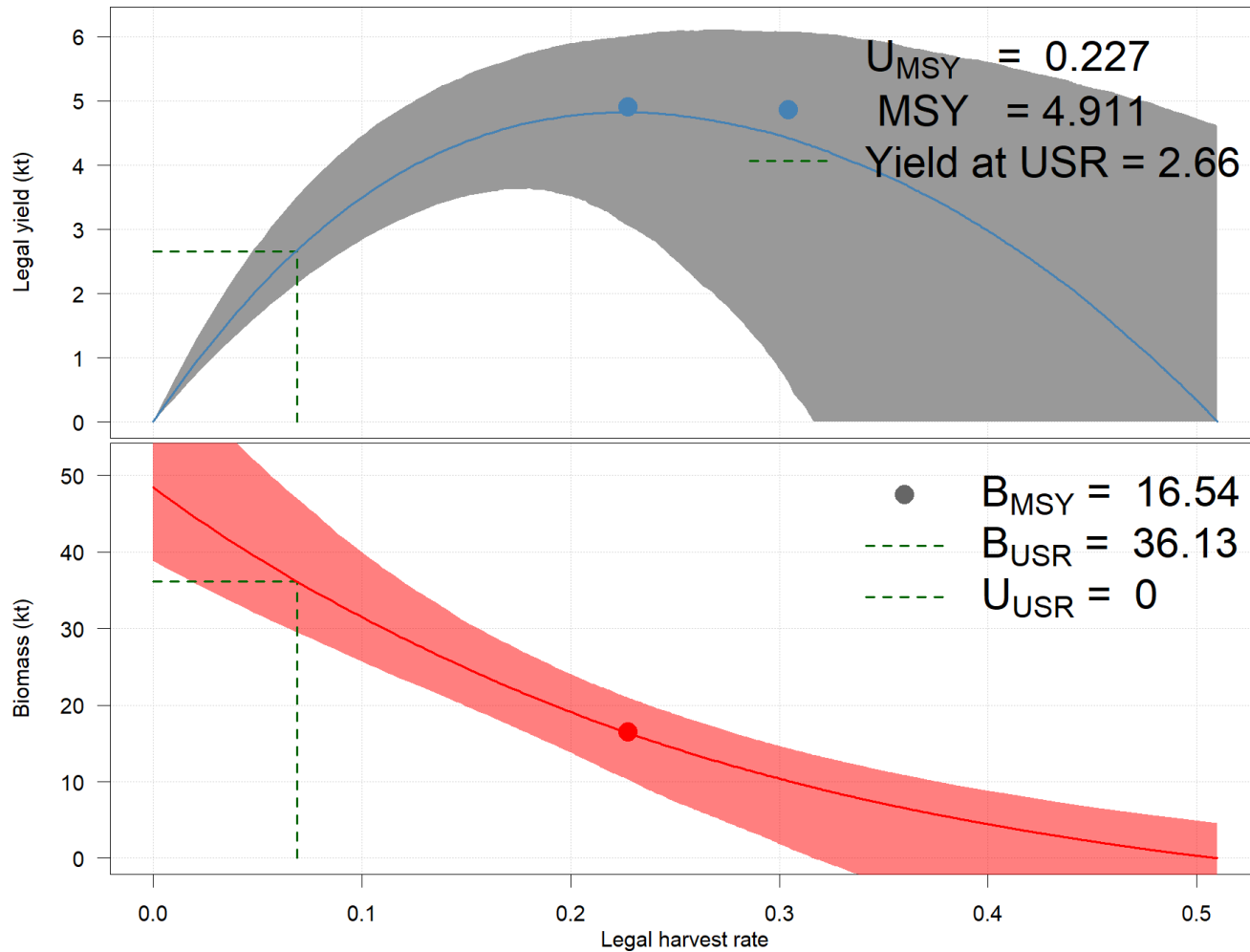


Figure D.33. Prince Rupert District herring MSY-based biological reference points, showing the effect of parameter uncertainty when integrated over SISCAH model posteriors. The top panel shows equilibrium yield, with the peak MSY at U_{MSY} (dark blue point), which is the harvest rate associated with producing MSY, and dashed line segments showing the equilibrium yield and harvest rate associated with the upper stock reference (USR). The second panel shows equilibrium spawning biomass, with a point at the biomass associated with MSY (B_{MSY}), as well as dashed line segments showing the upper stock reference B_{USR} . Harvest rate is calculated as catch divided by catch plus spawning biomass.

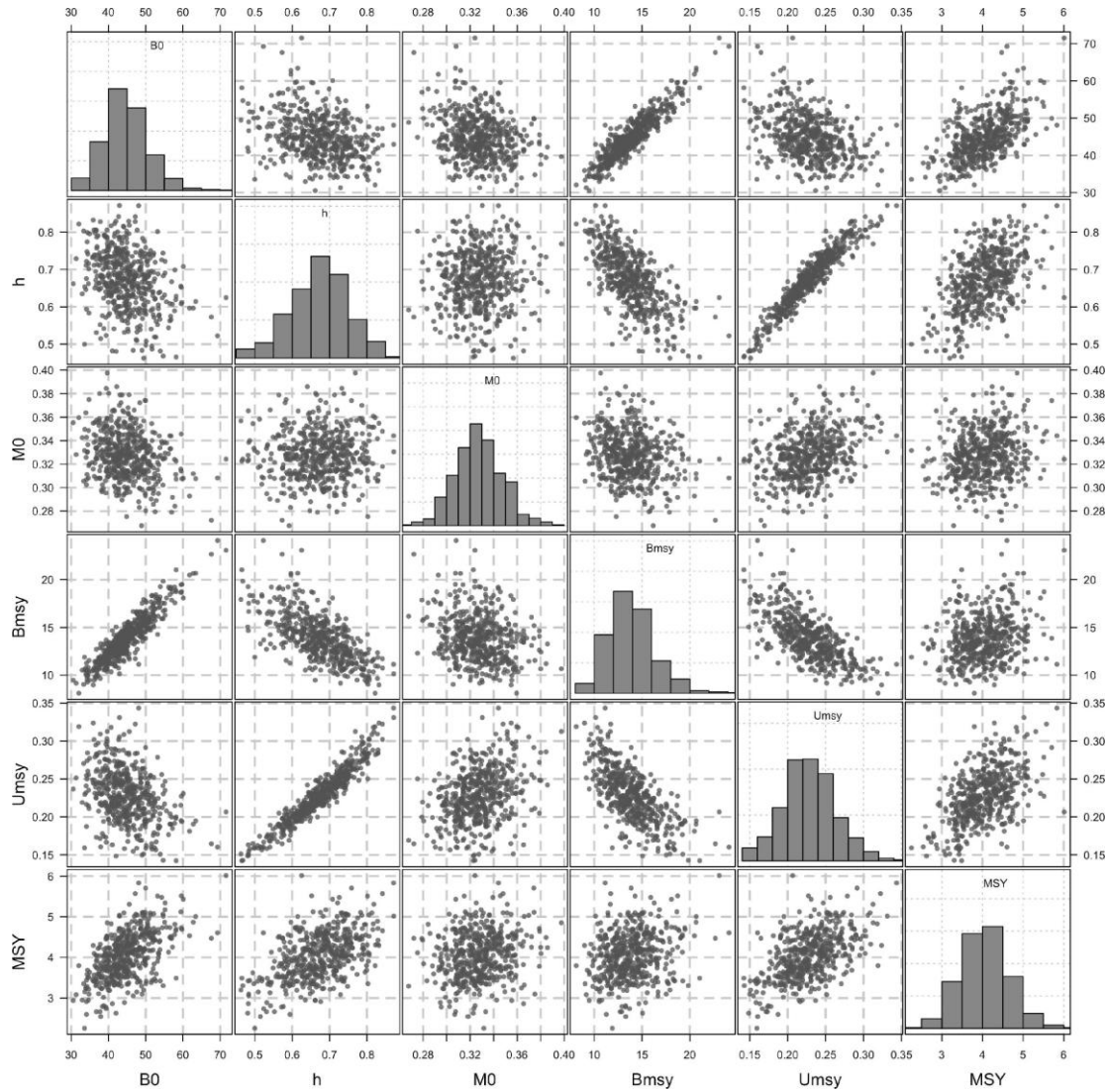


Figure D.34. Prince Rupert District: 500 random draws from joint marginal posterior distributions of selected life-history quantities and deterministic biological reference points, namely SB_0 = deterministic unfished equilibrium spawning biomass, h = stock-recruitment steepness, m_1 = depensation in density dependent mortality (if estimated), M_0 = deterministic unfished equilibrium mortality rate, B_{MSY} = deterministic optimal biomass, U_{MSY} = deterministic optimal harvest rate, MSY = deterministic maximum sustainable yield.

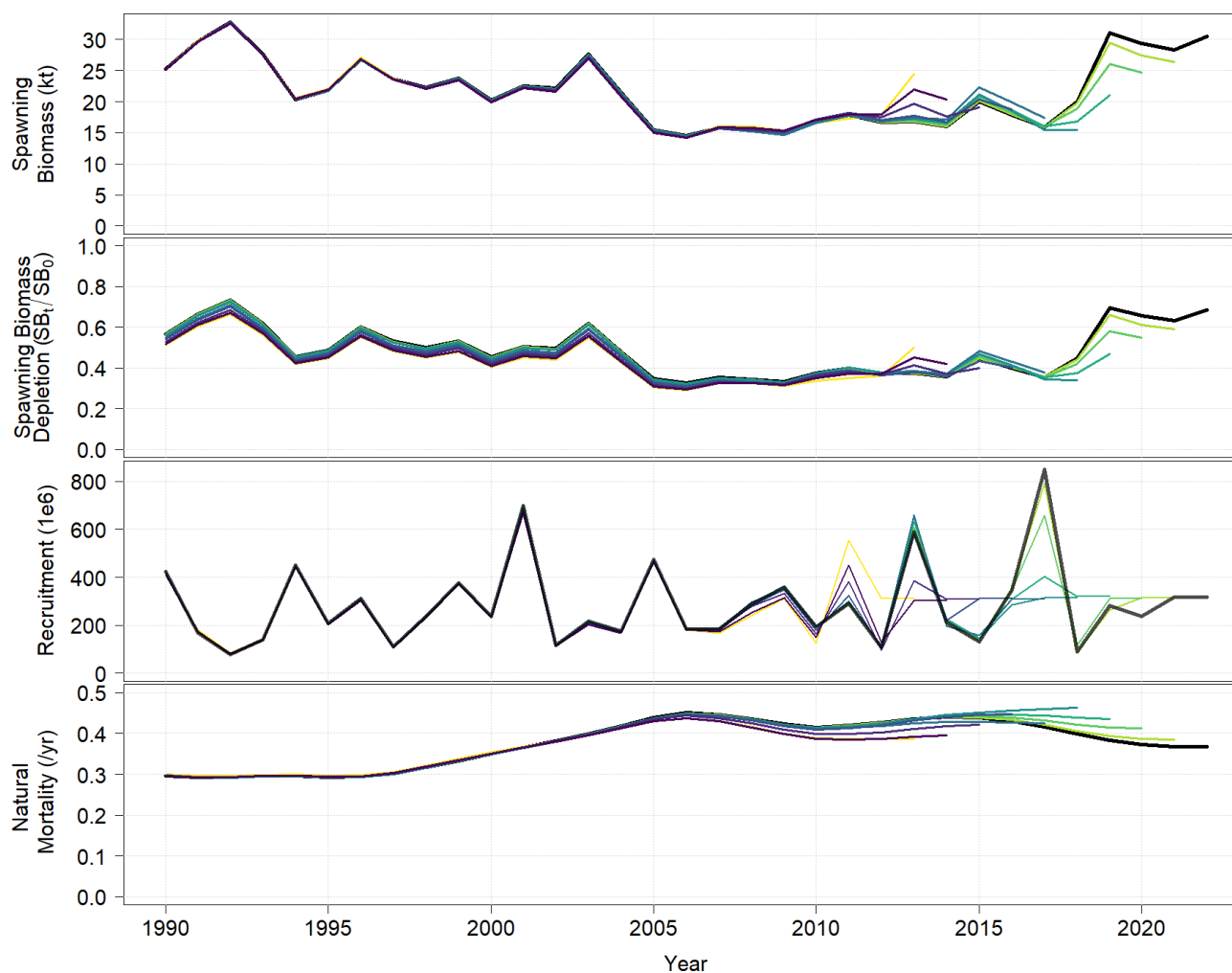


Figure D.35. Prince Rupert District SISCAN model retrospective estimates of spawning biomass (top) and spawning biomass depletion (second row), age-1 recruitment (3rd row), and natural mortality (bottom row), showing SISCAN model fits to successive data 'peels', which are truncated data sets with terminal years 2013–2022. The reference model is the largest data set in the 2022 peel, shown in black.

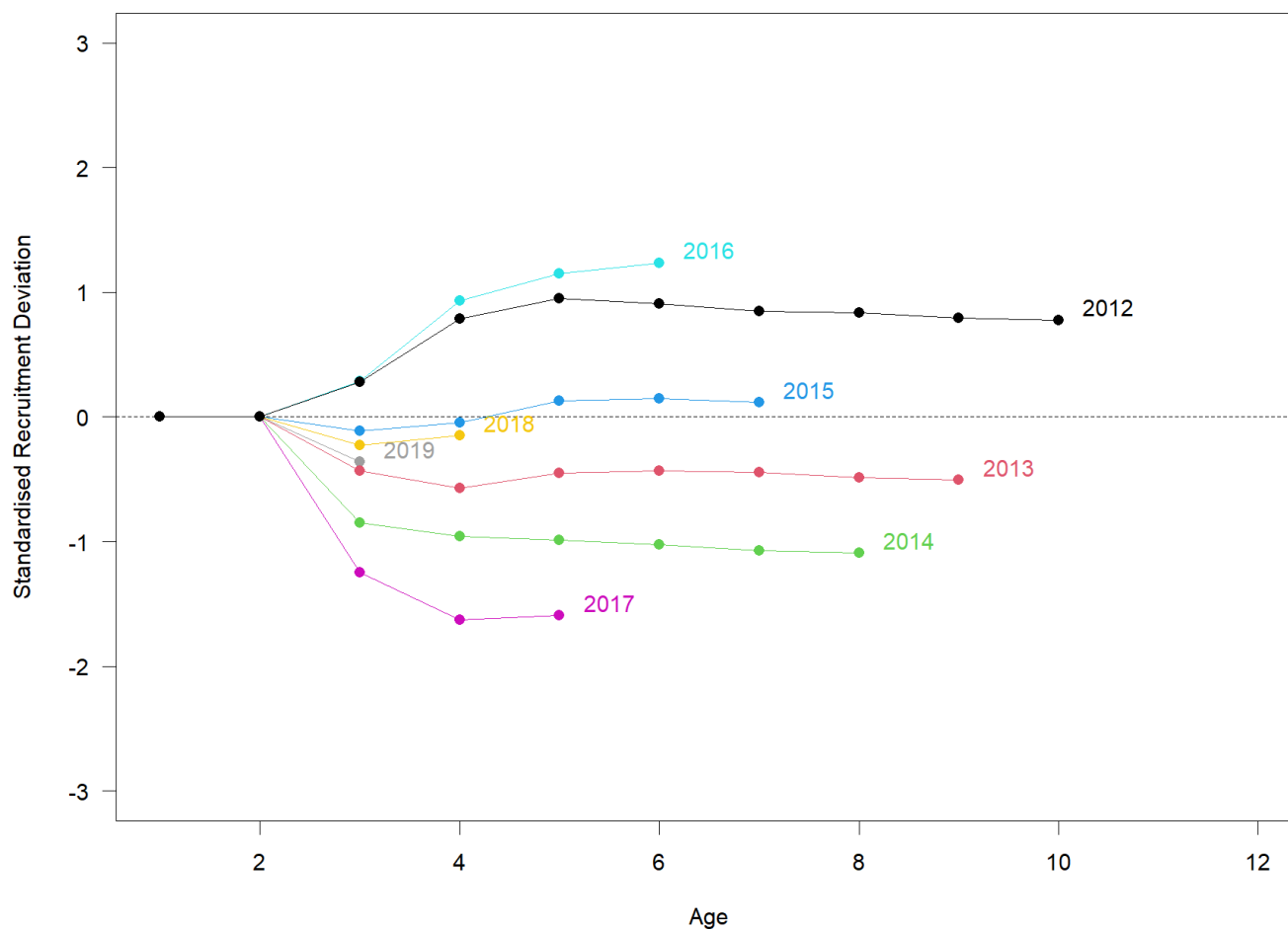


Figure D.36. Prince Rupert District SISCAH model retrospective estimates of standardised recruitment residuals, representing year class strength relative to the deterministic stock-recruitment relationship for models fit to successive data 'peels', which are truncated data sets with terminal years 2013–2022.

D.3. CENTRAL COAST

D.3.1. Goodness of fit

SISCAH model goodness of fit to Central Coast herring data was well within acceptable limits. Based on SISCAH model standard errors (Table D.9), all data series are consistent with the estimated population dynamics. Age composition data standard errors were all below 0.5, which is generally considered a good fit to the data and is commensurate with the previous herring stock assessment model. In contrast to the previous model, the two standard errors estimated for individual spawn survey designs had larger differences under SISCAH, with the surface survey design residuals around 1.5 times as variable as the dive survey design.

Spawn index observation residuals over time showed no indication of poor fits (Figure D.38). In addition to reasonable standard errors, the time series of blended spawn index residuals had no real bias, with a mean residual of -0.13 standard errors, a lag-1 auto-correlation coefficient estimate of -0.02, and no significant residual trend over the time series.

Estimates of age compositions reflect the relatively low standard errors of each fleet. The main source of model error is in the reduction fishery samples (Figure D.39), where the modal age class is missed in most of the first 12 years of the time series (1951–1963). This was a time period of high harvest, highly variable spawning biomass, and a time where the strengths of a year class doesn't necessarily follow through in following years. Once year class strength appears to follow more predictable patterns, SISCAH fits age compositions well, except for 1971, where SISCAH overfits the age 2 year class in response to the strength of that year class in following years. This is to be expected. Fits to age composition for the seine roe (Figure D.40) and gillnet (Figure D.41) fisheries are good. The only issue is the existence of some larger residuals when proportions-at-age in the data are large, some of this can be attributed to tail compression. Despite these larger residuals, SISCAH has no trouble matching the shape of the age compositions for the seine roe and gillnet fisheries, with the modal age classes identified in most year.

As with spawn-index residuals, the time-series of recruitment process errors has little indication of poor model fits (Figure D.42). As with HG herring, there is a significant negative residual trend ($p = 0.01$) from the early period of larger recruitments pre-1970, to the more recent period of lower average cohort strength. However, despite a residual trend there is little residual bias, with a mean recruitment deviation of 0.1 standard errors. Similarly, there are no long runs of positive or negative recruitment deviations, and lag-1 auto-correlation is very low at -0.042. Similarly, there are no indications of poor model fits when viewing recruitments relative to biomass around the stock-recruitment curve shows (Figure D.43).

D.3.2. Bayes posteriors

Standard Bayes posterior convergence metrics indicate that inferences can be drawn from the Bayes posteriors for the Central Coast SAR SISCAH model. Effective sample sizes for the bulk and tail sections of all marginal distributions are above 100 samples per chain, and all Gelman-Rubin potential scale reduction factors $\hat{R}$ are below the nominated threshold of 1.01 for all parameters (Figure D.44). Sampled posterior points included 64 divergent transitions out of 6000 total samples, or around 1% of all samples.

Visual inspection of joint marginal posteriors for leading life-history and selectivity parameters indicates that posterior geometry is of low concern (Figure D.45). As with Haida Gwaii there is correlation between SB_0 and m_1 , but the remaining joint marginal distributions are very symmetrical with low skew and low correlation.

Prior/posterior comparisons tell a similar story to other SARs. As with Haida Gwaii there is limited information in the data for estimating the stock-recruit steepness parameter. The prior and posterior mean are very close, and the variance parameters also very similar (Figure D.46). In contrast, there is a good indication of information in the M_0 posterior, with a slight drop in mean values mean but a larger drop in variance (Figure D.47); however, the variance may be artificially limited given the lower bound on M_0 induced by the model structure, which is hit as the HMC procedure samples higher m_1 values. Finally, spawn survey residual standard errors are well informed by the data. For both designs the posterior mean is lower than the prior mean, and variance drops a similar amount from 0.12 to 0.002–0.003 (Figure D.48).

D.3.3. Historical dynamics

Central Coast herring dynamics are characterised by a saw-tooth boom/bust pattern in spawning biomass and catch. Spawning biomass starts above unfished levels in 1951, before collapsing due to overfishing in the late 1960s (Table D.49). Catch levels are reduced to zero after the collapse with the ban of the reduction fishery, allowing the spawning stock biomass to recover in the presence of fairly close to average recruitment (i.e., close to the deterministic values off the stock-recruit curve), nearing unfished levels by the mid-1970s. A short run of negative recruitment deviations creates a sharp decline in biomass towards the end of the 1970s.

From 1980–1995 spawning biomass follows a persistent sawtooth pattern, fluctuating around SB_0 , after which biomass declines towards a low biomass state which persists from 2006–2012. The sawtooth pattern in spawning biomass is much more variable than natural mortality, harvest rates and/or catch, and is rather explained by SISCAN with a long run of near/below-average recruitments that are punctuated by large year classes in 1978, 1986, 1990, and a pair of consecutive large recruitments in 1995 and 1996. Those five large recruitments supported fishery catches that increased (for the most part) from around 2 kt in 1981 to around 11 kt in the mid 1990s, but over a similar time frame the absolute size of the sporadic large recruitments declined from about 2.5 billion age-1 herring in 1978 to around 1 billion in 1996. As such, the large year classes could no longer sustain the catches, and spawning biomass declined to an historic low point below 10 kt in 2006–2008, below the low point at the end of the 1960s.

The increase of Central Coast herring from the 2006 persistent low biomass state to the current level took about twice as long as the recovery to the same point back in 1966. Part of the reason for the slower recovery this time is that the decline in biomass generated an historic increase in natural mortality via the density dependent mortality model, reaching around 1.0/yr (posterior mean). This more recent high point is around 1.5 times the prior 1967 maximum of about 0.6/yr, which has reduced the survival and recruitment of any larger-than-average year classes since 2006. The low biomass and elevated natural mortality state has persisted in Central Coast herring despite a closure of the area from 2008 to 2013, and low catches since 2014. Indeed, the majority of catch in the last 10 years has been from the SOK fishery, with impounded herring biomass below 1 kt.

Despite taking a long time, herring biomass in the Central Coast region appears to have recovered. Spawning biomass in 2022 is estimated to be above 50% of unfished, and natural mortality has reduced towards the equilibrium unfished level. Recovery has been driven by a series of larger- than-average year classes in 2011, 2013, and 2017, increasing in size from about 900 million herring to about 1.5 billion. Increasing recruitments generate higher age-2+ biomass, reversing the depensation caused by density dependent natural mortality rates (Figure D.50), providing those fish, and any future year classes, a higher survival rate. This creates a reinforcing feedback loop that drives the stock recovery, as higher survival means

more fish growing and contributing to the spawning biomass, further reducing mortality (Figure D.49).

D.3.4. Biological reference points

SISCAH model equilibria for the Central Coast SAR show a maximum sustainable yield (MSY) of approximately 4.63 kt achieved when spawning biomass at around 21 kt, produced at a harvest of $U_{MSY} = MSY / (B_{MSY} + MSY) = 0.24$. As above, this accounts for around a 33% allocation of TAC to SOK fisheries. The crash point for CC herring is at a harvest rate of around 36%, associated with the steepest drop in biomass and recruitment (Figure D.51).

Joint marginal posteriors of life-history quantities and MSY-based reference points show a little more dependence between the DDM model parameter m_1 and the model equilibria (Figure D.52). As expected, biomass based quantities are correlated with m_1 values, as the DDM model links mortality and unfished biomass through its dependence on biomass depletion. In contrast to Haida Gwaii, the correlation between m_1 and U_{MSY} is noticeably positive, with less spread around the central axis of the distribution.

Per-capita demographic rates further inform equilibrium properties of SISCAH at very low biomass levels (Figure D.53). As in other areas, those sudden changes in equilibrium model states are driven by shifts in per-capita demographic rates (Figure D.53). Like in Haida Gwaii, the Central Coast per-capita surplus production becomes negative as biomass is reduced, this time at around 20 kt of age-2+ biomass.

D.3.5. Retrospective analyses

Results of the retrospective analysis suggests that Central Coast herring SISCAH estimates of biomass and life history parameters have low sensitivity to additional years of data. Spawning biomass (both absolute and depletion) are very consistent over the ten years of the retrospective peels (Figure D.54). Similarly, estimates of age-2+ natural mortality and recruitment time series are very consistent (Figure D.54).

Both spawning biomass and natural mortality have a tendency to miss changes in trend in the final years of each peel, but such behaviour is common for age-structured stock assessment models and the magnitude of over- and under- estimation is small. Usually, there are no recruitment process errors estimated for the final years of the assessment, as indicated by the flat recruitment series in the recruitment retrospective plots (Figure D.54). Moreover, any trend that is signaled by a small number of new data points at the end of a time series is indistinguishable from noise, so models tend to ignore them until a sufficiently long pattern in the data has emerged. Here, a lack of process errors forces SISCAH to use deterministic estimates of recruitment, which depending on the true recruitment can be an over- or under-estimate. Then, after a year or two of age-composition and index data are accrued, and process error parameters are freed up to allow non-deterministic estimates of recruitment, SISCAH estimates come into alignment over the history.

There is also a low amount variability in unfished equilibrium quantities over the retrospective peels (Table D.10). Unfished biomass SB_0 changes by around 2% over the ten years, and unfished recruitment $R_0 < 1\%$. Similarly, depensation rate m_1 and steepness are also fairly stable over all retrospective peels.

While recruitment process error does vary slightly over time, it appears that the individual year class strength resolves quickly and remains stable (Figure D.55). Most year classes are resolved by age-4; however, 2015 does show an adjustment back towards the stock recruit curve over the course of the retrospective analysis.

D.3.6. Sensitivity analyses

SISCAH estimates of Central Coast herring biomass and life history parameters were relatively insensitive to specific choices of priors (Table D.11). As with other SARs, the steepness prior was most influential on the steepness estimate, and the prior mean for unfished mortality M_0 was more influential on unfished biomass SB_0 . Unlike HG and PRD, the mortality process error variation σ_M value had some influence on the unfished biomass SB_0 and m_1 estimates, as the change in variability forced the DDM curve to change shape to produce the required mortality rates for fitting the data.

Out of the seven SISCAH initial condition configurations tested for the Central Coast SAR, six successfully converged. Similar to the previous scenarios, the primary impact of adjusting the fished initialization settings was on the first-year age-1 recruitment, observed in terms of either R_0 or R_{init} , and the unfished biomass SB_0 (see Table D.12). There were relatively smaller effects on M_0 , considering its correlation with SB_0 , and the stock-recruitment steepness h .

Moreover, the inclusion of F_{init} in the initial survivorship calculations led to an inflation of the initial recruitment parameter. Specifically, when stocks were initialized at a deterministic equilibrium (without initial recruitment deviations), R_{init} increased by approximately 20%. Under non-equilibrium starting conditions (when initial recruitment deviations were estimated), R_{init} increased by approximately 63%. The impact on unfished biomass exhibited more variability compared to previous cases, with SB_0 ranging from 47 kt to 57 kt across the six configurations.

Once again, there remained a significant degree of stability in biomass and recruitment estimates for each year, with only minor differences between models from 1951 to 1955. Beyond 1955, it appears that other model parameters, such as recruitment and mortality process errors, were able to compensate for variations stemming from the initial conditions of the model.

D.3.7. Tables

Table D.9. Estimated residual standard errors and lag-1 age residual correlations for Central Coast herring data. The first six columns show age data sampling standard errors τ_g^{age} and correlation coefficients ρ_g from the LN1 age composition likelihood function the Reduction and Food & Bait ($g = 1$), Seine-rope ($g = 2$), and gillnet fisheries ($g = 3$), and the last two columns show spawn survey index standard deviations for the surface (τ_s) and dive (τ_d) surveys.

SAR	τ_1^{age}	ρ_1	τ_2^{age}	ρ_2	τ_3^{age}	ρ_3	τ_s	τ_d
CC	0.468	0.094	0.357	0.211	0.43	0.261	0.395	0.284

Table D.10. Central Coast retrospective estimates of selected SISCAH model leading and derived life-history quantities over data peels from 2012–2022. Selected quantities are SB_0 = estimated unfished equilibrium spawning biomass(kt), R_0 = estimated unfished equilibrium recruitment (1e6), R_{init} = estimated initial recruitment (1e6), m_1 = depensation rate (unitless), M_b = asymptotic lower bound on age-2+ natural mortality (yr), M_0 = equilibrium unfished age-2+ natural mortality (yr), q_s = surface survey catchability (unitless).

Peel	B_0	R_0	m_1	M_0	h	q_s
2013	49.531	529.719	3.133	0.438	0.710	0.233
2014	49.866	522.061	3.250	0.433	0.712	0.235
2015	51.322	522.468	3.421	0.427	0.721	0.236

Peel	B_0	R_0	m_1	M_0	h	q_s
2016	52.053	513.307	3.645	0.420	0.721	0.238
2017	50.541	503.894	3.581	0.422	0.716	0.239
2018	49.161	511.619	3.335	0.430	0.715	0.237
2019	51.077	519.891	3.484	0.425	0.719	0.236
2020	50.677	516.468	3.491	0.424	0.717	0.236
2021	48.554	510.910	3.323	0.430	0.711	0.236
2022	48.000	523.920	3.150	0.437	0.709	0.233

Table D.11. Central Coast SISCAH model estimates of life-history and observation model quantities under sensitivity analyses.

Sensitivity	SB_0	R_0	m_1	M_0	h	q_s
base	48.192	525.218	3.157	0.437	0.710	0.233
jeffHi	42.167	513.342	2.738	0.459	0.706	0.234
jeffLo	48.192	525.218	3.157	0.437	0.710	0.233
meanMHi	39.124	529.028	2.450	0.480	0.698	0.231
meanMLow	53.457	531.626	3.699	0.419	0.708	0.235
qSurfSDHi	48.292	527.527	3.146	0.437	0.709	0.231
qSurfSDLo	47.810	516.613	3.197	0.435	0.712	0.243
sdMHi	48.748	525.564	3.208	0.434	0.710	0.234
sdMLow	46.869	524.682	3.039	0.442	0.709	0.233
sigmaMlo	52.922	545.304	3.455	0.426	0.720	0.229
steepMeanHi	46.136	510.225	3.091	0.439	0.889	0.237
steepSDHi	48.123	523.407	3.166	0.436	0.734	0.234

Table D.12. Central Coast SISCAH model estimates of life-history and observation model quantities under the initial conditions sensitivity analyses.

Initial Conditions											
initR	initF	initDevs	SB_0	R_0	R_{init}	F_{init}	m_1	M_b	M_0	h	q_s
R_0	TRUE	FALSE	57.634	557.235	–	0.223	3.946	0.394	0.413	0.706	0.232
R_0	FALSE	TRUE	48.192	525.218	–	0.000	3.157	0.394	0.437	0.710	0.233
R_{init}	FALSE	FALSE	49.401	523.746	914.349	0.000	3.293	0.394	0.431	0.712	0.233
R_{init}	TRUE	FALSE	55.777	543.347	1,171.325	0.229	3.874	0.394	0.415	0.709	0.233
R_{init}	TRUE	TRUE	54.078	535.094	844.516	0.324	3.739	0.394	0.418	0.709	0.237
R_{init}	FALSE	TRUE	47.592	519.267	518.241	0.000	3.151	0.394	0.437	0.710	0.234

D.3.8. Figures

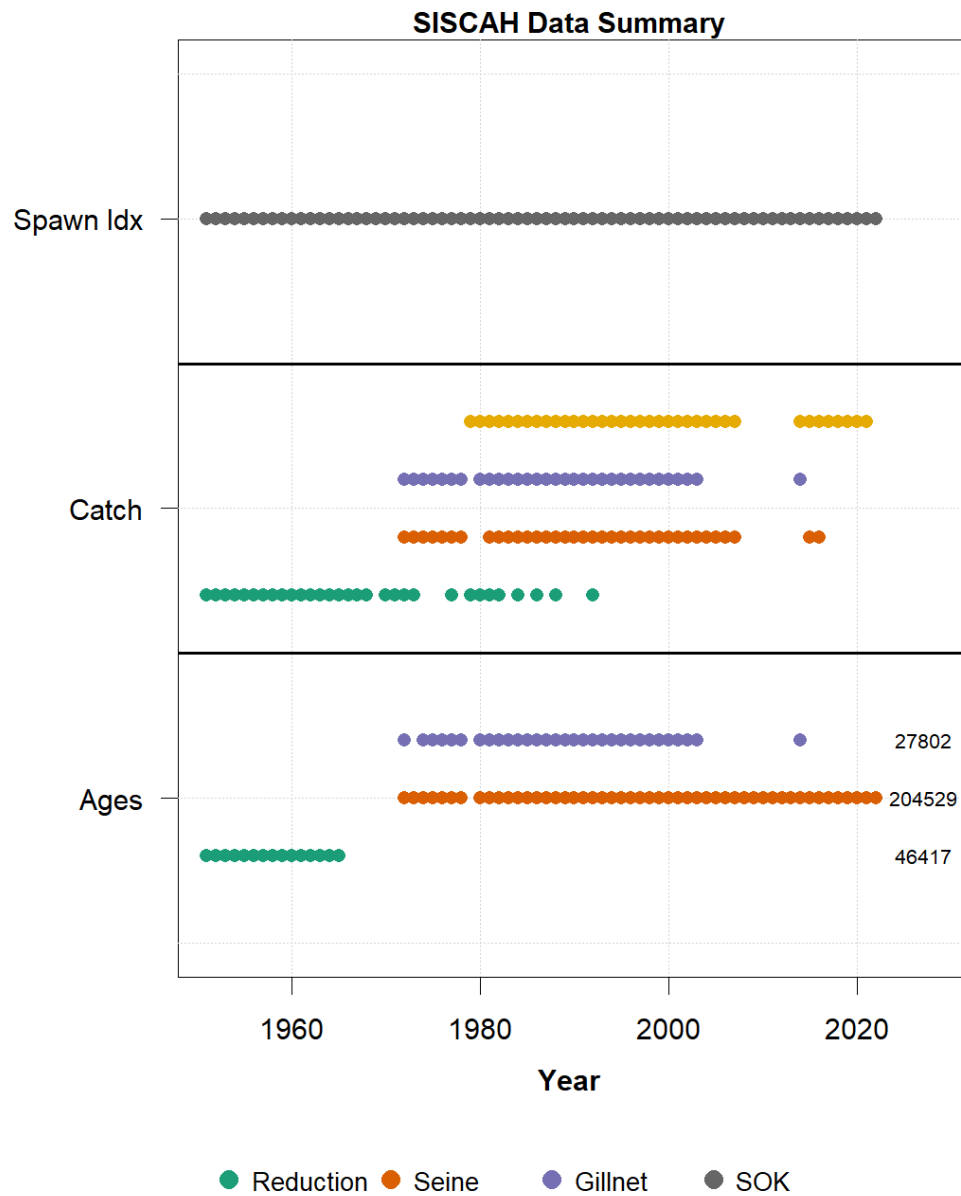


Figure D.37. Time series of Central Coast herring stock assessment data. Each dot shows the existence of data, and age data shows total number of samples over all years at the right hand end.

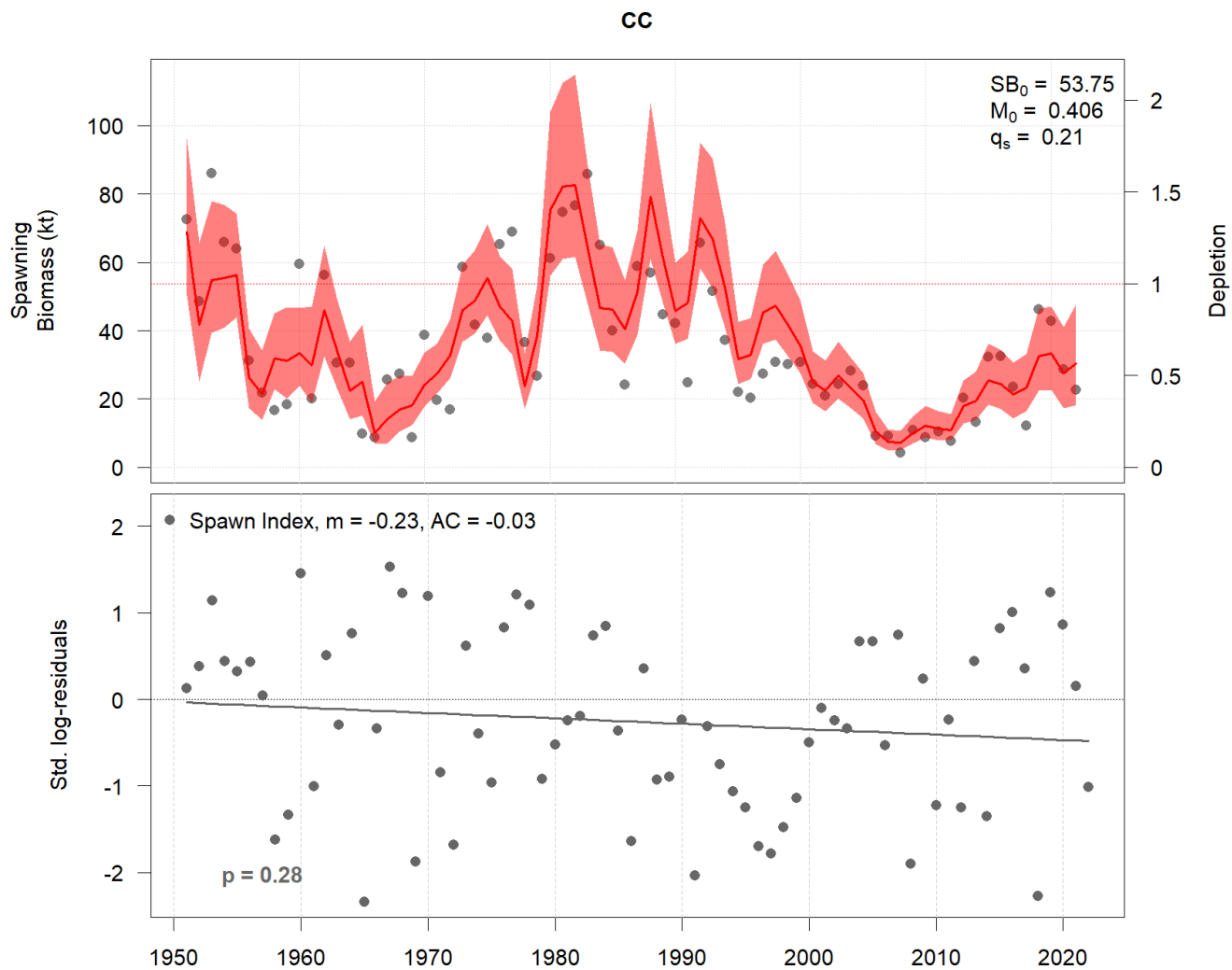


Figure D.38. Central Coast blended spawn index and SISCAN spawning biomass estimates (top) and standardised observation residuals (bottom). SB_0 and M_0 are the unfished equilibrium spawning stock biomass and the natural mortality respectively, q_s is the catchability coefficient for the surface surveys, m is the mean log residual of the spawning index, and AC is the autocorrelation.

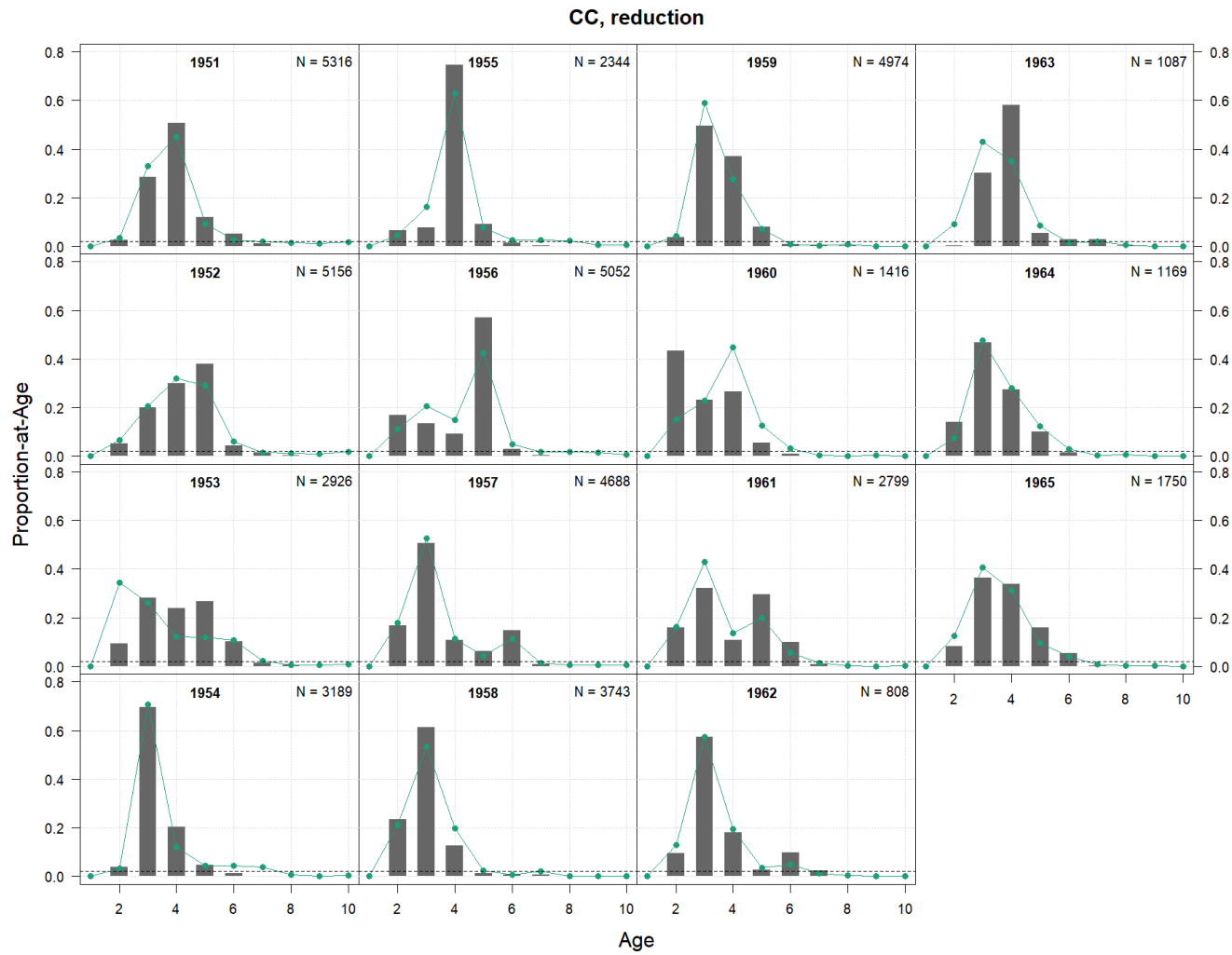


Figure D.39. SISCAH model fits to reduction age compositions collected from the Central Coast region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

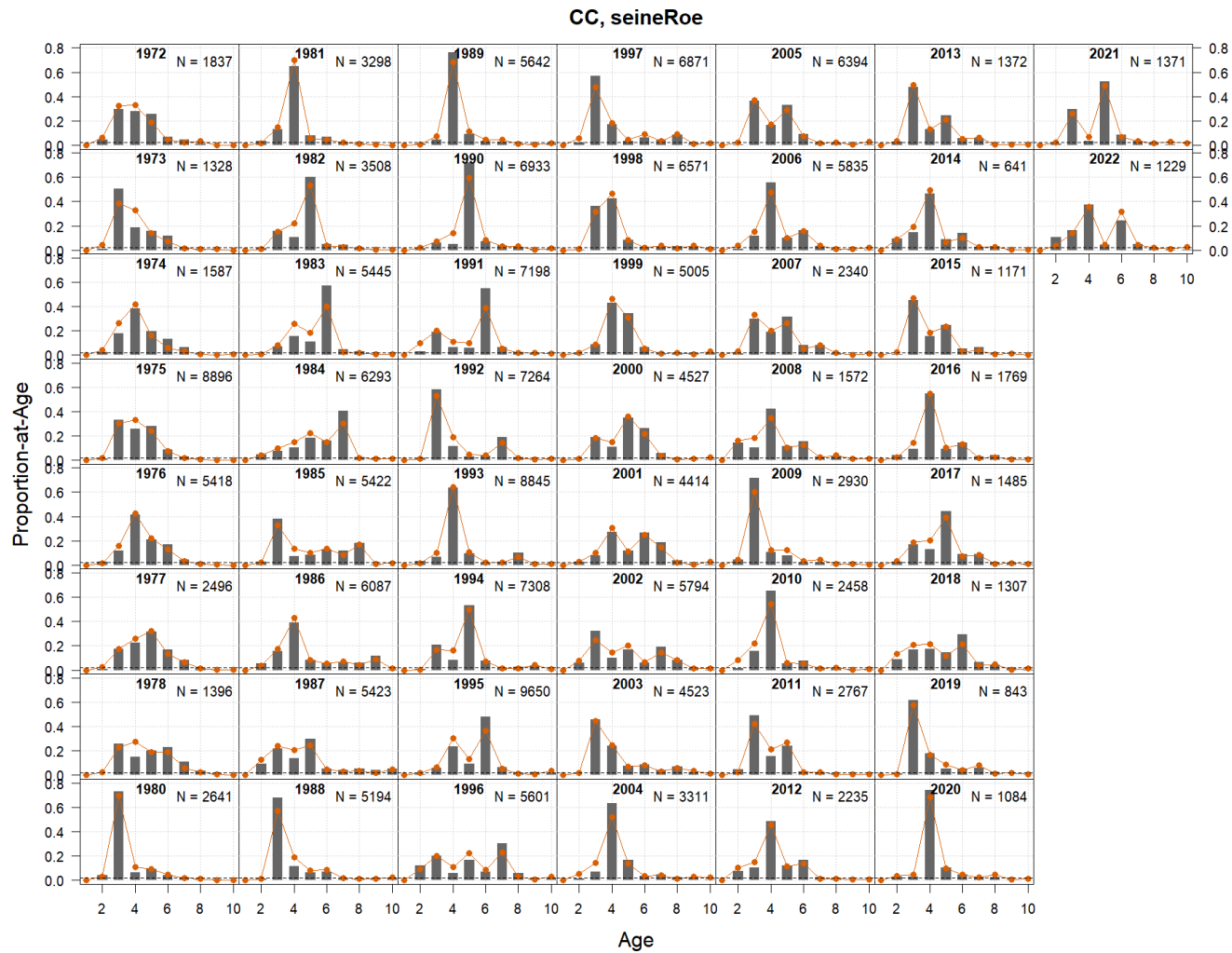


Figure D.40. SISCAH model fits to seine roe age compositions collected from the Central Coast region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

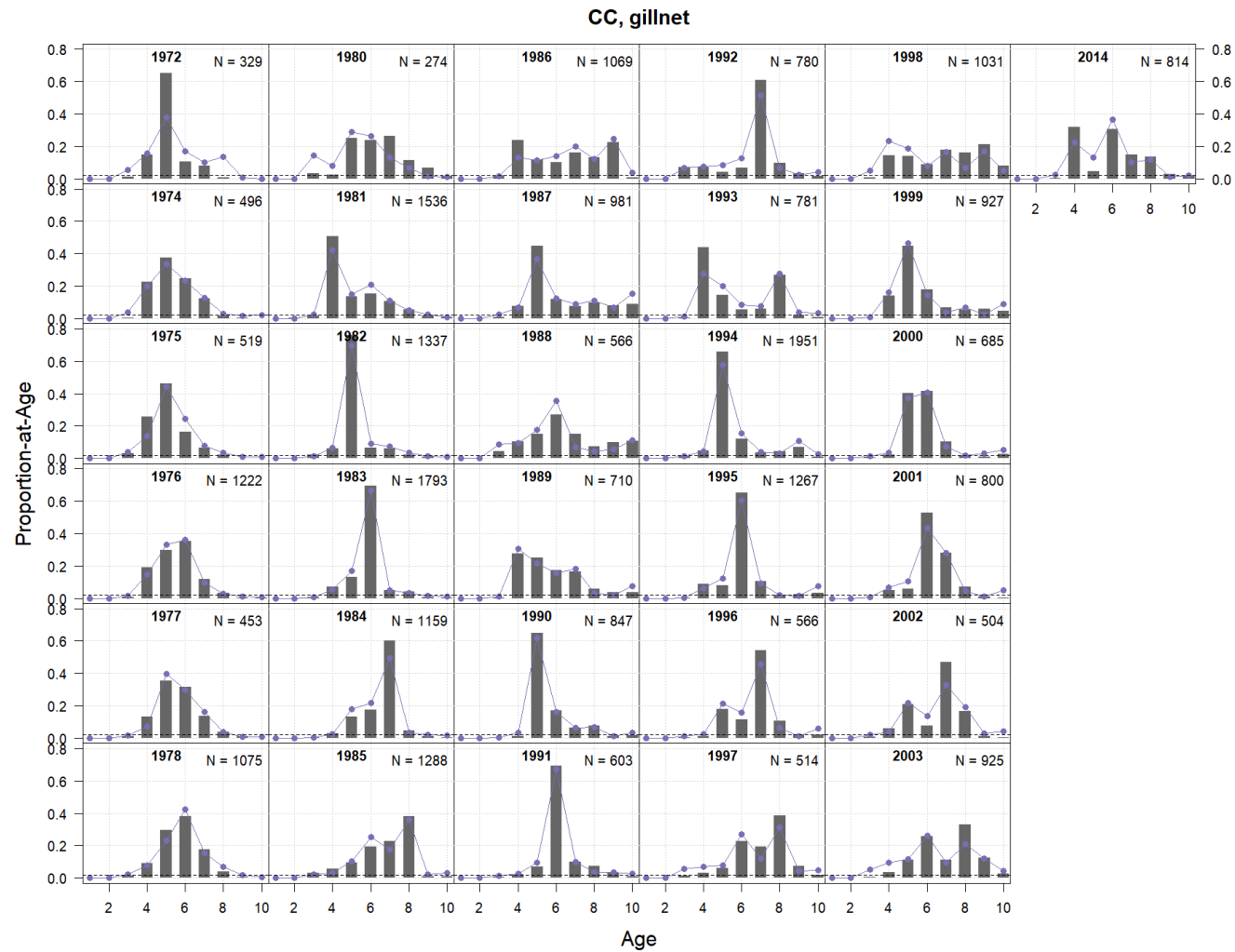


Figure D.41. SISCAN model fits to gillnet age compositions collected from the Central Coast region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

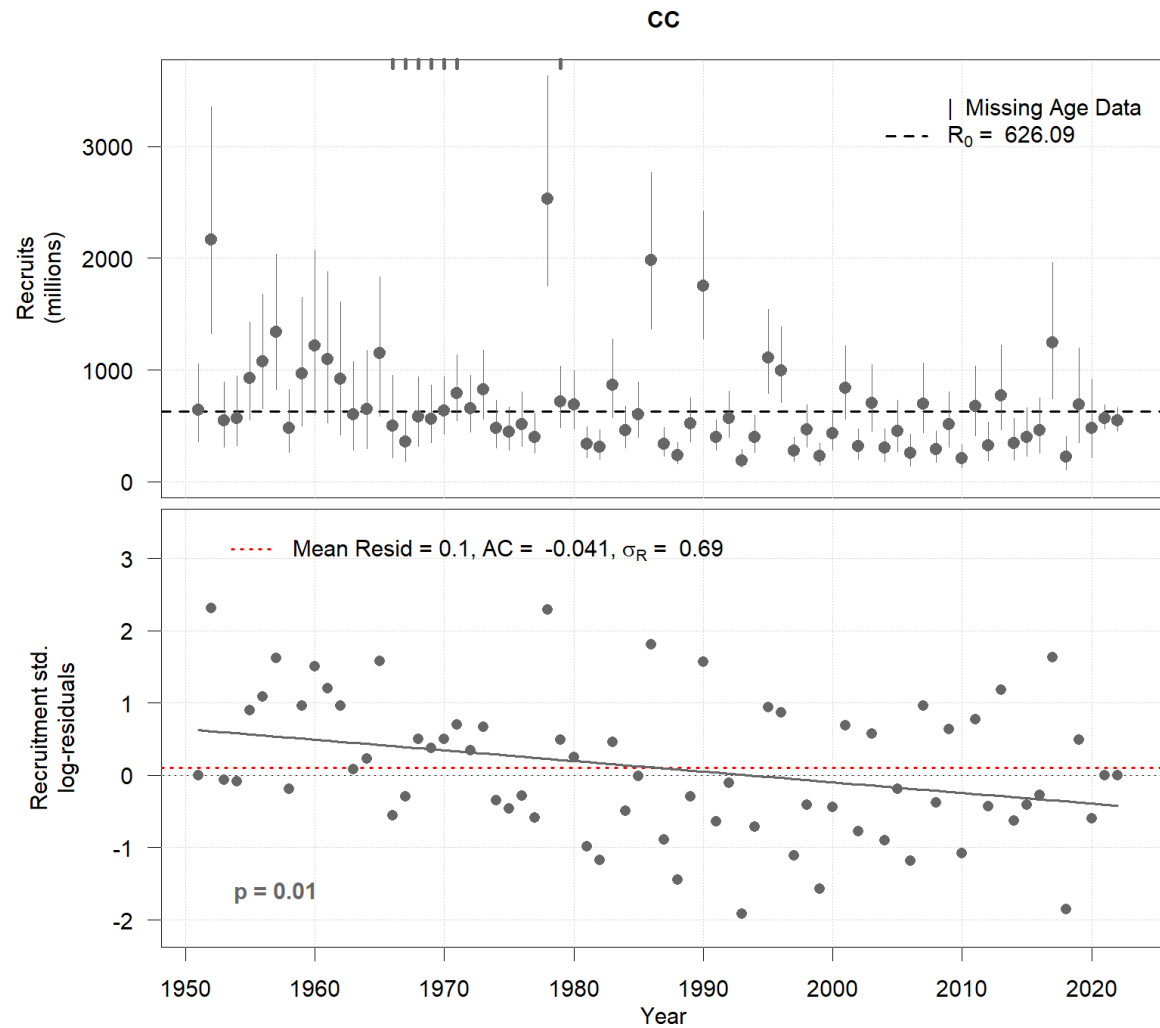


Figure D.42. Central Coast age-1 recruitments (top) and standardised recruitment process errors (bottom). Equilibrium unfished recruitment R_0 is indicated by the horizontal dashed line in the top panel, and the mean process error (Mean Resid) is shown by the horizontal red dashed line in the bottom panel. AC is auto correlation and σ_R is the standard error in the log residuals.

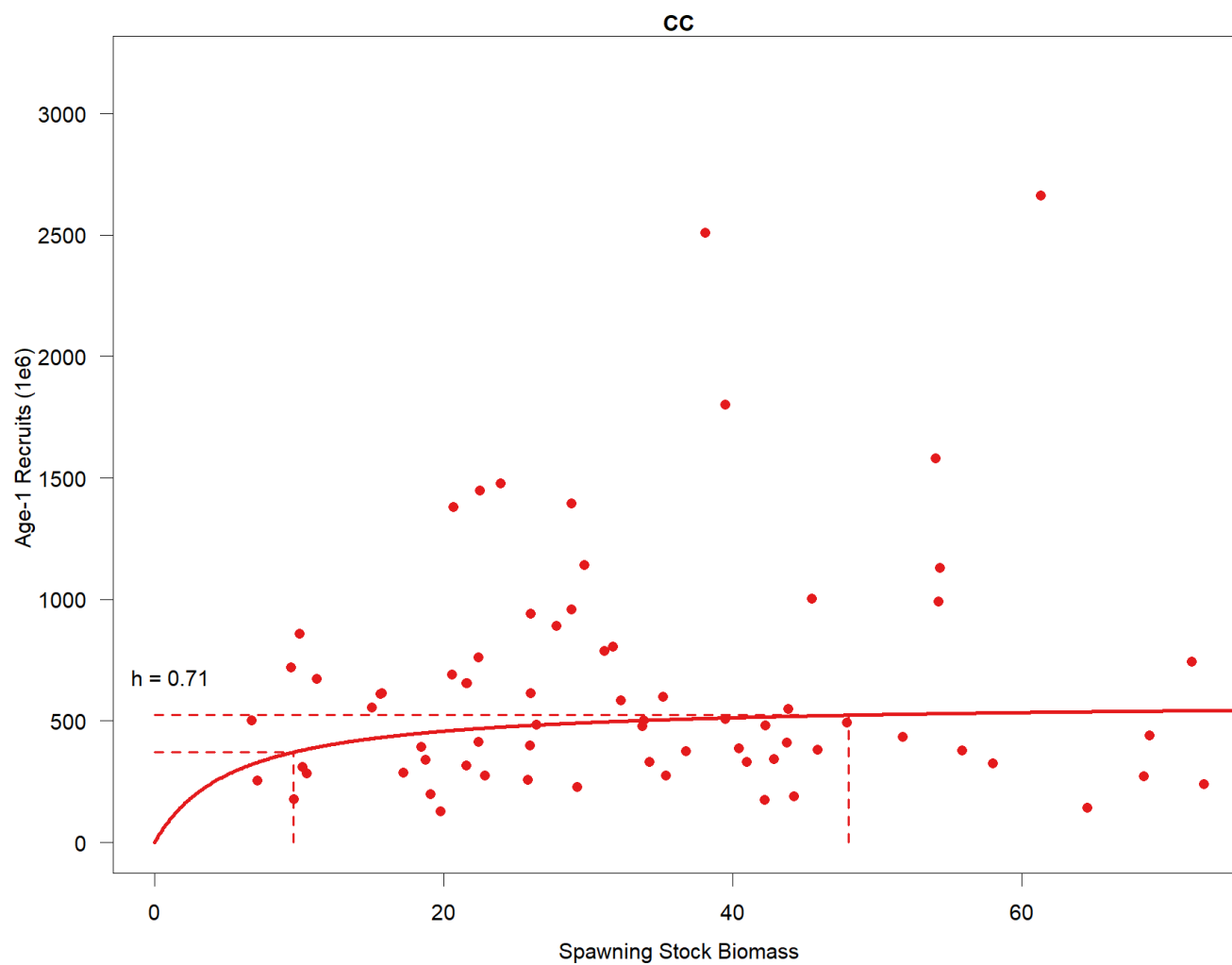


Figure D.43. Central Coast stock-recruitment curves (solid lines) and age-1 estimated recruitments (points), with unfished and 20% of unfished biomass and recruitment shown as dashed lines. h is the estimated stock recruit steepness.

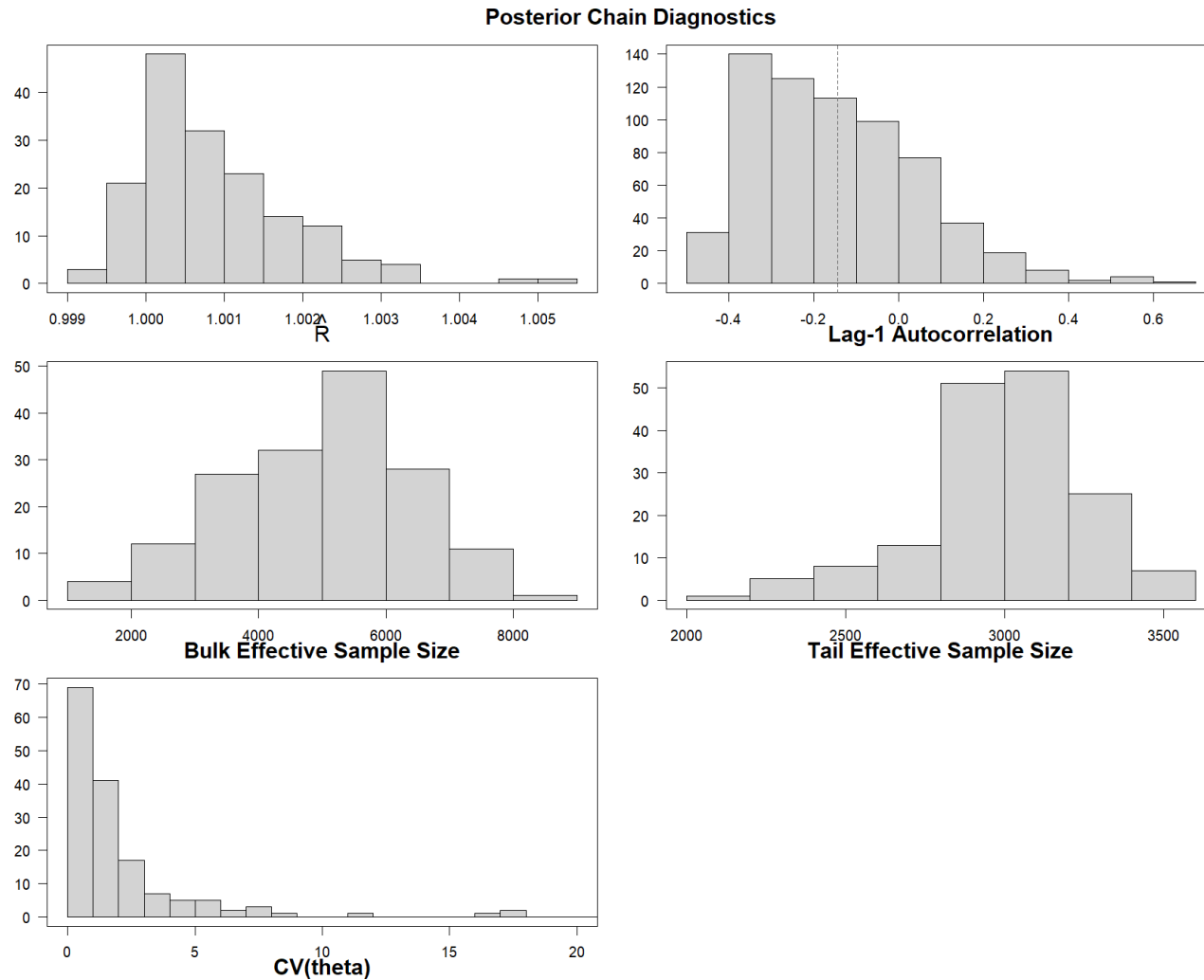


Figure D.44. Histograms of Central Coast SISCAH model Bayes posterior convergence diagnostics for each leading model parameter, showing the distribution of values of each metric across all parameters. From left-to-right, starting in the top row, metrics are Gelman-Rubin scale reduction factors ($\hat{R}$), lag-1 autocorrelation factors, (bulk) effective sample size of draws in the central quantiles, (tail) effective sample size in the outer quantiles, and coefficient of variation (CV) of each parameter. Vertical red dashed lines indicate convergence thresholds, and the vertical dashed grey line indicates the median lag-1 autocorrelation.

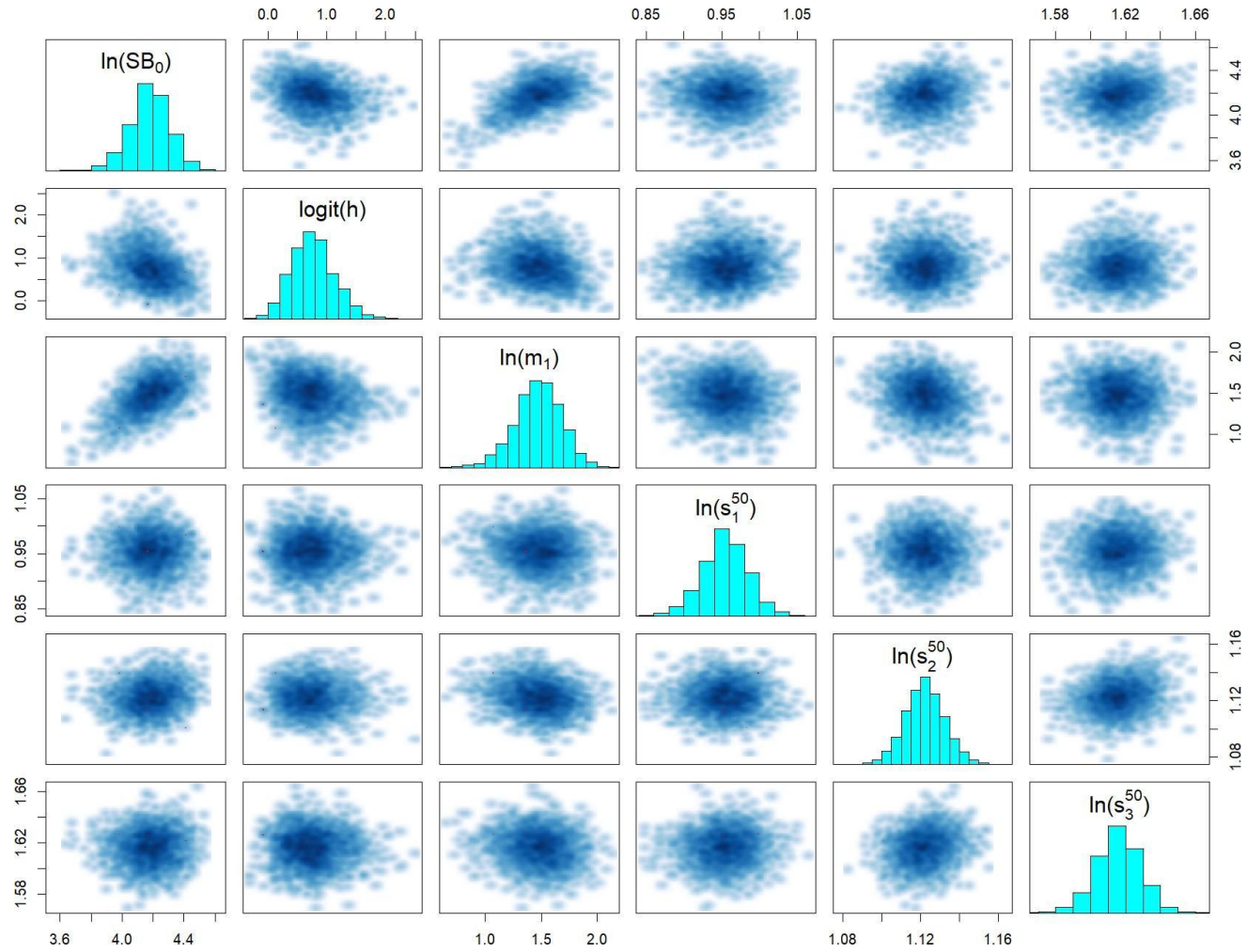


Figure D.45. Central Coast SISCAH model marginal Bayes posteriors (main diagonal) and pair-wise joint-marginal Bayes posteriors (off-diagonal) for selected life-history and selectivity parameters. Red points indicate samples associated with divergent transitions.

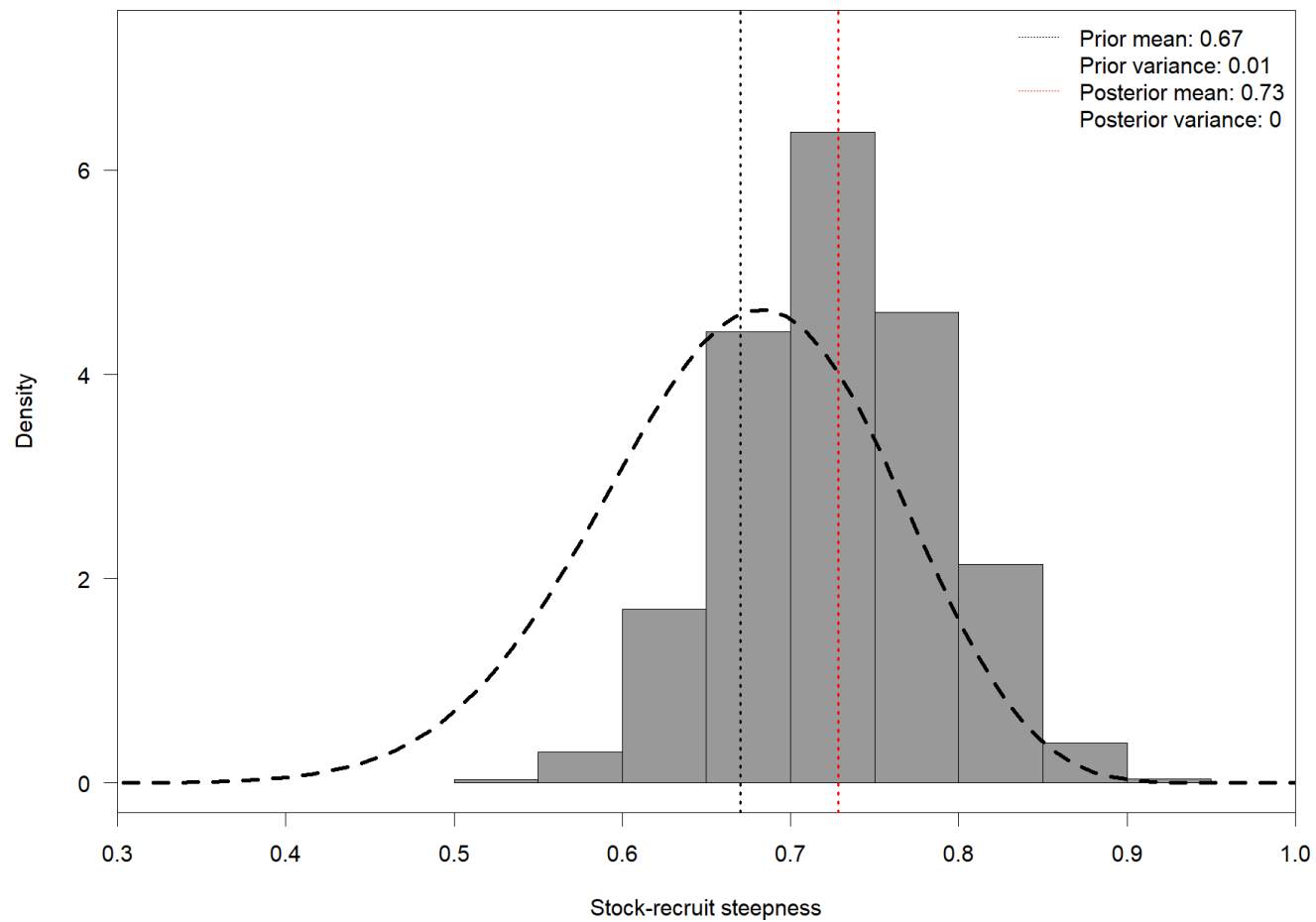


Figure D.46. Central Coast SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for stock-recruitment steepness.

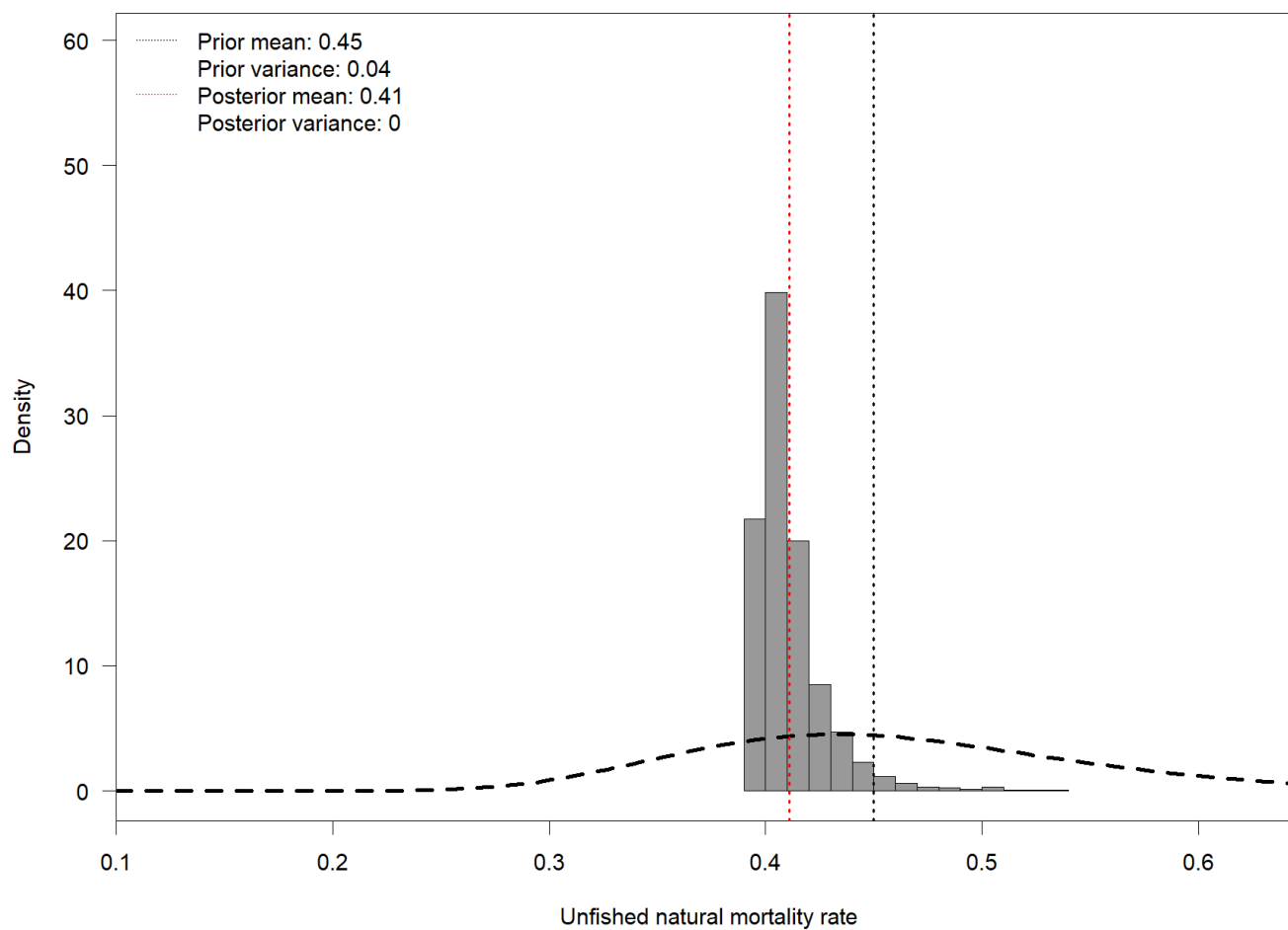


Figure D.47. Central Coast SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for the unfished natural mortality rate M_0 .

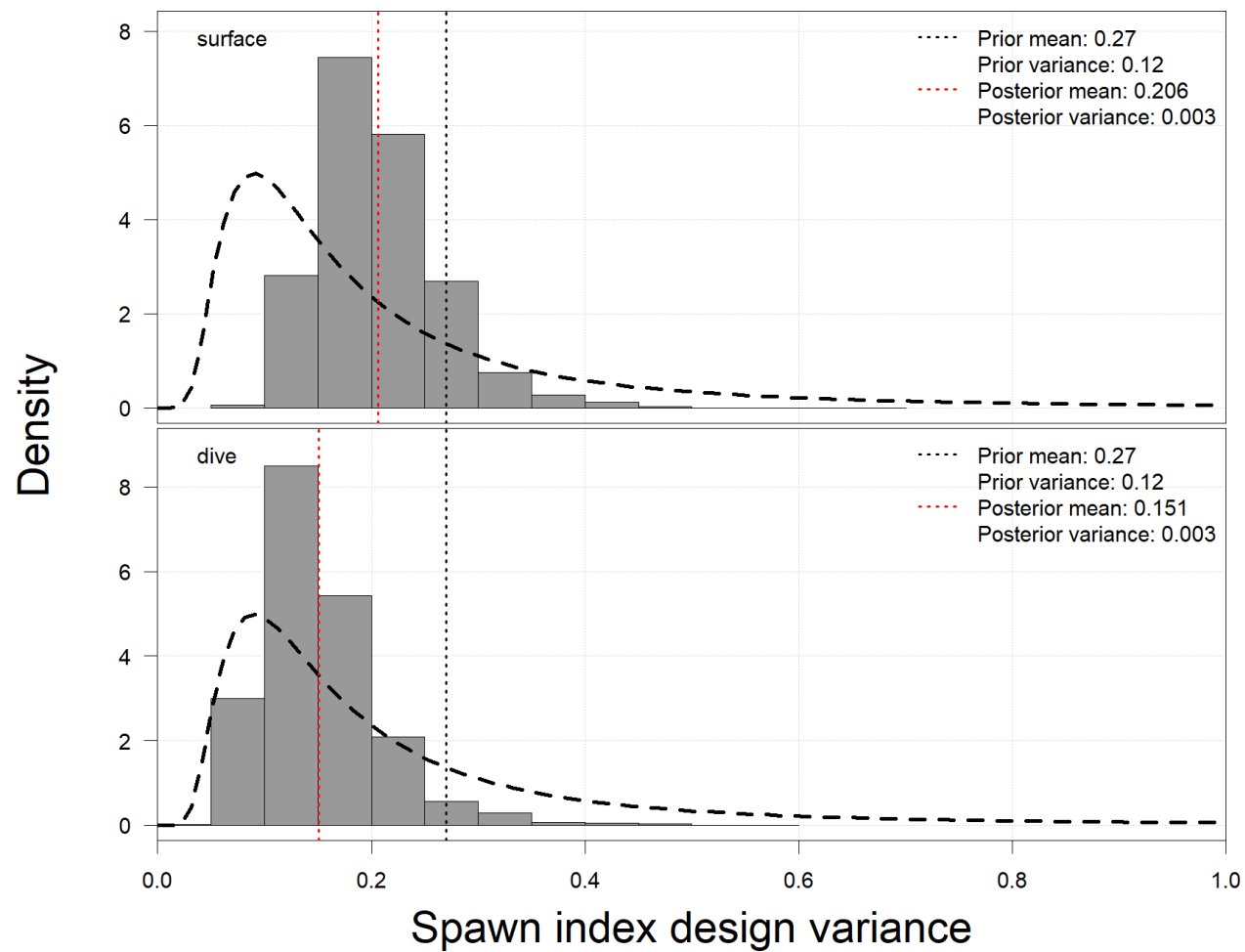


Figure D.48. Central Coast SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for spawn index observation residual standard error components from the Dive survey design (top) and surface survey design (bottom).

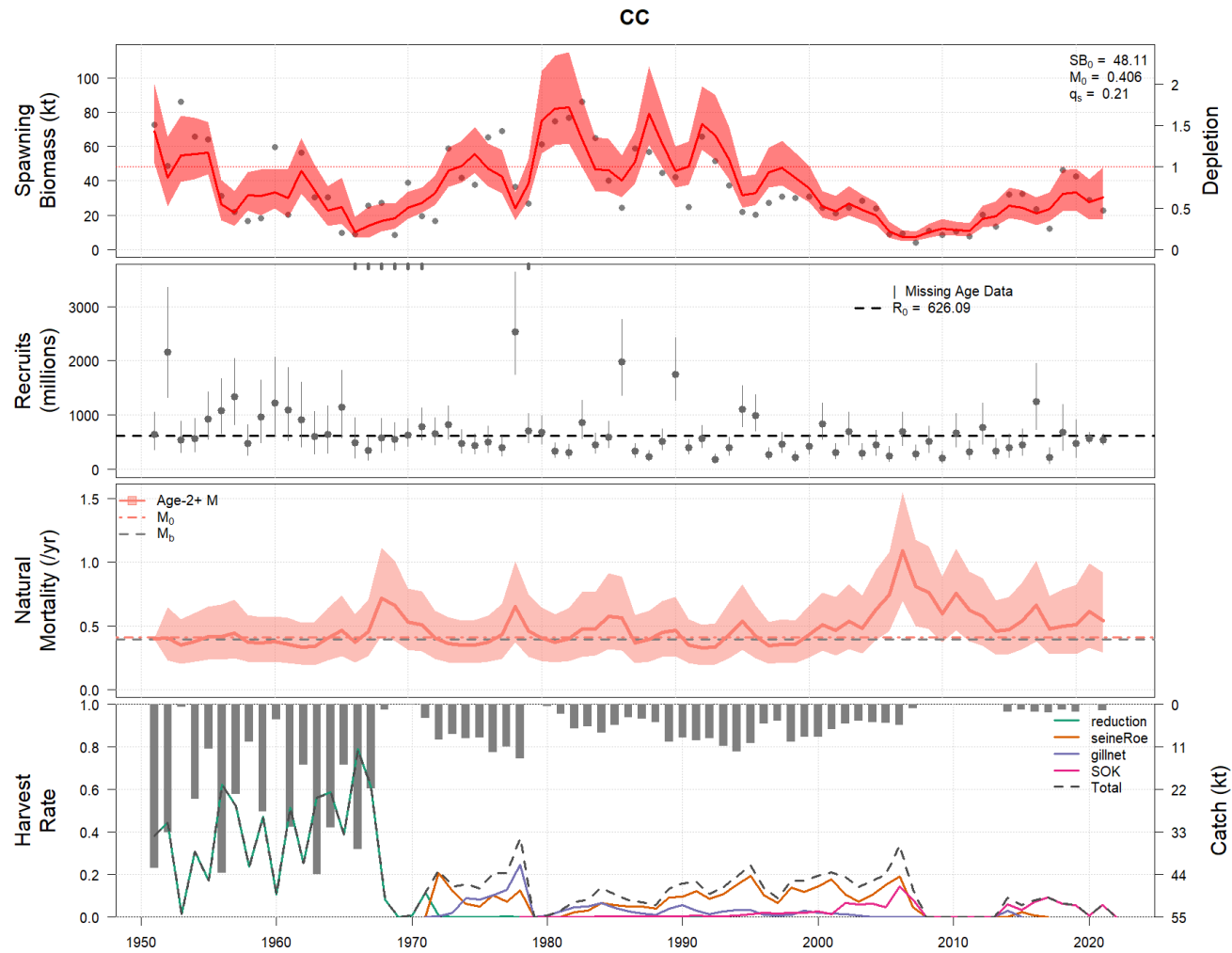


Figure D.49. Time series of Central Coast herring spawning biomass with scaled spawn indices (top), recruitments (second row), natural mortality (third row), and harvest rates (bottom row). SB_0 , M_0 , and R_0 are unfished equilibrium spawning stock biomass, natural mortality, and recruitment respectively. q_s is the catchability coefficient for the surface surveys. SOK is spawn-on-kelp. In the recruitment panel, years with missing age data are indicated with a tick along the top axis, denoted by a 'I' in the figure legend.

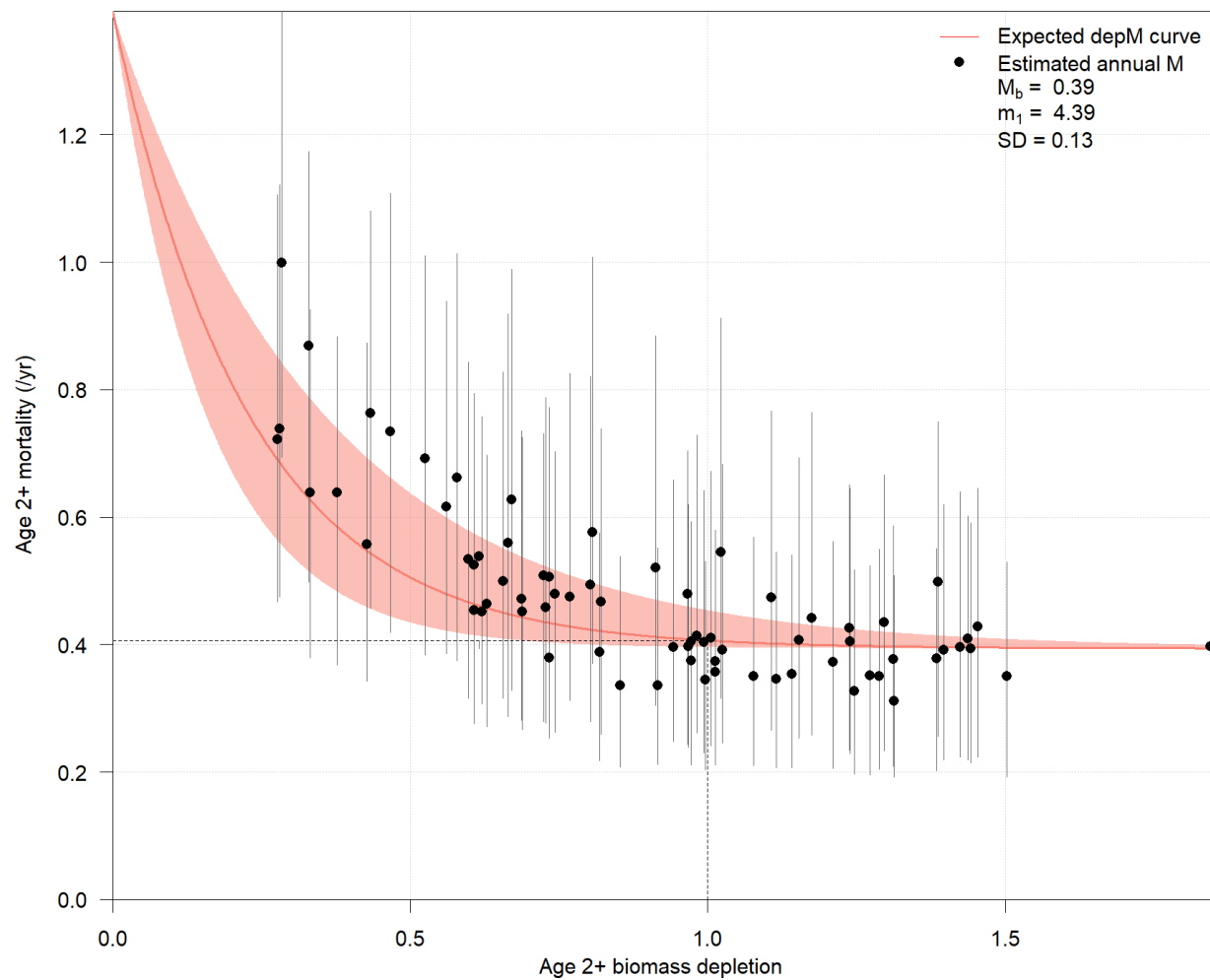


Figure D.50. Central Coast SISCAH model posterior estimate of the density dependent relationship between age-2+ biomass and age-2+ natural mortality. The median relationship is shown by a thick line, with the posterior 95% credibility range shown by the shaded region. Individual points show the annual posterior median natural mortality estimates. The parameters shown are: m_1 = depensation rate; and M_b = asymptotic lower limit of density dependent mortality.

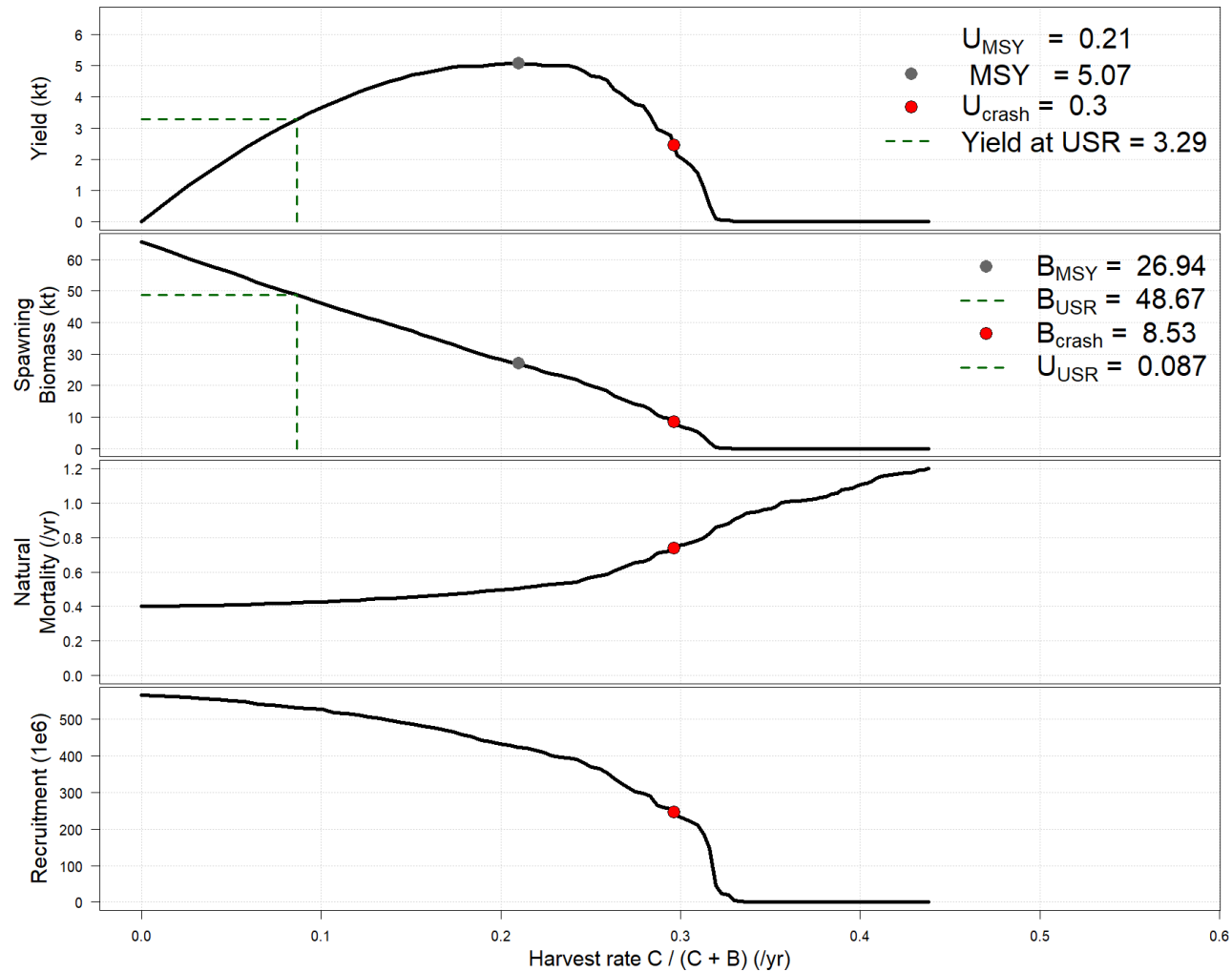


Figure D.51. Central Coast reference points derived via median model equilibria of 200 year fishing mortality simulations, using the SISCAH model, with panels for yield, spawning biomass, natural mortality and recruitment. Grey points show values associated with the maximum sustainable yield (MSY). Red points show values associated with the steepest decline in yield. Green dashed lines show values associated with the upper stock reference (USR). Harvest rates are calculated as catch divided by catch plus spawning biomass.

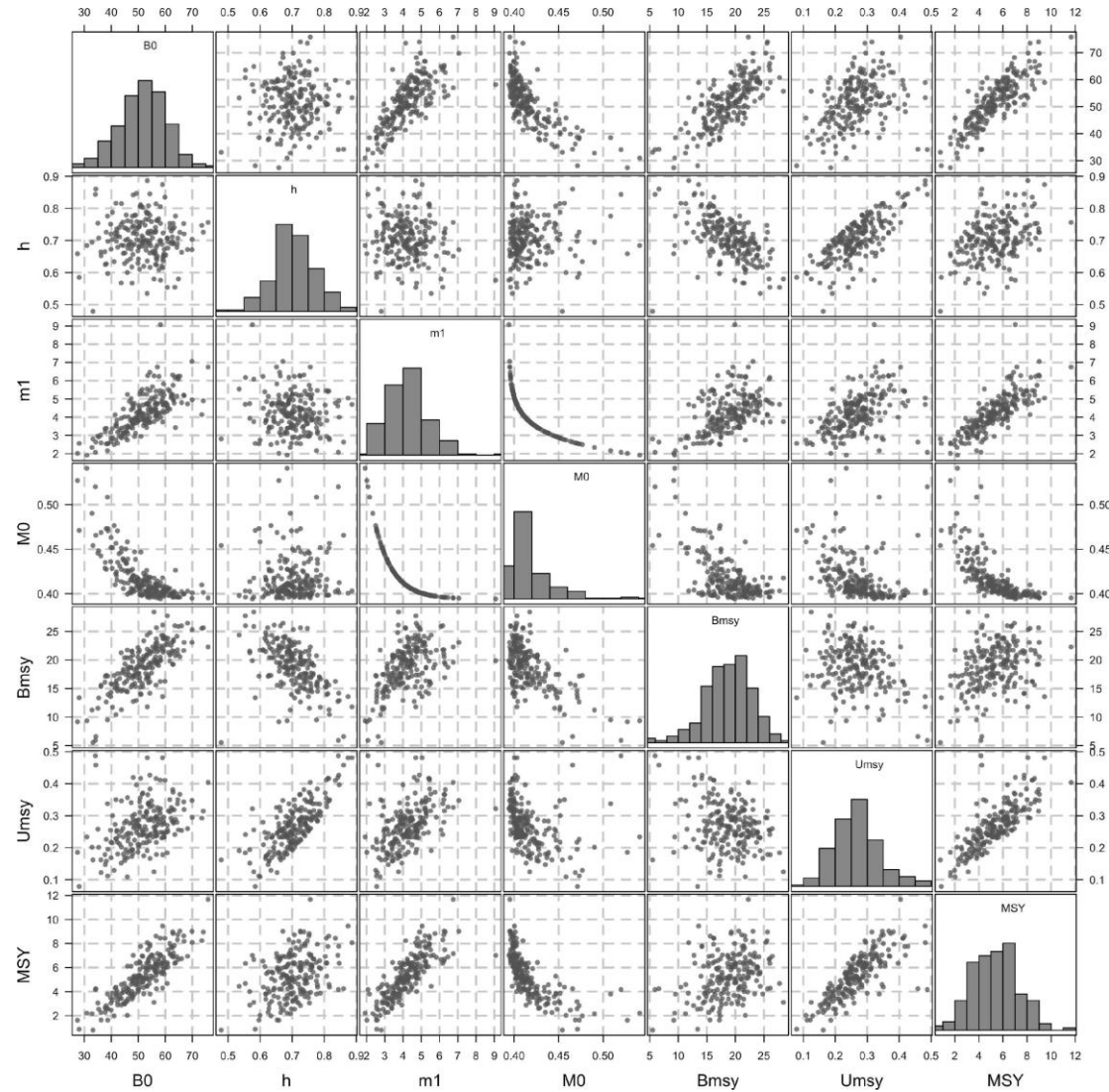


Figure D.52. Central Coast: 500 random draws from joint marginal posterior distributions of selected life-history quantities and deterministic biological reference points, namely SB_0 = deterministic unfished equilibrium spawning biomass, h = stock-recruitment steepness, m_1 = depensation in density dependent mortality (if estimated), M_0 = deterministic unfished equilibrium mortality rate, B_{MSY} = deterministic optimal biomass, U_{MSY} = deterministic optimal harvest rate, MSY = deterministic maximum sustainable yield.

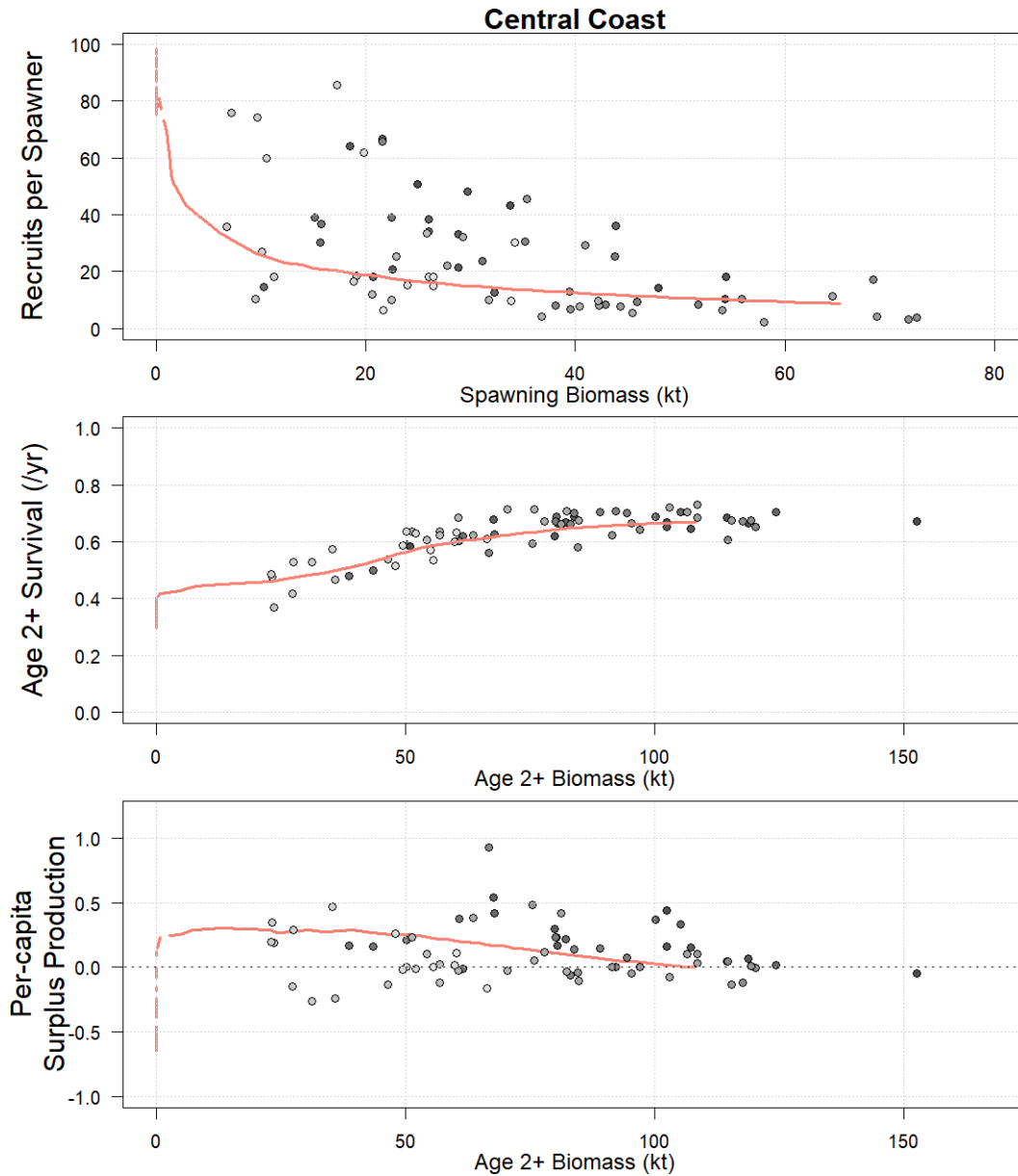


Figure D.53. Central Coast SISCAL model estimates (points) and deterministic equilibria (lines) of recruits-per-spawner vs spawning biomass (top), density dependent age-2+ mortality as a function of age-2+ biomass (middle), and per-capita surplus production as a function of age-2+ biomass (bottom). Points are coloured to show phase, with light points for later years.

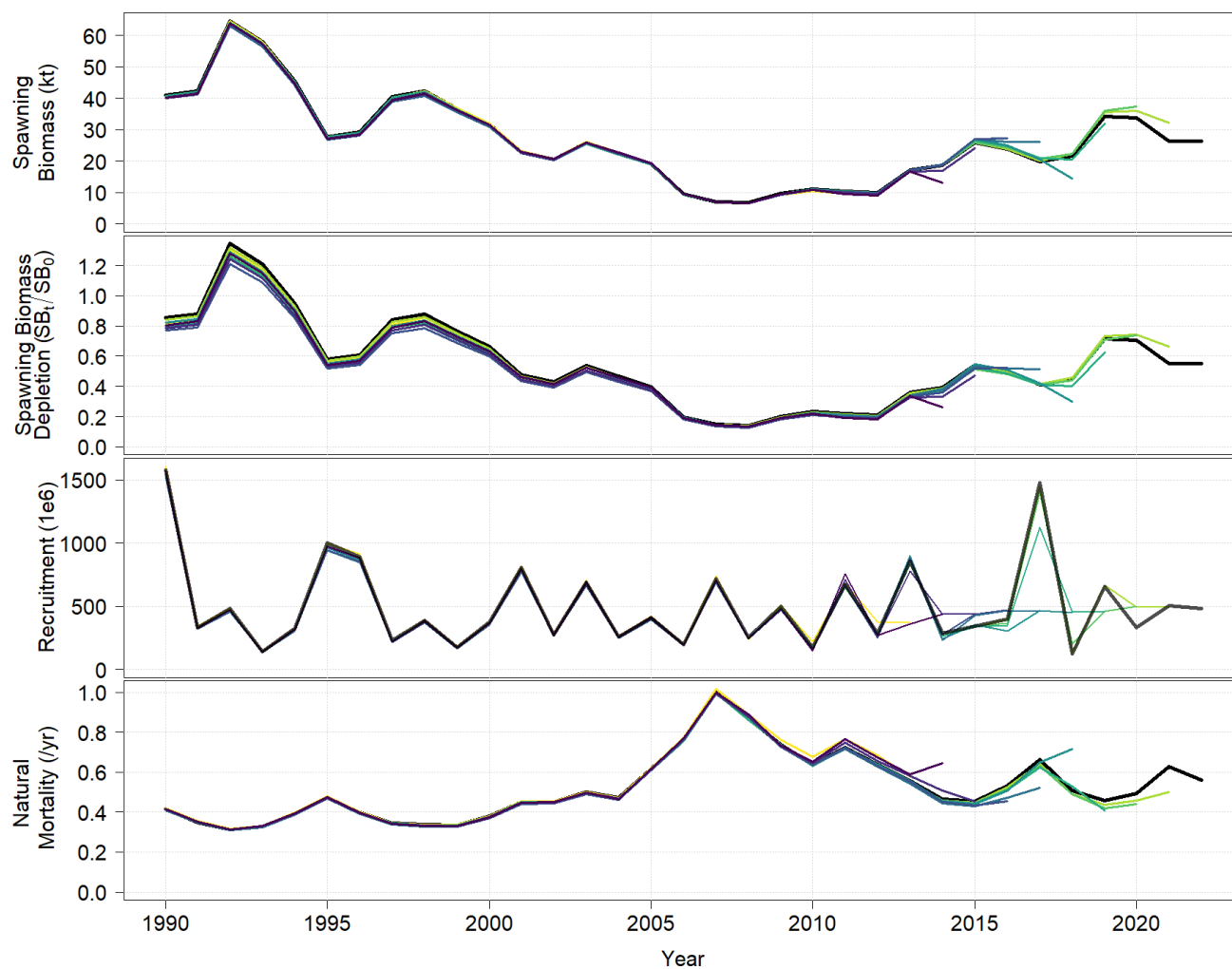


Figure D.54. Central Coast SISCAN model retrospective estimates of spawning biomass (top) and spawning biomass depletion (second row), age-1 recruitment (3rd row), and natural mortality (bottom row), showing SISCAN model fits to successive data 'peels', which are truncated data sets with terminal years 2013–2022. The reference model is the largest data set in the 2022 peel, shown in black.

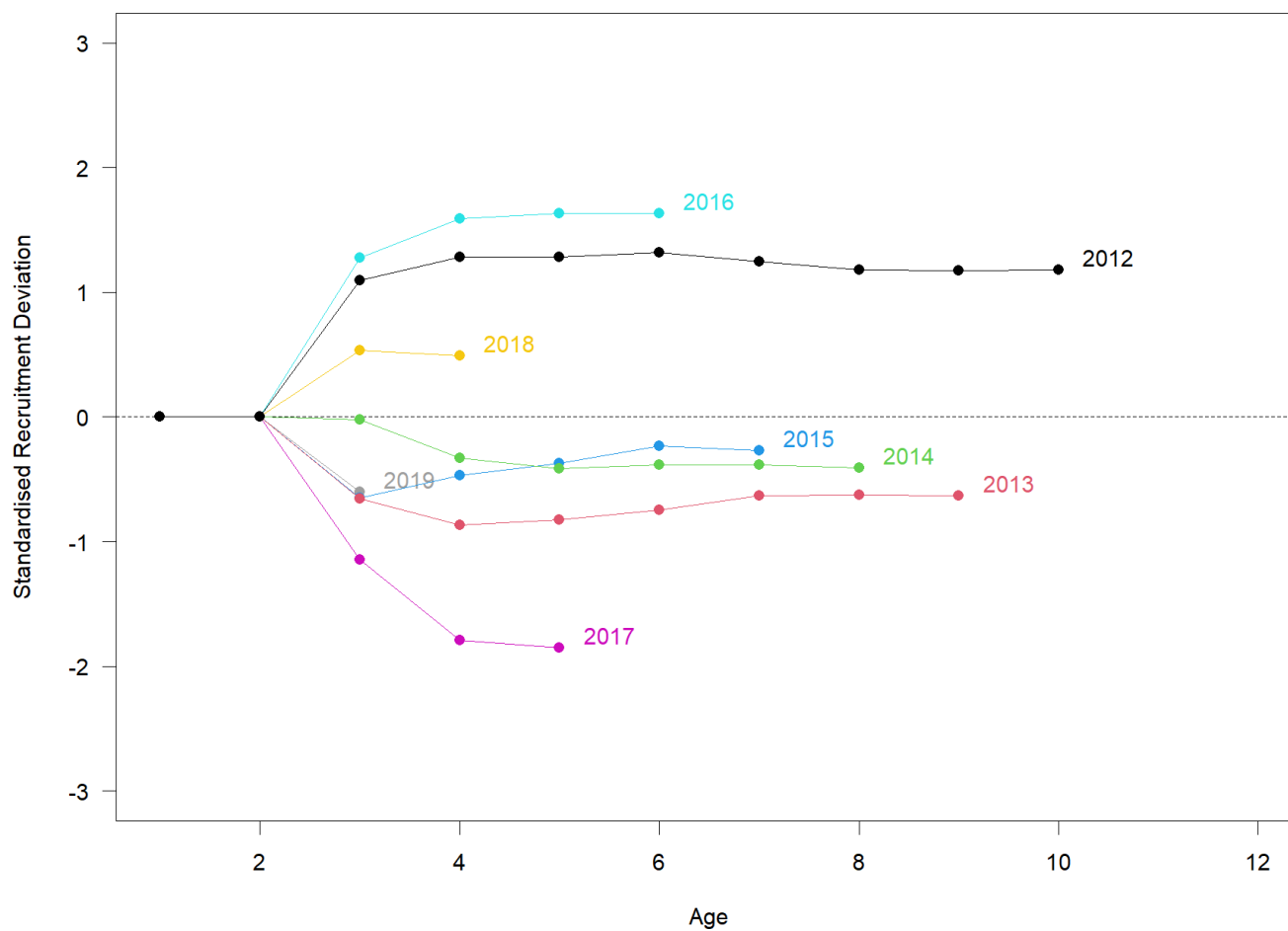


Figure D.55. Central Coast SISCAH model retrospective estimates of standardised recruitment residuals, representing year class strength relative to the deterministic stock-recruitment relationship for models fit to successive data 'peels', which are truncated data sets with terminal years 2013–2022.

D.4. STRAIT OF GEORGIA

D.4.1. Goodness of fit

SISCAH model goodness of fit to Strait of Georgia (SOG) herring data was acceptable. Based on SISCAH model standard errors (Table D.13), index data and age-composition data are consistent with the estimated population dynamics. The residual standard error for individual spawn survey designs had slight differences, with surface survey residuals ($\tau_s = 0.379$) about 32% higher in standard deviation than the dive survey design ($\tau_d = 0.286$). Reflecting the low standard errors, SISCAH model blended spawn index observation residuals over time showed no significant indication of poor fits (Figure D.57). The time series of residuals has low bias, with a mean residual of -0.18 standard errors. Unlike other areas, there was some indication of a weak time dependence to residuals, with an auto-correlation factor of 0.19; despite the auto-correlation, there was no significant time-trend overall ($p = 0.94$).

Age-composition data from all three fisheries fit reasonably well. SISCAH model residuals for all fisheries have standard errors below 0.7, which indicates an acceptable fit (Table D.13). For reference, an age composition residual standard error between 0.8 and 1.0 is marginally acceptable, while above 1.0 is a poor fit and may indicate poor sampling design or model mis-specification.

The seine roe fishery has the lowest age composition sampling standard error at 0.316 while, as in most areas, the reduction fishery has the highest at 0.654. Estimates of age compositions show that SISCAH generally captures the year-class trends over time. In some years, SISCAH over-estimates age-2 proportions for the seine roe fishery (e.g., 2008, 2010), and this occurs to estimate the modal age class correctly in the following year. Such large residuals associated with model predictions of a larger year class may indicate that estimated selectivity is too high for those ages. Age-2 proportions are under-estimated in 2022 for both the food and bait (Figure D.58) and seine roe fisheries, and modal age class is not correctly identified. However, in general, SISCAH is able to track the cohort signals.

Estimates of recruitment process errors show no indication of model bias or model mis-specification (Figure D.61). Specifically, the mean recruitment process error deviation is 0.14 standard errors, and there is no indication of a time-trend ($p = 0.98$) or significant auto-correlation in the deviations. There is also no indication of poor model fits when viewing recruitments relative to biomass around the stock-recruitment curve (Figure D.62).

D.4.2. Bayes posteriors

Standard Bayes posterior convergence metrics indicate that inferences can be drawn from the Bayes posteriors for the SOG SAR SISCAH model. Effective sample sizes for the bulk and tail sections of all marginal distributions are above 100 samples per chain, and all Gelman-Rubin potential scale reduction factors $\hat{R}$ are below the nominated threshold of 1.01 for all parameters (Figure D.63). Sampled posterior points included 35 divergent transitions out of 4000 total samples, or 0.8% of sampled points.

Visual inspection of joint marginal posteriors for leading life-history and selectivity parameters indicates that posterior geometry is of low concern (Figure D.64). Like in other SARs with a DDM model there is positive correlation between the m_1 parameter and SB_0 parameter, but all other distributions shown are close to symmetrical with low skew and low correlation. The remaining joint marginal posteriors of process error terms and nuisance parameters were similar, although there was a low level of lag-1 autocorrelation between successive recruitment process errors (i.e., year class strength relative to the stock-recruit curve has some correlation).

Prior/posterior comparisons tell a similar story to other SARs. As with Haida Gwaii there is limited information in the data for estimating the stock-recruit steepness parameter. The prior and posterior mean are very close, and the variance parameters also very similar (Figure D.65). In contrast, there is a good indication of information in the M_0 posterior, with a slight drop in mean values mean but a larger drop in variance (Figure D.66); however, the variance may be artificially limited given the lower bound on M_0 induced by the model structure, which is hit as the HMC procedure samples higher m_1 values. Finally, spawn survey residual standard errors are well informed by the data. For both designs the posterior mean is lower than the prior mean, and variance drops a similar amount from 0.12 to 0.002–0.003 (Figure D.67).

D.4.3. Historical dynamics

While the Strait of Georgia herring biomass is by far the largest in BC, the dynamics over the historical period show many similarities with the other major SARs. The early period is similar, characterised by higher average recruitments until the collapse towards the end of the 1960s. The post-collapse period spans a wide range of biomass levels but none as low as the collapse (Figure D.68). The main difference with other areas is that median biomass peaks in the time series do not exceed the unfished level, and periods of low biomass do not often decline below 50% of unfished levels, despite continuous and sometimes growing fisheries over the years since 1970.

The main reasons for the relatively stable health of SOG herring is the overall size of the stock and higher m_1 value (Figure D.69). The large stock means that even recruitments that are close to ‘average’ (i.e., close to the Beverton-Holt stock recruit curve) are quite a bit higher than other areas, meaning that the stock sustains higher levels of removals in an absolute sense. In addition, the natural mortality rate time series is quite close to stationary, resulting from the higher m_1 value ($m_1 = 4.49$, Table 11). Therefore, when SOG mortality increases, the recovery can be much faster following a string of higher recruitments, since mortality can quickly return to the unfished mortality level M_0 .

In a relative sense, harvest rates post-1968 have been kept well below the SISCAN model estimates of U_{MSY} (Figure D.70, described further below). As a result, catches have largely been removing surplus production, increasing the productivity of the stock. Therefore, the estimated declines in SOG herring biomass since the 1970s are largely attributed to low recruitments rather than higher removals. The main exception is the 2 years of harvest rates above 20% just before the decline to around 45 kt in the mid-1980s; however, that decline was already occurring due to a preceding string of lower recruitments, and fishing was reduced or stopped when the decline became apparent (Figure D.68).

D.4.4. Biological reference points

SISCAN model equilibria, or biological reference points (BRPs), estimates a maximum sustainable yield (MSY) of approximately 22.7 kt, achieved when spawning biomass at around 41.8 kt. This equates to an optimal harvest rate of around $U_{MSY} = MSY / (B_{MSY} + MSY) = 0.36$. Unlike other SARs, this harvest rate does not account for any SOK fishing, so all removals are associated with mortality. As in other areas, there is a crash point where yield drops fastest, around a 53% harvest rate for SOG, following which the equilibrium biomass, yield, and recruitment all decline to zero (Figure D.70).

Joint marginal posteriors of life-history quantities and MSY-based reference points show a little more dependence between the DDM model parameter m_1 and the model equilibria (Figure D.71). As expected, biomass based quantities are correlated with m_1 values, as the

DDM model links mortality and unfished biomass through its dependence on biomass depletion. As with Haida Gwaii, and in contrast to the Central Coast SAR, the correlation between m_1 and U_{MSY} is weakly positive.

Per-capita demographic rates shed more light on the equilibrium properties of SISCAH at low biomass levels (Figure D.72). Sudden changes in equilibrium model states are driven by shifts in per-capita demographic rates (Figure D.72). Unlike other areas, SOG dynamics do not show any negative per-capita surplus production; however, there is evidence that the instability begins around 50 kt of age-2+ biomass, below which the per-capita surplus production curve snaps close to the vertical axis.

D.4.5. Retrospective analyses

Results of the retrospective analysis suggests that SISCAH estimates of Strait of Georgia herring biomass and life history parameters are somewhat sensitive to additional years of data. Spawning biomass (both absolute and depletion) for the years before the first peel are very consistent over the all peels (Figure D.73); however, there is some tendency of SISCAH to consistently under-estimate biomass for the last couple of years peels (exception: 2021 and 2018 peels). Under-estimates of biomass are caused by the SISCAH assumption of deterministic recruitments in the final two years of each peel, which for the SOG area are under-estimates of the real recruitments for the retrospective period. As the retrospective analysis moves from peel to peel forward in time, recruitment process errors are only estimated for cohorts starting at age-3. Because recent recruitments have had positive residuals (Figure D.74), smaller deterministic age-2 cohorts are revised to larger age-3 cohorts, bringing the under-estimates of biomass back upwards to the 2022 reference peel (Figure D.73).

Similarly, estimates of age-2+ natural mortality and recruitment time series are very consistent before 2010 (Figure D.73). However, recent variations in spawning biomass between peels tends to create revised natural mortality rates as year-class strength is revised between age-2 and age-3, most notably for 2016, 2017, and 2018 peels.

There is a higher degree of variability in unfished equilibrium quantities over the retrospective peels (Table D.14). Unfished biomass SB_0 changes by around 15% over the ten years, and unfished recruitment R_0 by around 14%. Despite this higher variability in life-history parameters, estimates of biomass across peels are consistent (once process errors are estimated). As above, such stability in model states like biomass, recruitment, and mortality time series is partly a result of process errors that adjust over time to compensate for the variability in life-history quantities (Figure D.74), producing relatively stable recruitments.

While recruitment process error does vary slightly over time, it appears that the individual year class strength resolves quickly and remains stable (Figure D.74). Most year classes are resolved by age-4. Notably, the 2012 year class stabilises more slowly, only stabilising around age 6 after steadily trending upwards to around 1 standard deviation from close to zero at age-3. As noted above, most recruitment deviations for the recent period covered by the retrospective period are positive, indicating a relatively productive recent period. While the distribution of recent recruitment deviations is not balanced with respect to the stock-recruitment curve, it is only a relatively small window of time compared to the whole historic time series, which as described above has no indication of an imbalance (Figure D.61).

D.4.6. Sensitivity analyses

SISCAH estimates of Strait of Georgia herring biomass and life history parameters were somewhat sensitive to specific choices of priors (Table D.15). As above, priors on unfished

mortality M_0 had a larger effect on unfished biomass levels SB_0 and the depensation rate m_1 , while priors on stock-recruit steepness had a larger effect on the steepness parameter. Similar to the CC SAR, the standard deviation for mortality process errors σ_M had a noticeable effect on unfished biomass scale, with the highest and lowest SB_0 estimates under those sensitivities, related to the link between depletion levels and the deterministic component of mortality rates. Specifically, unfished biomass SB_0 and m_1 need to shift so that a more or less variable mortality process errors can be accommodated while producing similar overall population dynamics.

Out of seven SISCAH initial condition configurations tested for the Strait of Georgia SAR, six successfully converged. Similar to the previous case, the primary impact of adjusting the fished initialization settings was observed in the first-year age-1 recruitment, either in terms of R_0 or R_{init} , and the unfished biomass SB_0 (see Table D.16). This adjustment had indirect effects on M_0 due to its correlation with SB_0 and stock-recruitment steepness ϕ .

Unlike the previous scenario, the relationship between F_{init} and the initial age-1 recruitment value was not as straightforward. In non-equilibrium conditions, where initial recruitment deviations were present, the inclusion of F_{init} led to an increase in R_{init} . On the other hand, in cases where there were no initial recruitment deviations and the initial population was in equilibrium, adding F_{init} to the model resulted in a lower R_{init} value. The primary reason for the lower R_{init} when F_{init} was included under equilibrium initialisation is the reduced unfished natural mortality M_0 , indicating a redistribution of the initial mortality between natural and fishing mortality to achieve a similar initial age structure under deterministic conditions. In the same two models, a side effect of the shift from fishing to natural mortality was a lower B_0 of 65 kt when F_{init} was excluded, which is roughly half of the estimated 130 kt when F_{init} was used in the initial survival calculations. This significant shift in SB_0 was accompanied by substantial changes in m_1 , h , and M_0 .

Despite these substantial fluctuations in R_{init} , M_0 , and SB_0 , there was still a considerable degree of stability in biomass and recruitment estimates in each year, with only minor differences between models from 1951 to 1953. After 1953, the biomass trend remained very similar across all models, with some divergence observed in the R_{init} only model, where SB_0 was roughly half that of other models. As in the previous case, it appears that other model parameters, such as recruitment and mortality process errors, were capable of compensating for changes originating from the initial conditions of the model.

D.4.7. Tables

Table D.13. Estimated residual standard errors and lag-1 age residual correlations for Strait of Georgia herring data. The first six columns show age data sampling standard errors τ_g^{age} and correlation coefficients ρ_g from the LN1 age composition likelihood function the Reduction and Food & Bait ($g = 1$), Seine-roe ($g = 2$), and gillnet fisheries ($g = 3$), and the last two columns show spawn survey index standard deviations for the surface (τ_s) and dive (τ_d) surveys.

SAR	τ_1^{age}	ρ_1	τ_2^{age}	ρ_2	τ_3^{age}	ρ_3	τ_s	τ_d
SOG	0.654	0.769	0.312	0.483	0.538	0.743	0.342	0.309

Table D.14. Strait of Georgia retrospective estimates of selected SISCAN model leading and derived life-history quantities over data peels from 2012–2022. Selected quantities are SB_0 = estimated unfished equilibrium spawning biomass(kt), R_0 = estimated unfished equilibrium recruitment (1e6), R_{init} = estimated initial recruitment (1e6), m_1 = depensation rate (unitless), M_b = asymptotic lower bound on age-2+ natural mortality (yr), M_0 = equilibrium unfished age-2+ natural mortality (yr), q_s = surface survey catchability (unitless).

Peel	B_0	R_0	m_1	M_0	h	q_s
2013	89.509	2,552.376	2.326	0.674	0.712	0.687
2014	88.691	2,448.128	2.420	0.665	0.715	0.698
2015	93.079	2,679.242	2.317	0.675	0.712	0.671
2016	98.919	2,955.908	2.231	0.683	0.710	0.642
2017	99.975	2,582.158	2.659	0.646	0.714	0.685
2018	98.200	2,487.213	2.739	0.641	0.714	0.698
2019	104.631	2,728.856	2.639	0.647	0.715	0.670
2020	103.482	2,581.168	2.817	0.636	0.717	0.689
2021	98.523	2,477.582	2.793	0.637	0.713	0.702
2022	102.034	2,524.819	2.873	0.633	0.709	0.699

Table D.15. Strait of Georgia SISCAN model estimates of life-history and observation model quantities under sensitivity analyses.

Sensitivity	SB_0	R_0	m_1	M_0	h	q_s
base	102.034	2,524.819	2.873	0.633	0.709	0.699
jeffHi	96.457	2,515.291	2.666	0.646	0.708	0.698
jeffLo	102.034	2,524.819	2.873	0.633	0.709	0.699
meanMHi	94.442	2,600.240	2.488	0.659	0.705	0.686
meanMLow	109.046	2,468.451	3.356	0.611	0.707	0.712
qSurfSDHi	102.021	2,528.777	2.865	0.633	0.709	0.697
qSurfSDLo	102.087	2,509.756	2.901	0.631	0.709	0.705
sdMHi	94.489	2,599.725	2.490	0.659	0.705	0.686
sdMLow	112.962	2,442.692	3.734	0.600	0.703	0.722

Sensitivity	SB_0	R_0	m_1	M_0	h	q_s
sigmaMhi	80.902	2,563.274	2.130	0.695	0.670	0.728
sigmaMlo	124.534	2,712.327	3.665	0.602	0.717	0.657
steepMeanHi	99.113	2,494.085	2.802	0.637	0.886	0.691
steepSDHi	101.897	2,518.781	2.877	0.632	0.731	0.698
steepSDLo	102.025	2,529.686	2.864	0.633	0.693	0.699

Table D.16. Strait of Georgia SISCAH model estimates of life-history and observation model quantities under the initial conditions sensitivity analyses.

Initial Conditions			SB_0	R_0	R_{init}	F_{init}	m_1	M_b	M_0	h	q_s
initR	initF	initDevs									
R_0	TRUE	FALSE	130.970	2,686.873	–	0.800	4.475	0.576	0.587	0.675	0.726
R_0	FALSE	TRUE	102.034	2,524.819	–	0.000	2.873	0.576	0.633	0.709	0.699
R_{init}	FALSE	FALSE	65.450	2,870.010	4,167.281	0.000	1.583	0.576	0.781	0.645	0.656
R_{init}	TRUE	FALSE	130.274	2,670.421	3,531.207	0.795	4.492	0.576	0.587	0.676	0.729
R_{init}	TRUE	TRUE	129.829	2,657.185	3,306.592	0.786	4.525	0.576	0.587	0.677	0.732
R_{init}	FALSE	TRUE	124.835	2,613.120	1,466.947	0.000	4.125	0.576	0.592	0.687	0.732

D.4.8. Figures

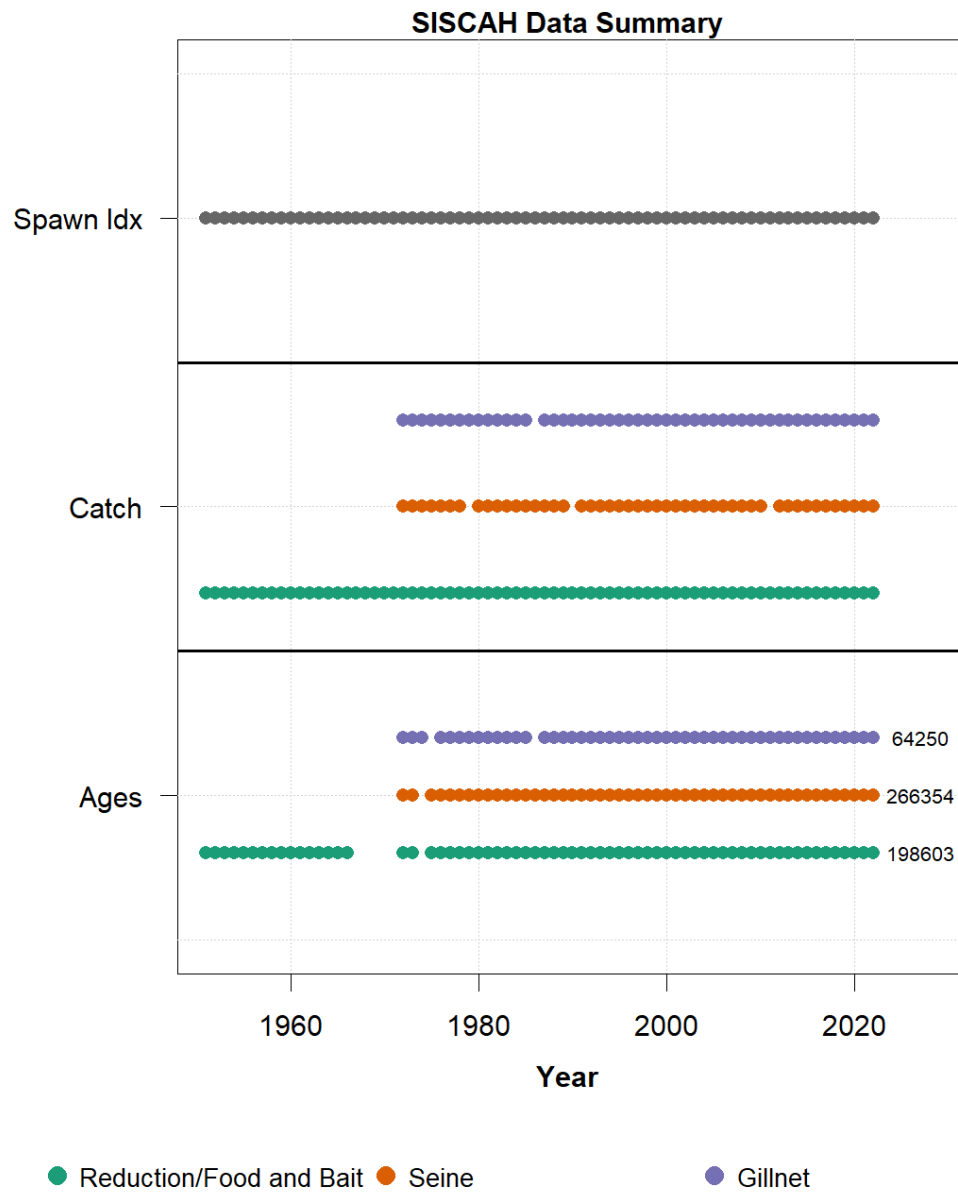


Figure D.56. Time series of Strait of Georgia herring stock assessment data. Each dot shows the existence of data, and age data shows total number of samples over all years at the right hand end.

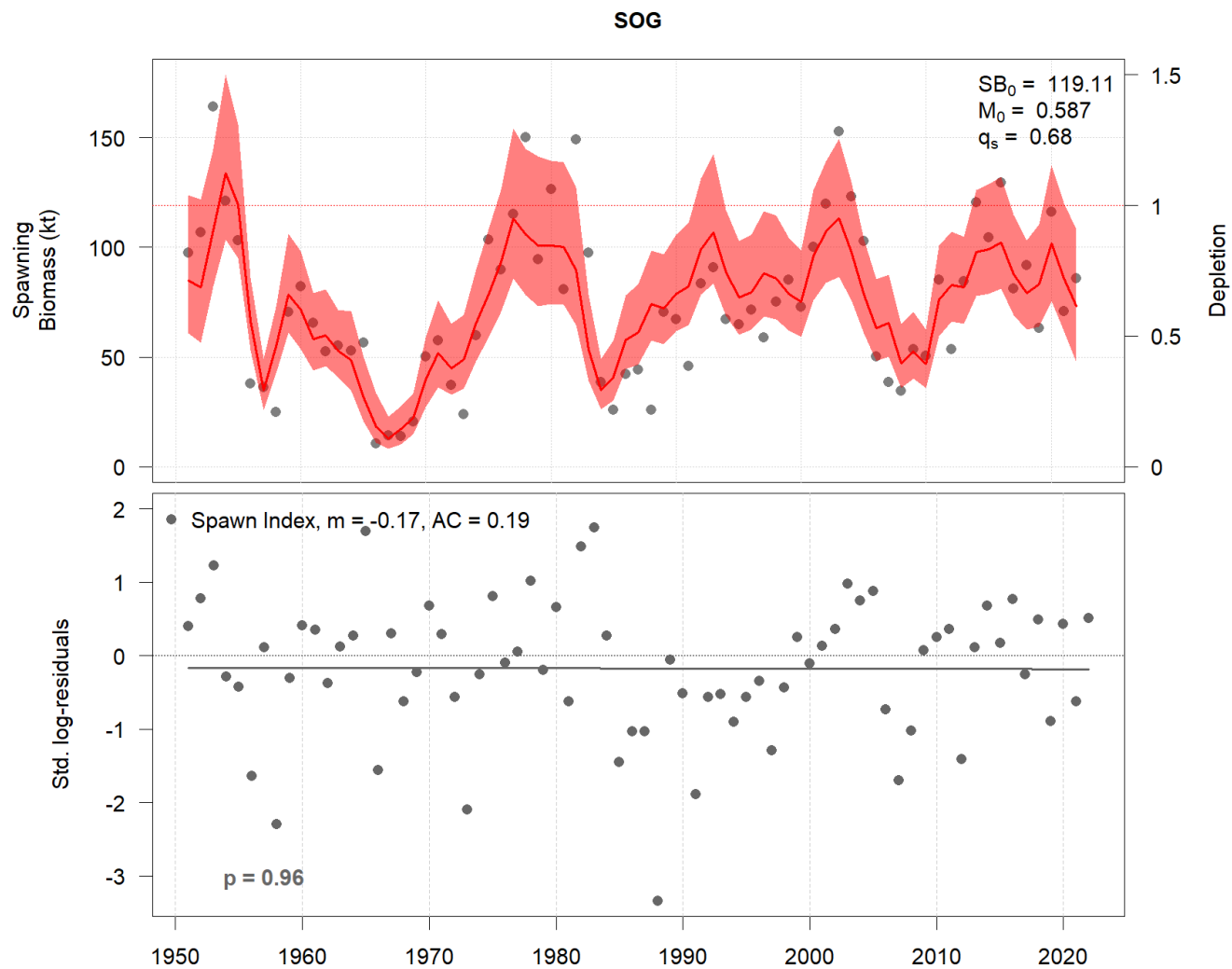


Figure D.57. Strait of Georgia blended spawn index and SISCAH spawning biomass estimates (top) and standardised observation residuals (bottom). SB_0 and M_0 are the unfished equilibrium spawning stock biomass and the natural mortality respectively, q_s is the catchability coefficient for the surface surveys, m is the mean log residual of the spawning index, and AC is the autocorrelation.

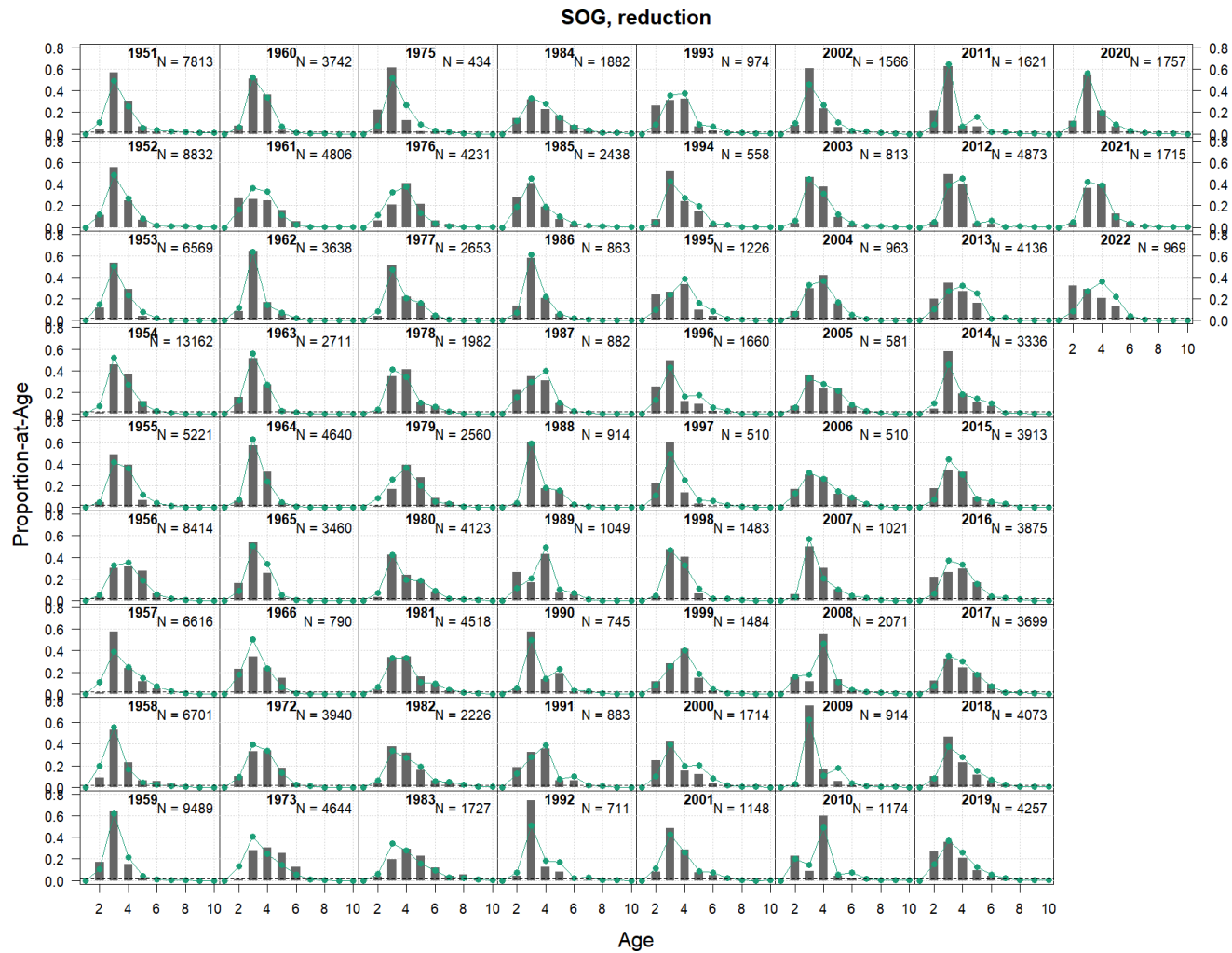


Figure D.58. SISCAH model fits to reduction and food and bait age compositions collected from the Strait of Georgia region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

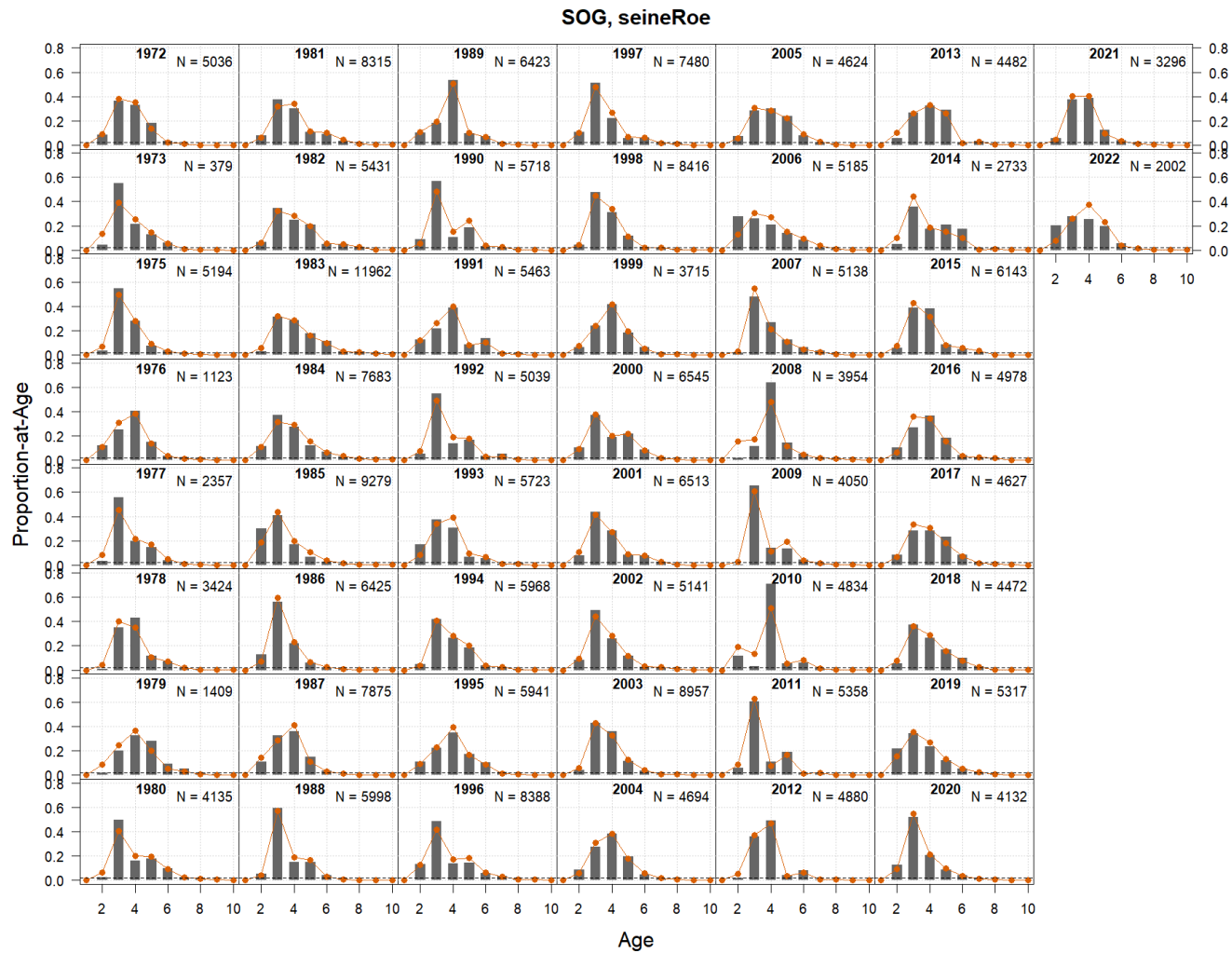


Figure D.59. SISCAH model fits to seine roe age compositions collected from the Strait of Georgia region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

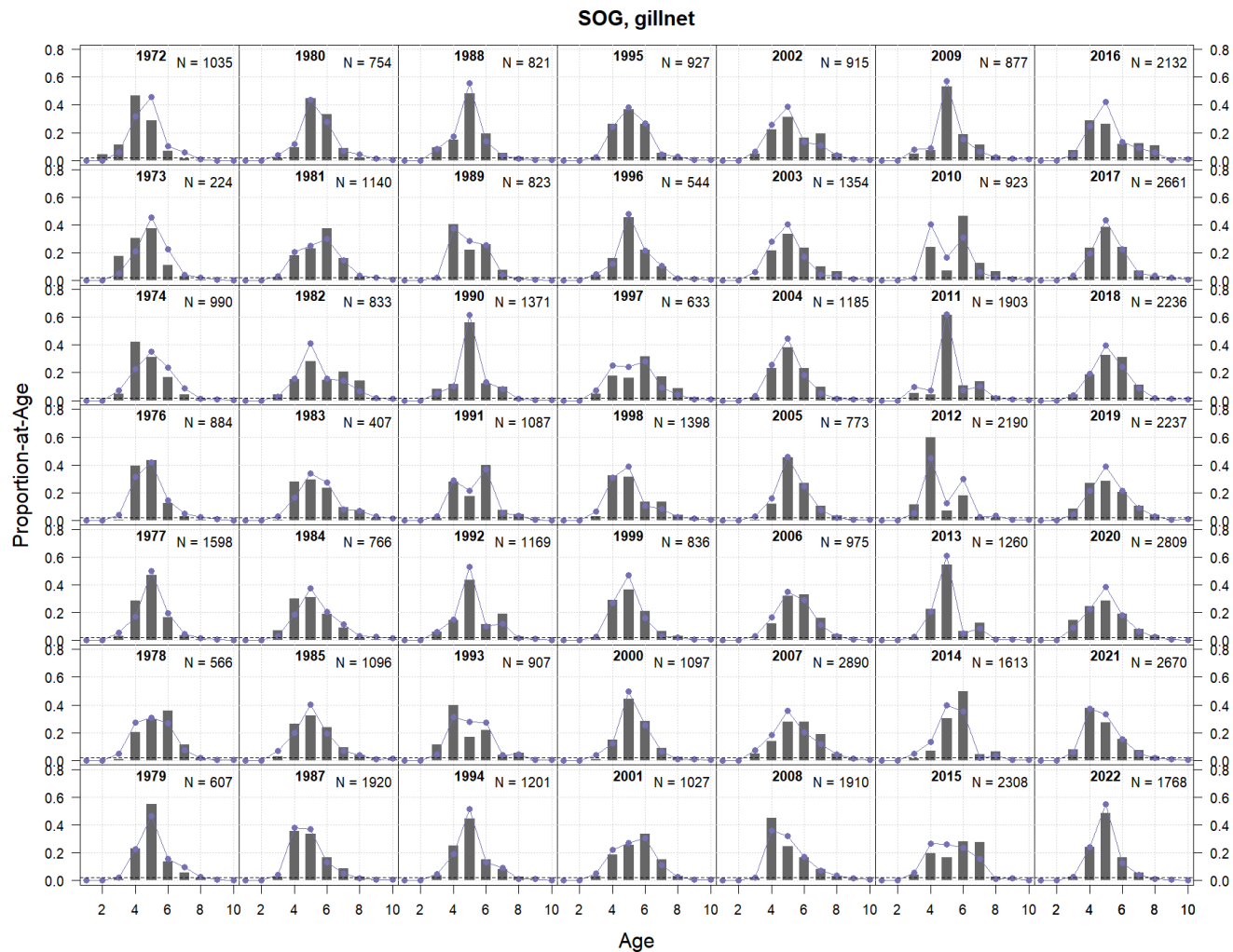


Figure D.60. SISCAH model fits to gillnet age compositions collected from the Strait of Georgia region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

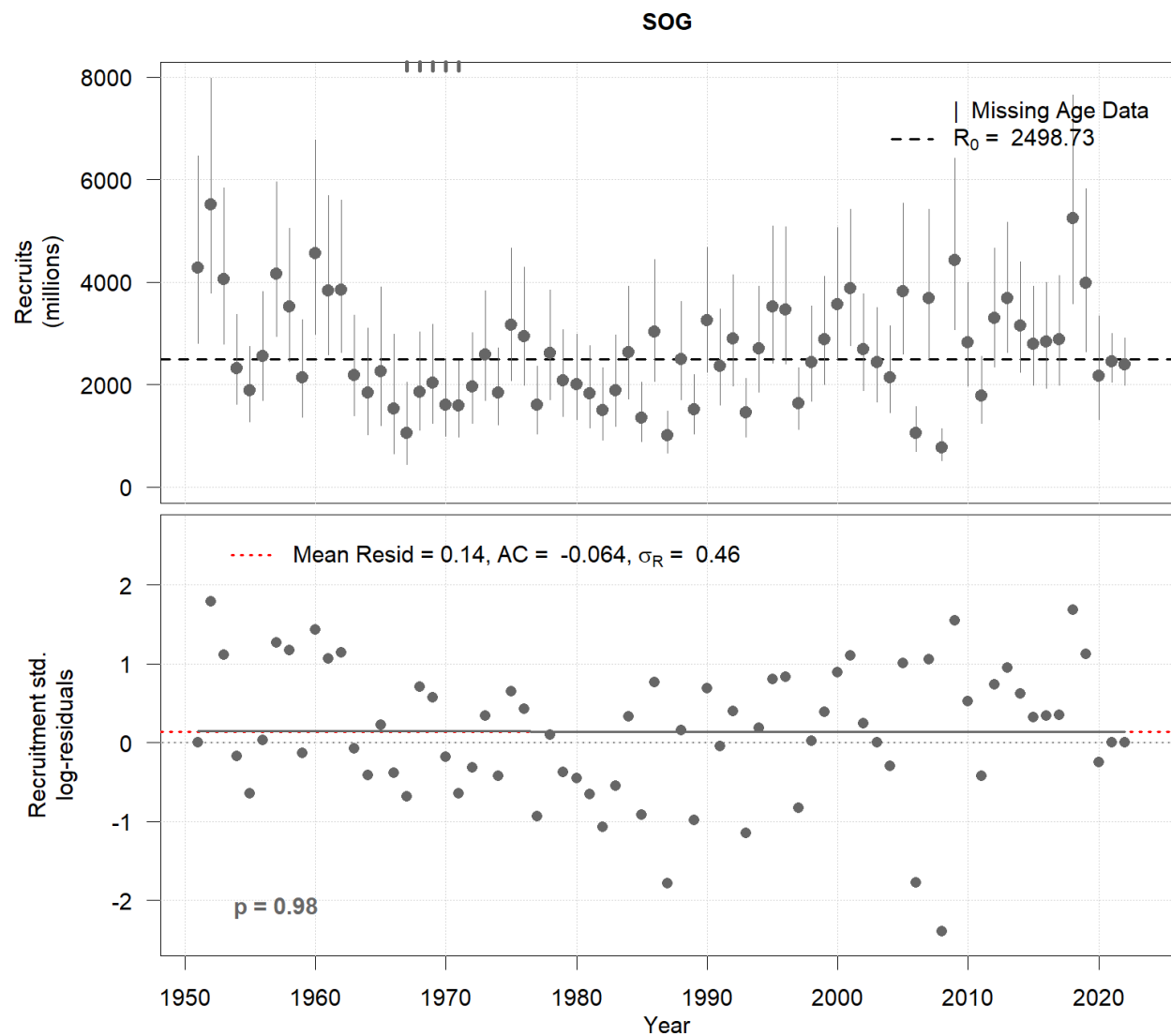


Figure D.61. Strait of Georgia age-1 recruitments (top) and standardised recruitment process errors (bottom). Equilibrium unfished recruitment R_0 is indicated by the horizontal dashed line in the top panel, and the mean process error (Mean Resid) is shown by the horizontal red dashed line in the bottom panel. AC is auto correlation and σ_R is the standard error in the log residuals.

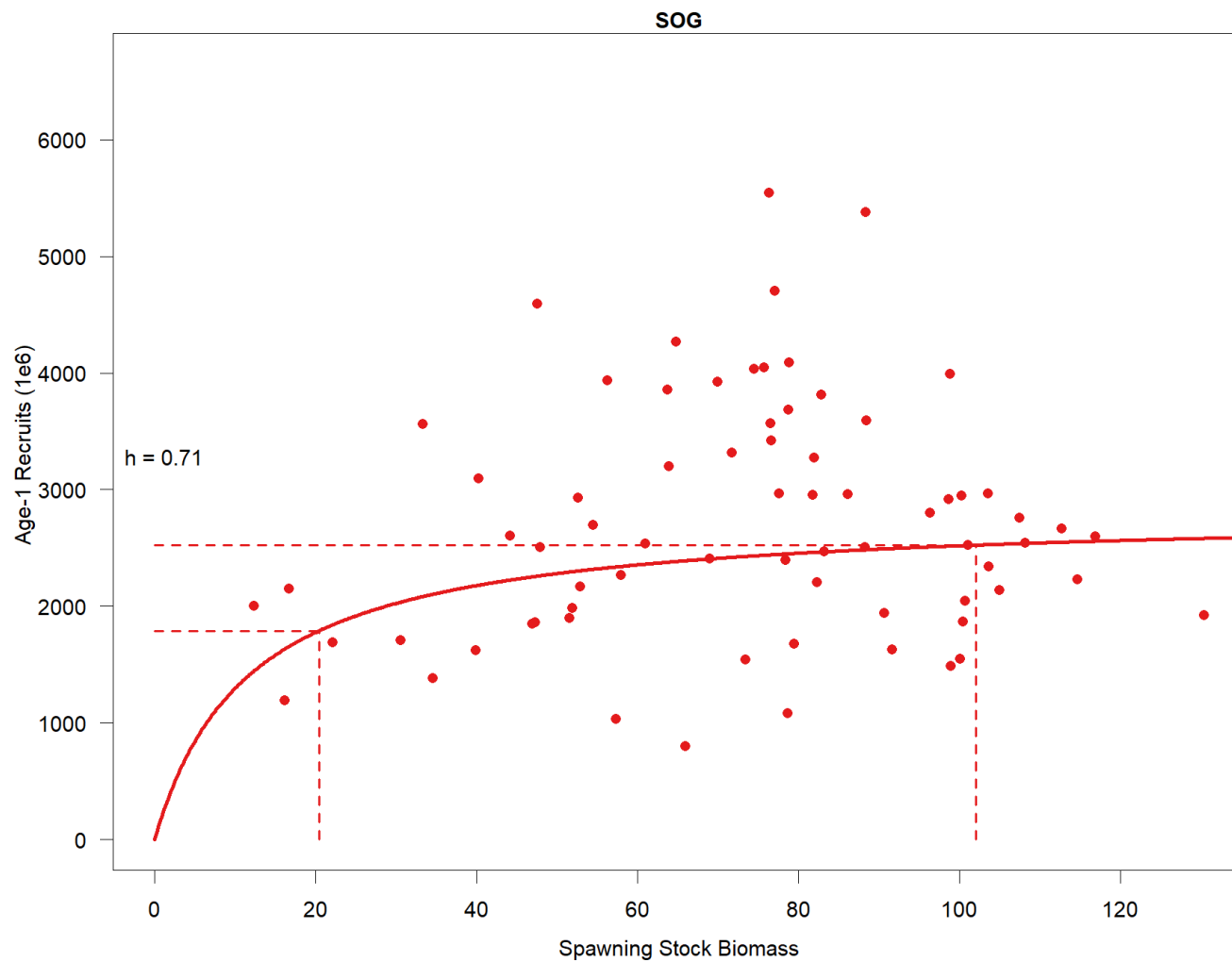


Figure D.62. Strait of Georgia stock-recruitment curves (solid lines) and age-1 estimated recruitments (points), with unfished and 20% of unfished biomass and recruitment shown as dashed lines. h is the estimated stock recruit steepness.

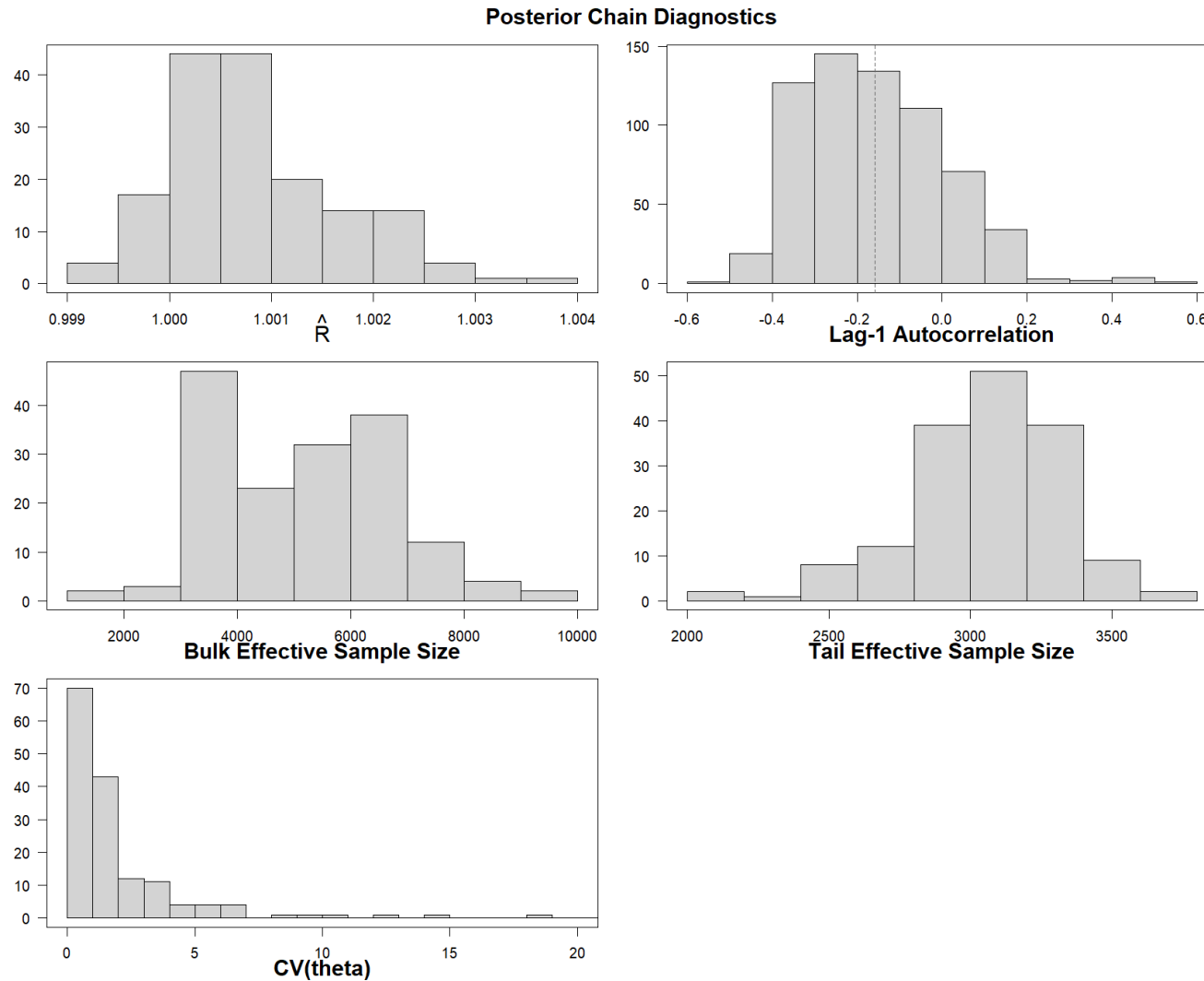


Figure D.63. Histograms of Strait of Georgia SISCAN model Bayes posterior convergence diagnostics for each leading model parameter, showing the distribution of values of each metric across all parameters. From left-to-right, starting in the top row, metrics are Gelman-Rubin scale reduction factors ($\hat{R}$), lag-1 autocorrelation factors, (bulk) effective sample size of draws in the central quantiles, (tail) effective sample size in the outer quantiles, and coefficient of variation (CV) of each parameter. Vertical red dashed lines indicate convergence thresholds, and the vertical dashed grey line indicates the median lag-1 autocorrelation.

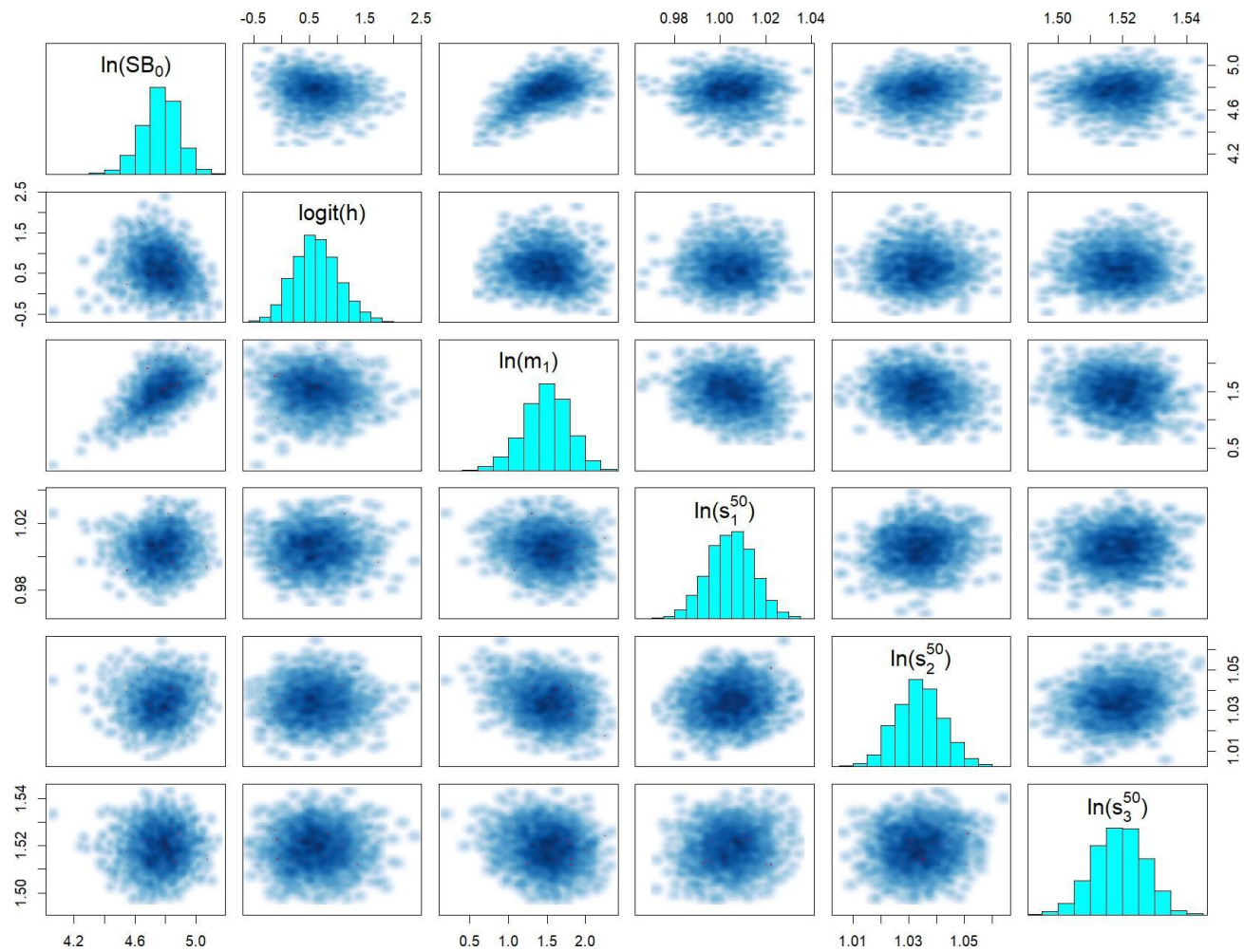


Figure D.64. Strait of Georgia SISCAL model marginal Bayes posteriors (main diagonal) and pair-wise joint-marginal Bayes posteriors (off-diagonal) for selected life-history and selectivity parameters. Red points indicate samples associated with divergent transitions.

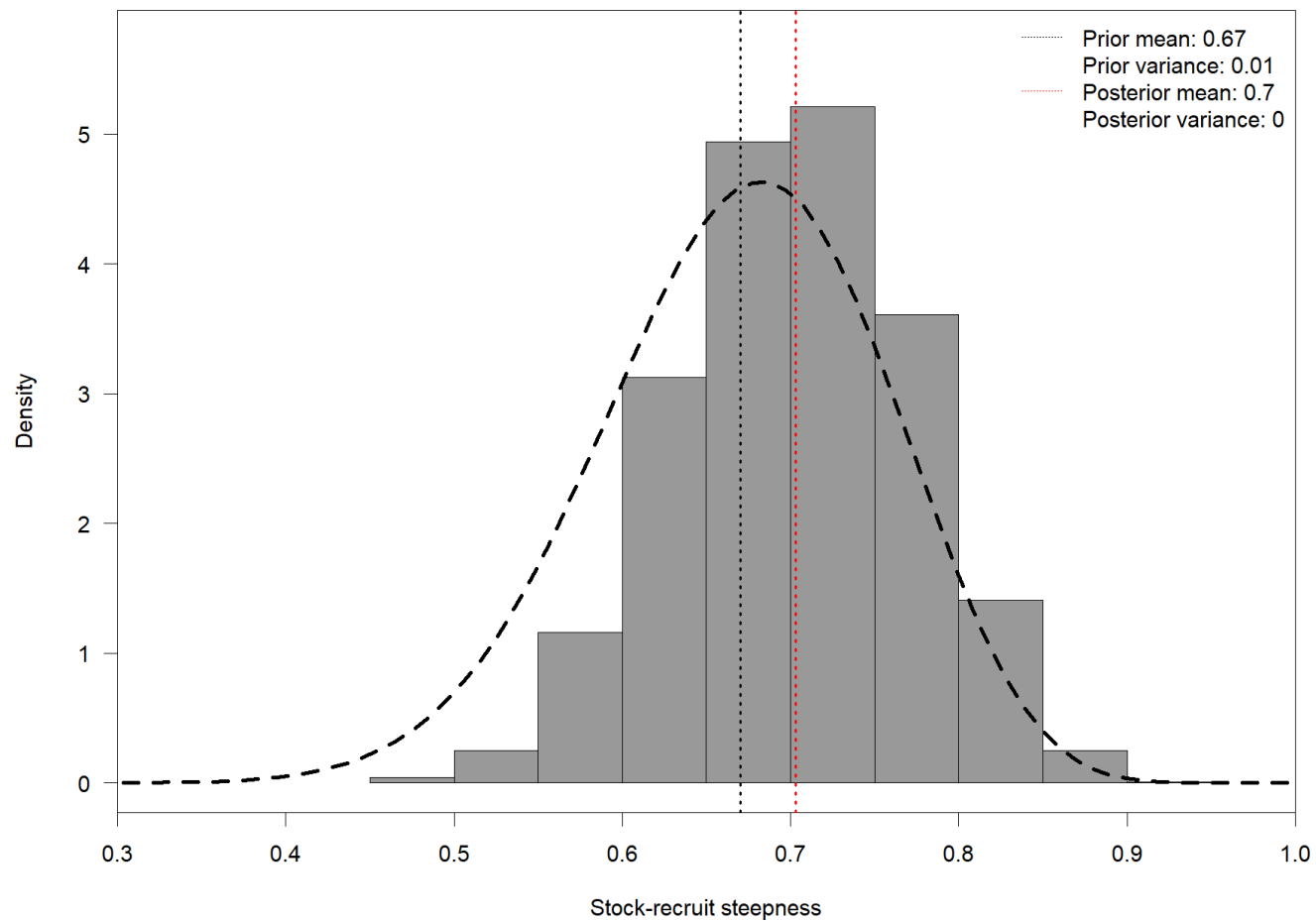


Figure D.65. Strait of Georgia SISCAN model marginal Bayes posterior (rectangles) and prior (line) distributions for stock-recruitment steepness.

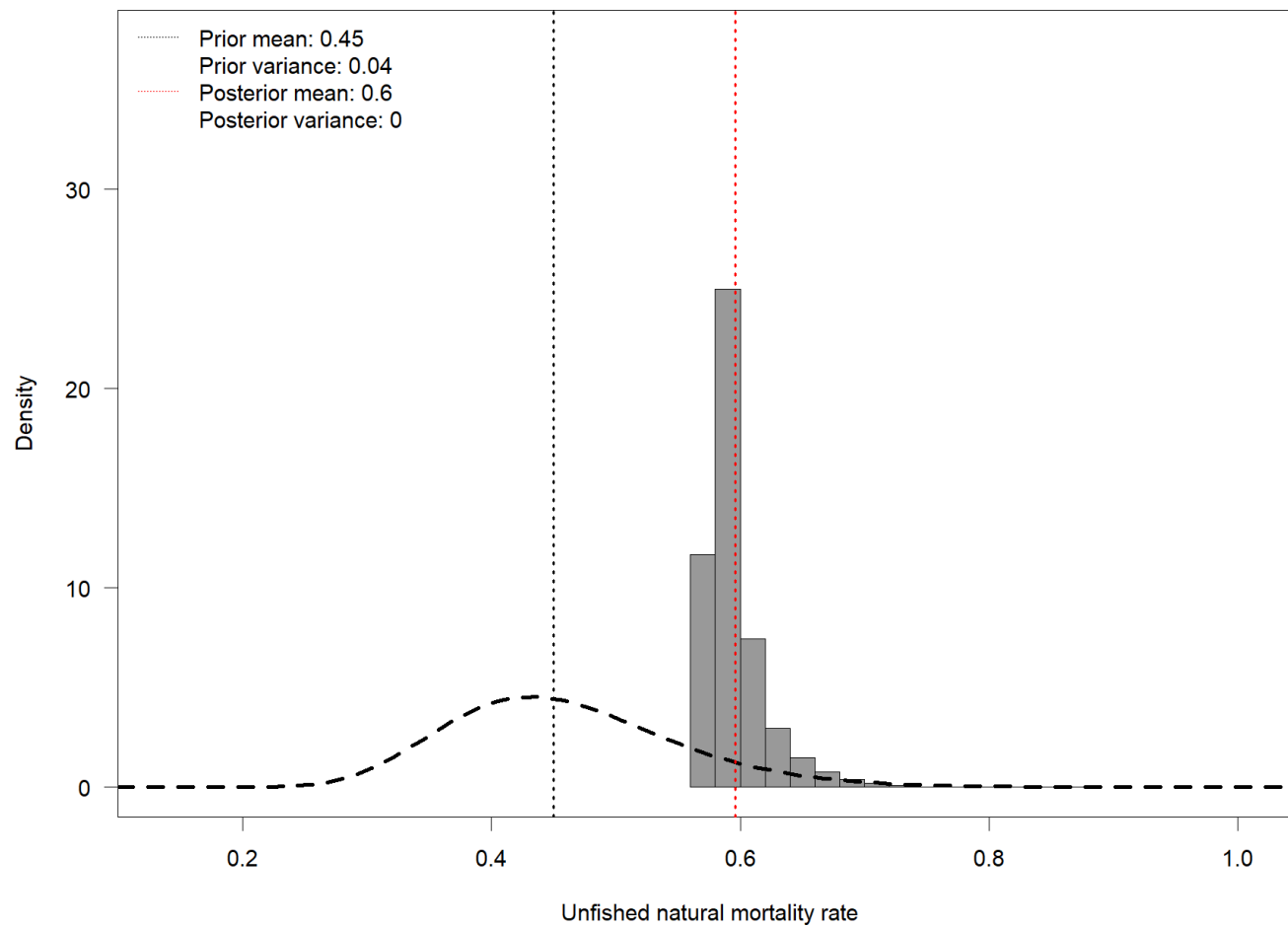


Figure D.66. Strait of Georgia SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for the unfished natural mortality rate M_0 .

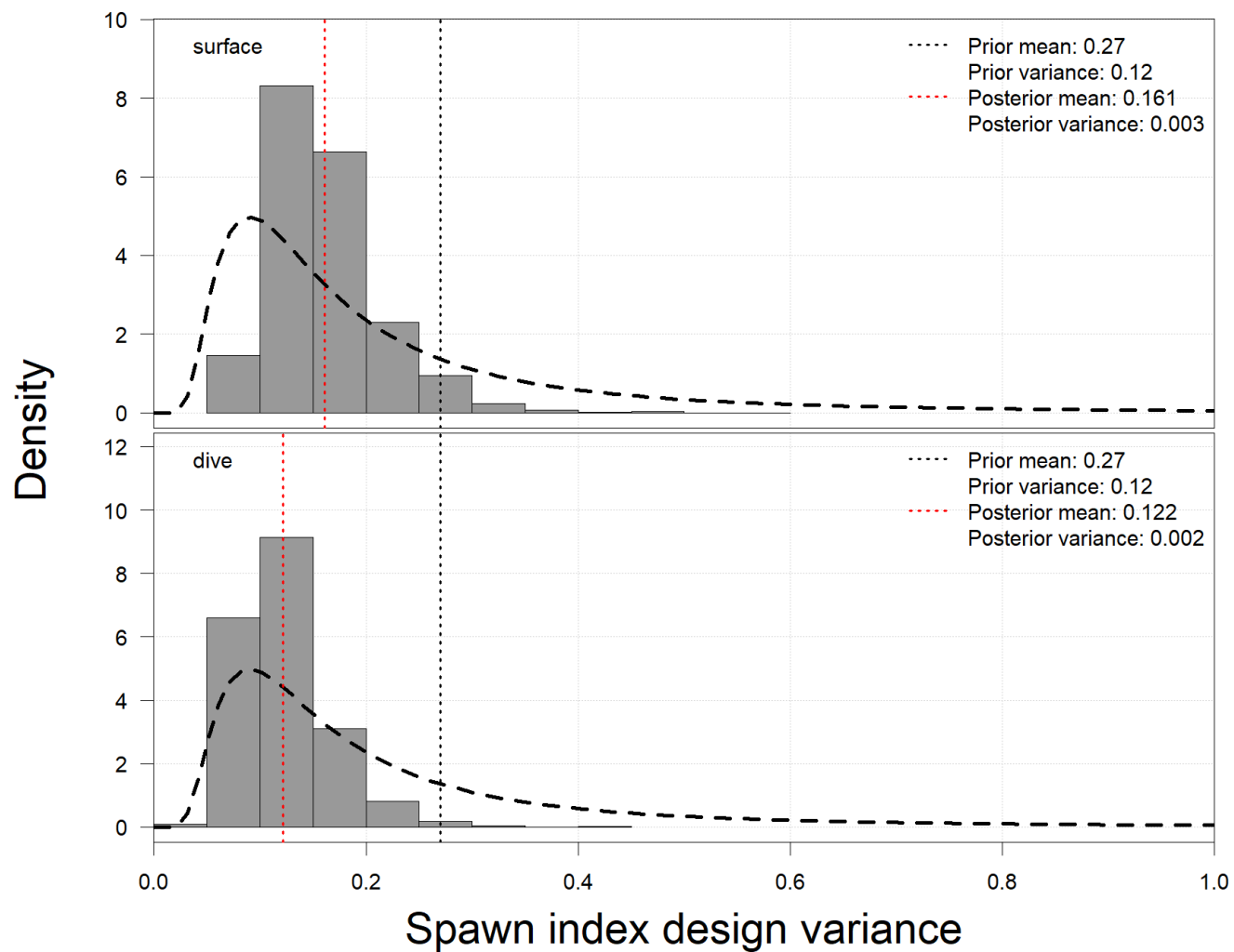


Figure D.67. Strait of Georgia SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for spawn index observation residual standard error components from the Dive survey design (top) and surface survey design (bottom).

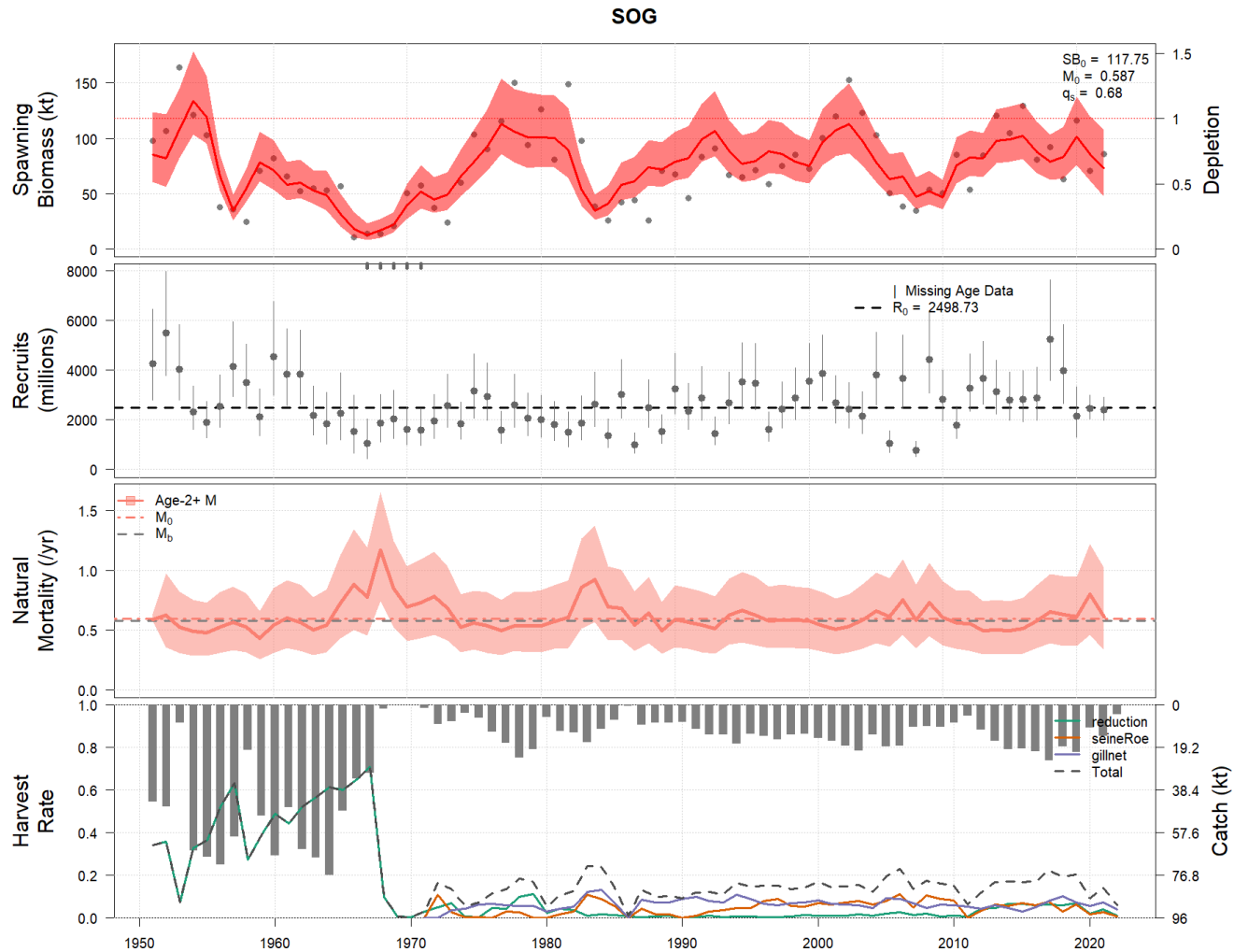


Figure D.68. Time series of Strait of Georgia herring spawning biomass with scaled spawn indices (top), recruitments (second row), natural mortality (third row), and harvest rates (bottom row). SB_0 , M_0 , and R_0 are unfish equilibrium spawning stock biomass, natural mortality, and recruitment respectively. q_s is the catchability coefficient for the surface surveys. SOG is spawn-on-kelp. In the recruitment panel, years with missing age data are indicated with a tick along the top axis, denoted by a ']' in the figure legend.

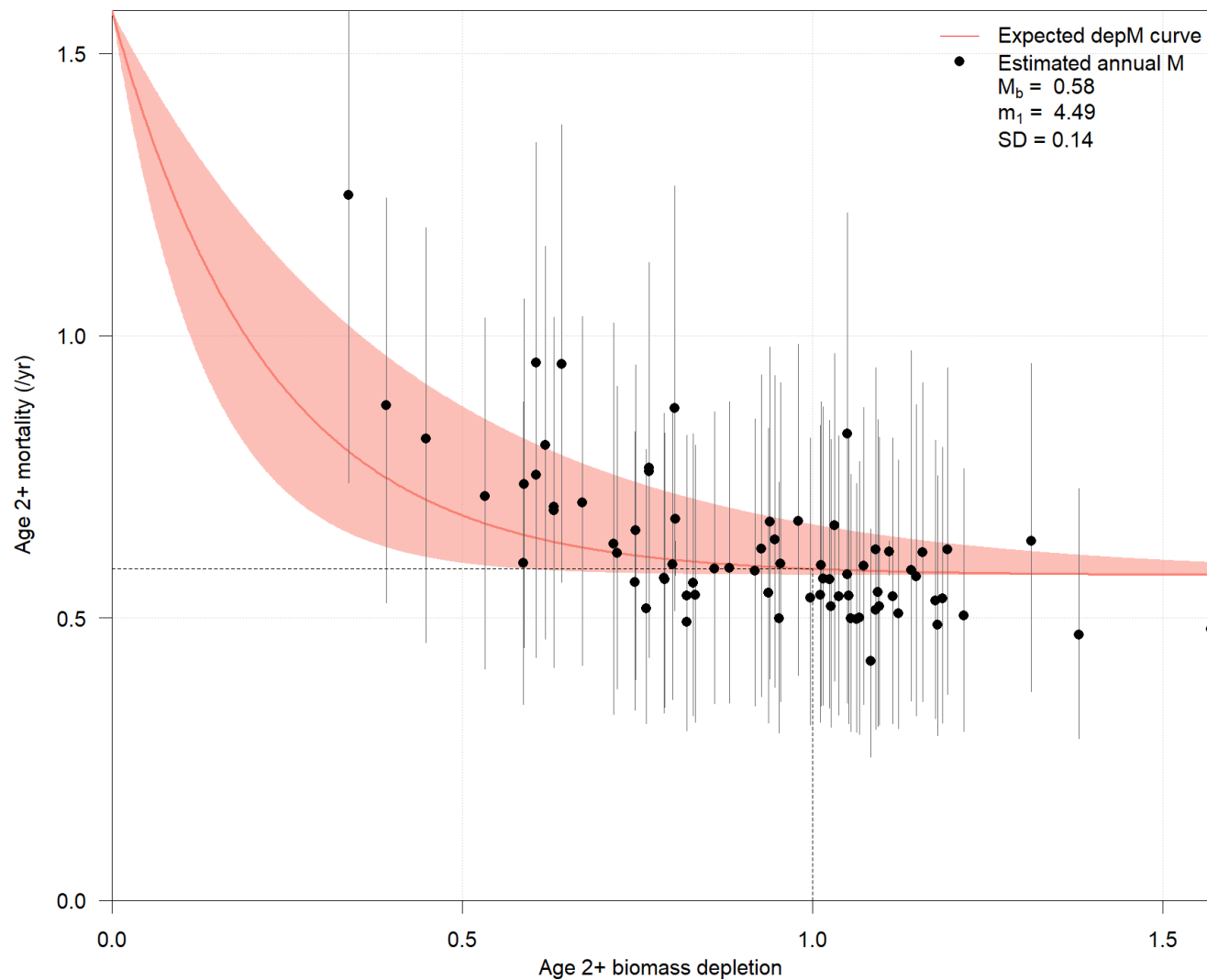


Figure D.69. Strait of Georgia SISCAH model posterior estimate of the density dependent relationship between age-2+ biomass and age-2+ natural mortality. The median relationship is shown by a thick line, with the posterior 95% credibility range shown by the shaded region. Individual points show the annual posterior median natural mortality estimates. The parameters shown are: m_1 = depensation rate; and M_b = asymptotic lower limit of density dependent mortality.

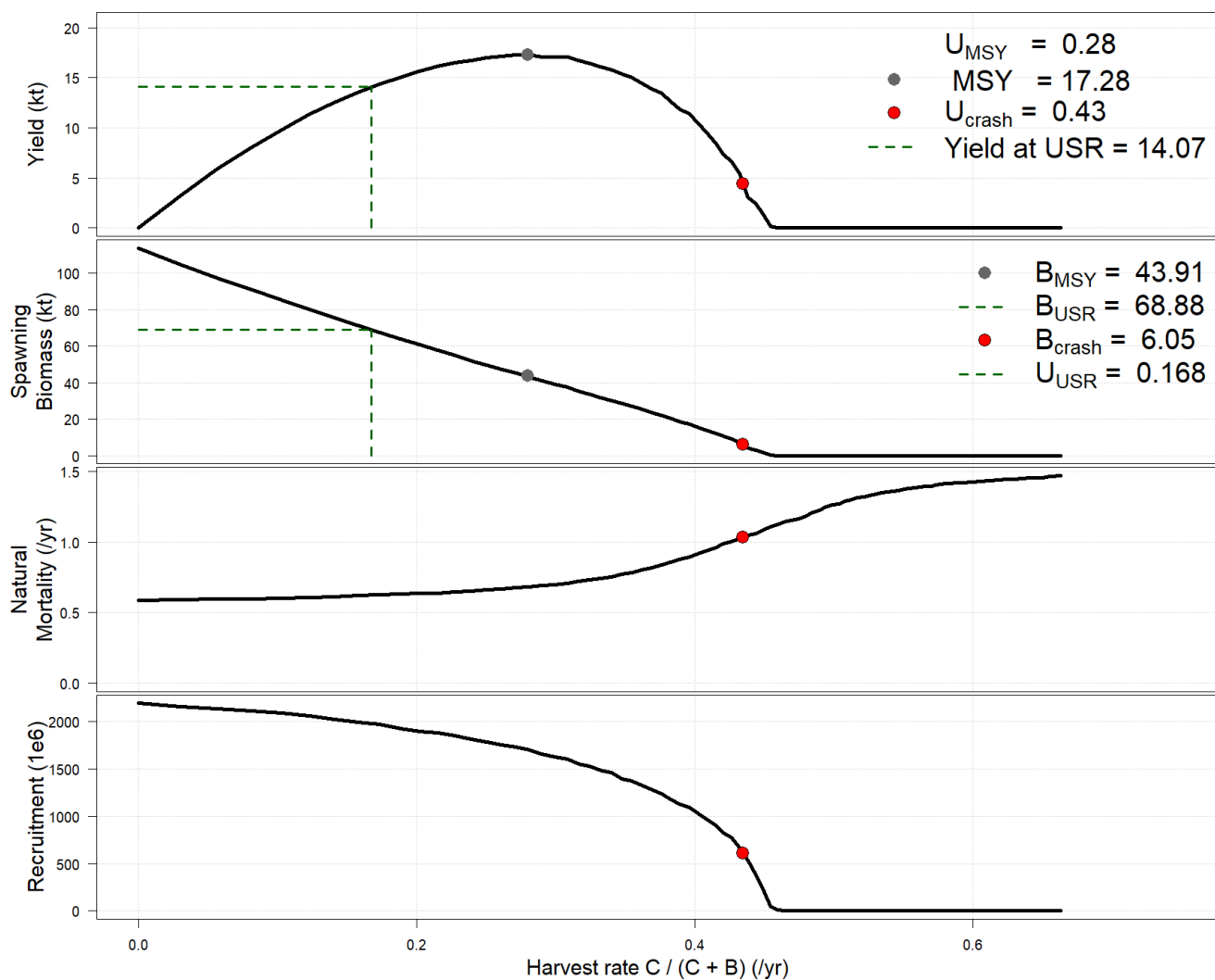


Figure D.70. Strait of Georgia reference points derived via median model equilibria of 200 year fishing mortality simulations, using the SISCAH model, with panels for yield, spawning biomass, natural mortality and recruitment. Grey points show values associated with the maximum sustainable yield (MSY). Red points show values associated with the steepest decline in yield. Green dashed lines show values associated with the upper stock reference (USR). Harvest rates are calculated as catch divided by catch plus spawning biomass.

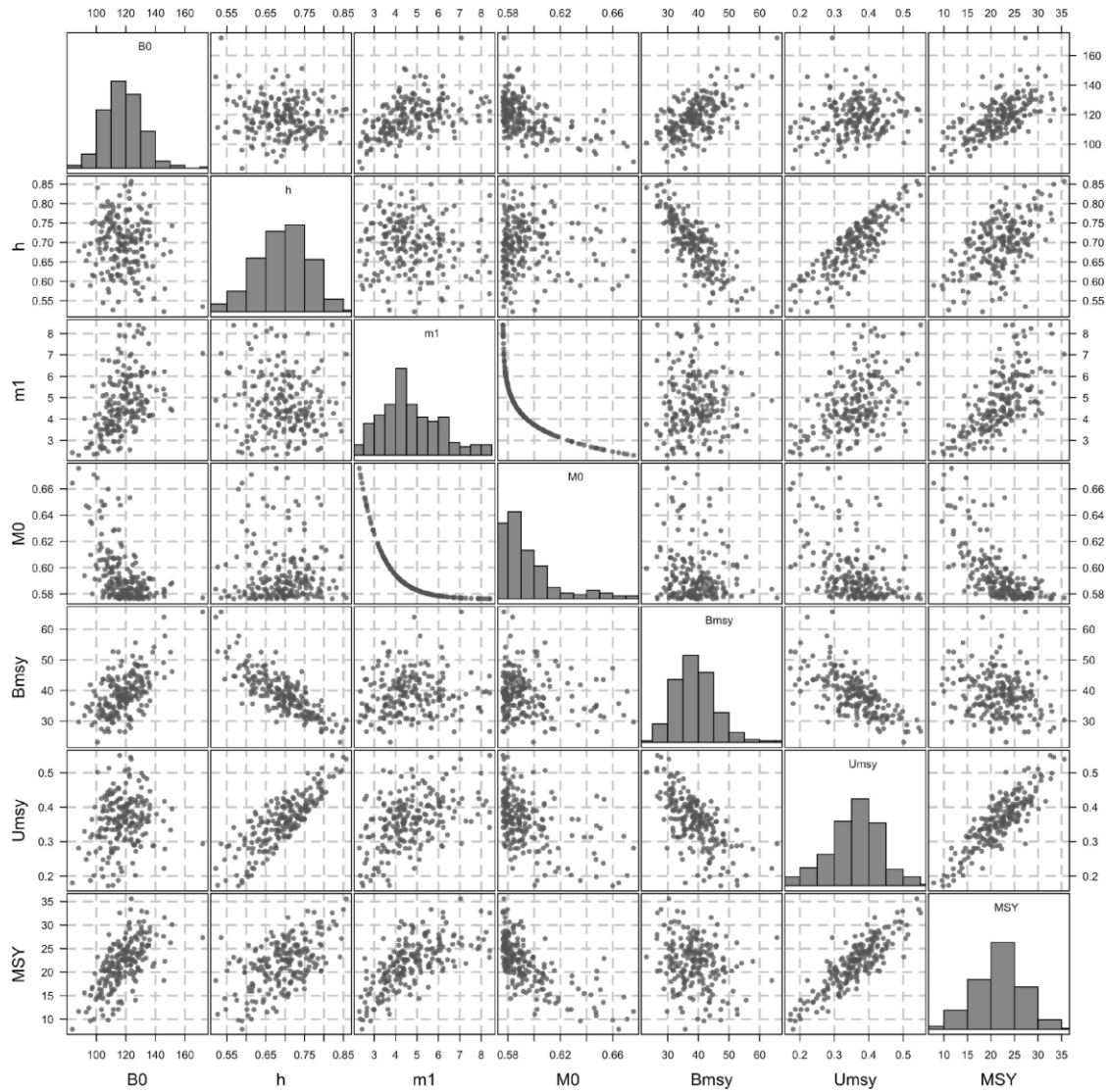


Figure D.71. Strait of Georgia: 500 random draws from joint marginal posterior distributions of selected life-history quantities and deterministic biological reference points, namely SB_0 = deterministic unfished equilibrium spawning biomass, h = stock-recruitment steepness, m_1 = depensation in density dependent mortality (if estimated), M_0 = deterministic unfished equilibrium mortality rate, B_{MSY} = deterministic optimal biomass, U_{MSY} = deterministic optimal harvest rate, MSY = deterministic maximum sustainable yield.

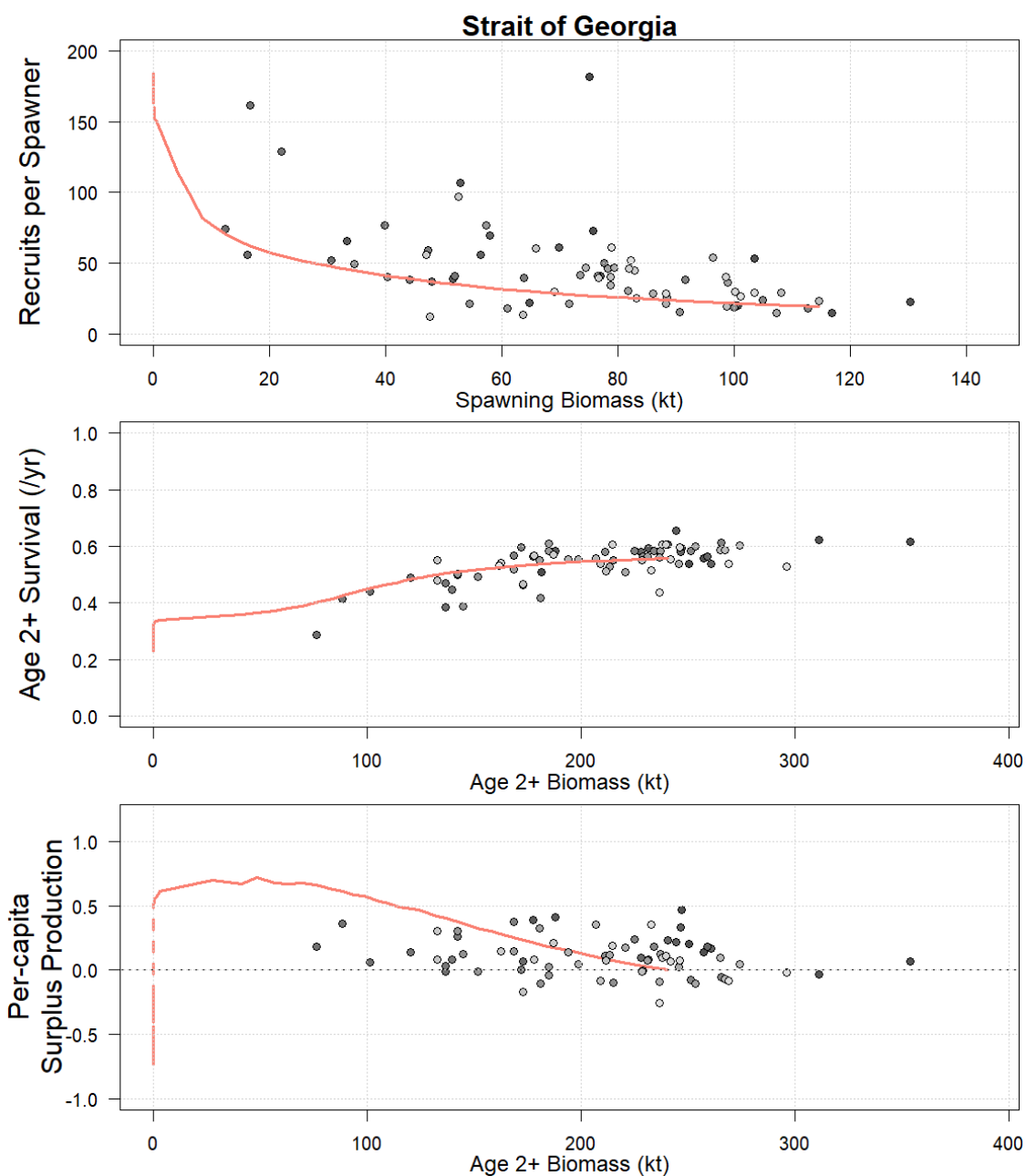


Figure D.72. Strait of Georgia SISCAN model estimates (points) and deterministic equilibria (lines) of recruits-per-spawner vs spawning biomass (top), density dependent age-2+ mortality as a function of age-2+ biomass (middle), and per-capita surplus production as a function of age-2+ biomass (bottom). Points are coloured to show phase, with light points for later years.

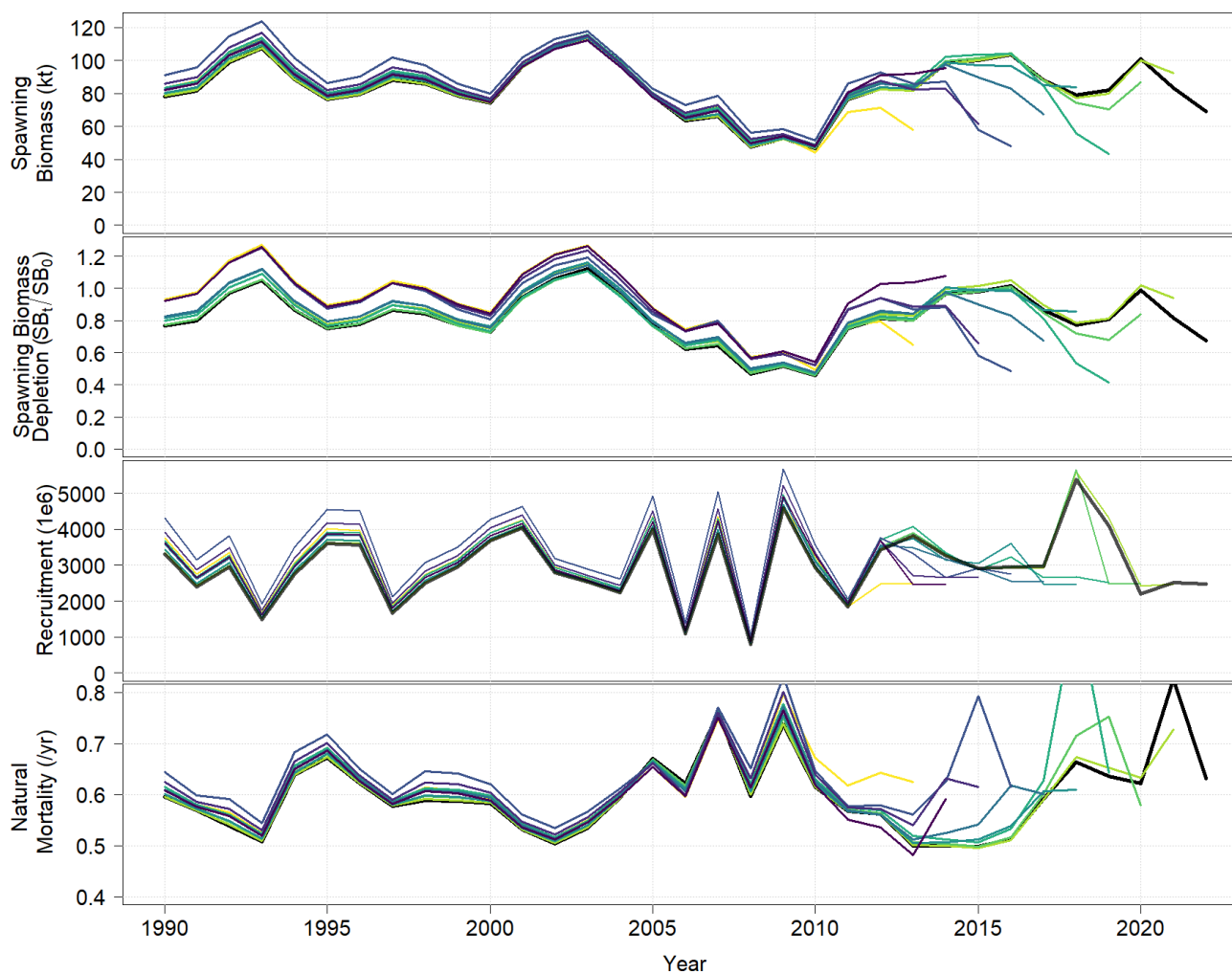


Figure D.73. Strait of Georgia SISCAN model retrospective estimates of spawning biomass (top) and spawning biomass depletion (second row), age-1 recruitment (3rd row), and natural mortality (bottom row), showing SISCAN model fits to successive data 'peels', which are truncated data sets with terminal years 2013–2022. The reference model is the largest data set in the 2022 peel, shown in black.

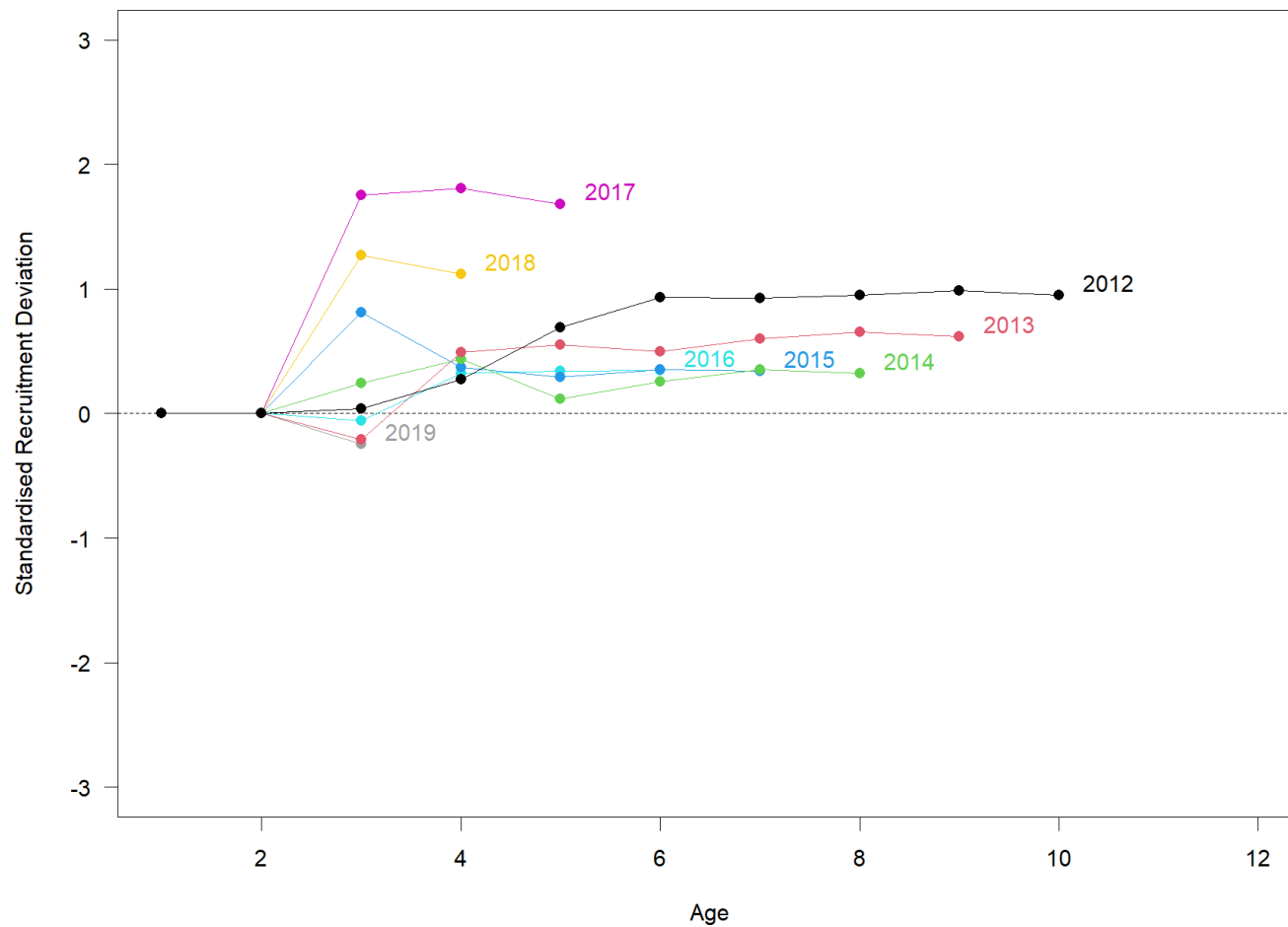


Figure D.74. Strait of Georgia SISCAN model retrospective estimates of standardised recruitment residuals, representing year class strength relative to the deterministic stock-recruitment relationship for models fit to successive data 'peels', which are truncated data sets with terminal years 2013–2022.

D.5. WEST COAST OF VANCOUVER ISLAND

D.5.1. Goodness of fit

SISCAH model goodness of fit to West Coast of Vancouver Island (WCVI) herring data is acceptable. Based on SISCAH model standard errors (Table D.17), all data series are consistent with the estimated population dynamics. The residual standard error for individual spawn survey designs had slight differences, with surface survey residuals ($\tau_s = 0.41$) about 32% higher in standard deviation than the dive survey design ($\tau_d = 0.271$). That difference is about twice as high as ISCAM, which assumes a 16% increase for the years assigned to the surface survey. Reflecting a low standard error, SISCAH model blended spawn index observation residuals over time showed no significant indication of poor fits (Figure D.76). The time series of residuals had low bias, with a mean residual of -0.07 standard errors. There is very weak time dependence to residuals, with an auto-correlation factor of 0.06, and no significant time-trend overall ($p = 0.64$). Age-composition data from all three fisheries fit reasonably well. SISCAH model residuals for all fisheries have standard errors at most 0.61, which is within acceptable limits (Table D.17). The seine roe fishery has the lowest age composition sampling standard error at 0.43, while the gillnet fishery has the highest at 0.61. Visual inspection of the annual fits to age-composition data for all fisheries shows that the higher residuals come from some years where age-classes with low selectivity were under-estimated, or where higher ages were over-estimated to compensate for under-estimates of larger modal age classes (Figures D.77–D.79). For all fisheries, SISCAH is able to track cohort signals.

Estimates of recruitment process errors show a small amount of residual bias and a negative residual trend (Figure D.80), but have no indication of significant issues. As in HG and CC, the negative residual trend is consistent with early large recruitments estimated during the reduction fishery years, which also have higher uncertainty given poor data collection. Despite this trend, the mean residual and auto-correlation are low, at 0.11 standard deviations and 0.13, respectively. Additionally, the distribution of recruitments around the stock recruitment curve is visually well balanced (Figure D.81).

D.5.2. Bayes posteriors

Standard Bayes posterior convergence metrics indicate that inferences can be drawn from the Bayes posteriors for the WCVI SAR SISCAH model. Effective sample sizes for the bulk and tail sections of all marginal distributions are above 100 samples per chain, and all Gelman-Rubin potential scale reduction factors $\hat{R}$ are below the nominated threshold of 1.01 for all parameters (Figure D.82). Sampled posterior points included 91 divergent transitions out of a total of 4000 samples, or 0.023%.

Visual inspection of joint marginal posteriors for leading life-history and selectivity parameters indicates that posterior geometry is of low concern (Figure D.83). Most joint marginal distributions have a high level of symmetry and low skew. As above, there is correlation between the m_1 and SB_0 parameters, but also some correlation between m_1 and h at lower m_1 values, and m_1 and R_{init} . As before, this indicates that SISCAH may benefit from future re-parameterisations to reduce correlation among these parameters where possible.

Prior/posterior comparisons tell a similar story to other SARs. As with Haida Gwaii there is limited information in the data for estimating the stock-recruit steepness parameter. The prior and posterior mean are very close, and the variance parameters also very similar (Figure D.84).

In contrast, there is a good indication of information in the M_0 posterior, with a slight drop in mean values mean but a larger drop in variance (Figure D.85); however, the variance may be

artificially limited given the lower bound on M_0 induced by the model structure, which is hit as the HMC procedure samples higher m_1 values. Finally, spawn survey residual standard errors are well informed by the data. For both designs the posterior mean is lower than the prior mean, and variance drops a similar amount from 0.12 to 0.002–0.004 (Figure D.86).

D.5.3. Historical dynamics

The West Coast of Vancouver Island herring population stock dynamics over the historical period have a lot in common with the Central Coast and Haida Gwaii major SARs. The early pre-collapse period is similar, characterised by higher average recruitments until the collapse towards the end of the 1960s (Figure D.87). Here, as in Haida Gwaii and the Central Coast, the historical biomass peaks in the mid 1970s. That peak was driven by a series of large recruitments combined with a few years with no fishing after 1968. As the fishery reopened with seine roe and gillnet fisheries, the peak biomass declined below the model estimates of unfished SB_0 in the early-mid 1980s and then fluctuates above and below the unfished level until the mid-1990s. From 1980–1995, WCVI herring spawning biomass and fisheries were sustained by 5 large recruitments, each contributing more than 1 billion herring.

Following the last large recruitment in 1995, WCVI herring biomass peaked again around unfished levels in 1997 before slowly declining to a historic low point in 2006. The slow decline is explained by SISCAN with a series of lower-than-average recruitments which were not large enough to maintain the biomass given increasing natural mortality rates and removals from annual fisheries. Harvest rates exceeded 20% from 2003–2005. Since that time fisheries have not been prosecuted (Figure D.87). Along with the decline in biomass to historic lows in 2006, the natural mortality rate climbed to an historic high, with posterior median mortality around 1.2.

As in other areas with a low m_1 value, this high-mortality, low-biomass combination creates a feedback effect, where recruitments have to be much larger to grow the stock due to lower survival rates. Therefore, even though there have been some higher-than-average recruitments since 2006, those large year classes do not result in as much spawning biomass as similar sized recruitments in the past because of lower life expectancy given the elevated mortality rates. This feedback is much more prominent in low m_1 value areas, as the shape of the density dependent curve is much shallower over the range of biomass depletion levels (Figure D.88). For WCVI, compensatory M occurs up to biomass depletion levels of $1.5SB_0$.

D.5.4. Biological reference points

SISCAN model equilibria, or biological reference points (BRPs), for the WCVI SAR have a similar shape to the Haida Gwaii SAR. SISCAN estimates show a maximum sustainable yield (MSY) of approximately 2.16 kt, which is achieved when spawning biomass around 18.87 kt. Using the usual calculation for herring harvest rates as $U = C/(SB + C)$, the optimal harvest rate is calculated as $U_{MSY} = MSY/(B_{MSY} + MSY) = 0.11$. This accounts for an 11% allocation of TAC to closed pond SOK fishing. As with Haida Gwaii, the low m_1 value means that SISCAN model equilibrium yield and biomass curves show slow crash dynamics at higher harvest rates. Yield drops fastest as sustained harvest rates approach 28%, a similar level to HG, above which the equilibrium biomass, yield, and recruitment all decline to zero (Figure D.89).

Joint marginal posteriors of life-history quantities and reference points tell a similar story to other SARs. As usual, biomass related quantities such as SB_0 and SB_{MSY} have positive correlation with m_1 , and U_{MSY} has positive correlation with stock-recruit steepness h . Here, as in Haida Gwaii and SOG, there is low correlation between m_1 and U_{MSY} ; furthermore, the weak correlation between m_1 and U_{MSY} appears to be negative, in contrast to other areas.

Inspection of per-capita demographic rates shows that the per-capita surplus production curve has a high degree of skew leading to a peak near zero biomass (Figure D.91), but there is considerable variation all along the equilibrium curve indicating larger effects of process errors than in other areas, which may contribute to instabilities. The high skew in surplus production appears to compensate for the high removals, leading to a higher U_{crash} and a smooth tapering down of the yield, biomass, and recruitment towards zero as biomass drops slightly faster than yield above U_{crash} .

D.5.5. Retrospective analyses

Results of the retrospective analysis suggests that SISCAH estimates of West Coast of Vancouver Island herring biomass and life history parameters have low sensitivity to additional years of data. Spawning biomass (both absolute and depletion), recruitment, and natural mortality are all very consistent across all years for all peels (Figure D.92). As usual, there is some feathering that is largely related to deterministic recruitments in the final years, but the effect is minor and there are no large changes in any time series as a result.

Cohort strength is very stable for all year classes except two. Most year classes have fully resolved their relative cohort strength by age-3 or age-4 (Figure D.93). The exceptions are 2012 and 2013, which take until around age-6. Interestingly, cohort strength is revised upwards for both 2012 and 2013 year classes in each peel after age-3 (the first year of estimation). The 2012 year class went from a negative residual of 1 standard deviation to close to zero (i.e., close to the stock-recruitment curve), and the 2013 year class went from a positive residual of 1 standard deviation to around 1.5 standard deviations. This is visible on the retrospective recruitment time series for age-1 recruitment in 2013 and 2014 (Figure D.92), and is related to the slight reduction in R_0 values over the retrospective peels and possibly the slight increase in steepness h values (Table D.18).

Similar to other SARs, SISCAH estimates negligible declines in SB_0 , R_0 , and M_0 (up to 5%) over the ten years (Table D.18).

D.5.6. Sensitivity analyses

SISCAH estimates of WCVI herring biomass and life history parameters were responded to changes in specific priors similar to other SARs. Mortality priors had a larger effect on the unfished biomass estimates, and steepness priors affected estimates of steepness more. As in SOG and CC, changes in σ_M had a large effect on SB_0 and m_1 estimates.

Out of the seven SISCAH initial condition configurations tested for the West Coast of Vancouver Island SAR, only two successfully converged. Consequently, it is challenging to discern the direct effects of each configuration option. The two configurations that did converge were R_{init} models, excluding F_{init} (Table D.20), and they differed in terms of whether the starting age structure was at deterministic equilibrium (with no initial recruitment deviations) or had a non-equilibrium initialization (with initial recruitment deviations). When initial recruitment deviations were estimated, it resulted in a decrease in M_0 , leading to an increase in SB_0 and a decrease in R_{init} .

D.5.7. Tables

Table D.17. Estimated residual standard errors and lag-1 age residual correlations for West Coast of Vancouver Island herring data. The first six columns show age data sampling standard errors τ_g^{age} and correlation coefficients ρ_g from the LN1 age composition likelihood function the Reduction and Food & Bait ($g = 1$), Seine-rope ($g = 2$), and gillnet fisheries ($g = 3$), and the last two columns show spawn survey index standard deviations for the surface (τ_s) and dive (τ_d) surveys.

SAR	τ_1^{age}	ρ_1	τ_2^{age}	ρ_2	τ_3^{age}	ρ_3	τ_s	τ_d
WCVI	0.495	0.525	0.432	0.686	0.609	0.614	0.41	0.271

Table D.18. West Coast of Vancouver Island retrospective estimates of selected SISCAN model leading and derived life-history quantities over data peels from 2012–2022. Selected quantities are SB_0 = estimated unfished equilibrium spawning biomass(kt), R_0 = estimated unfished equilibrium recruitment (1e6), R_{init} = estimated initial recruitment (1e6), m_1 = depensation rate (unitless), M_0 = asymptotic lower bound on age-2+ natural mortality (yr), M_0 = equilibrium unfished age-2+ natural mortality (yr), q_s = surface survey catchability (unitless).

Peel	B_0	R_0	R_{init}	m_1	M_0	h	q_s
2013	48.057	880.173	703.785	1.840	0.579	0.690	0.605
2014	47.817	873.996	699.250	1.845	0.578	0.690	0.607
2015	47.780	879.895	702.818	1.838	0.579	0.694	0.607
2016	47.357	870.407	696.242	1.846	0.578	0.692	0.610
2017	46.771	860.977	692.740	1.846	0.578	0.689	0.613
2018	47.680	854.777	674.661	1.888	0.571	0.696	0.613
2019	45.804	841.184	683.547	1.854	0.577	0.686	0.617
2020	46.470	846.059	678.920	1.869	0.574	0.690	0.615
2021	47.301	855.307	675.670	1.883	0.572	0.695	0.614
2022	46.092	849.098	683.937	1.856	0.576	0.689	0.615

Table D.19. West Coast of Vancouver Island SISCAH model estimates of life-history and observation model quantities under sensitivity analyses.

Sensitivity	SB_0	R_0	R_{init}	m_1	M_0	h	q_s
jeffHi	44.091	817.385	612.198	1.847	0.578	0.692	0.627
jeffLo	46.092	849.098	683.937	1.856	0.576	0.689	0.615
meanMHi	37.424	866.246	838.481	1.554	0.631	0.667	0.609
qSurfSDHi	46.144	851.056	685.695	1.854	0.577	0.689	0.612
qSurfSDLo	45.897	841.665	677.239	1.863	0.575	0.691	0.625
sdMHi	38.530	863.530	814.599	1.592	0.623	0.670	0.610
sigmaMlo	51.531	887.511	670.359	1.962	0.561	0.707	0.579
steepMeanHi	47.582	799.562	613.307	2.004	0.555	0.832	0.636
steepSDHi	46.569	846.508	675.005	1.877	0.573	0.698	0.616
steepSDLo	45.657	851.213	691.946	1.838	0.579	0.682	0.614

Table D.20. West Coast of Vancouver Island SISCAH model estimates of life-history and observation model quantities under the initial conditions sensitivity analyses.

Initial Conditions			SB_0	R_0	R_{init}	F_{init}	m_1	M_b	M_0	h	q_s
initR	initF	initDevs									
R_{init}	FALSE	FALSE	39.108	867.372	1,123.677	0	1.605	0.42	0.621	0.669	0.606
R_{init}	FALSE	TRUE	46.092	849.098	683.937	0	1.856	0.42	0.576	0.689	0.615

D.5.8. Figures

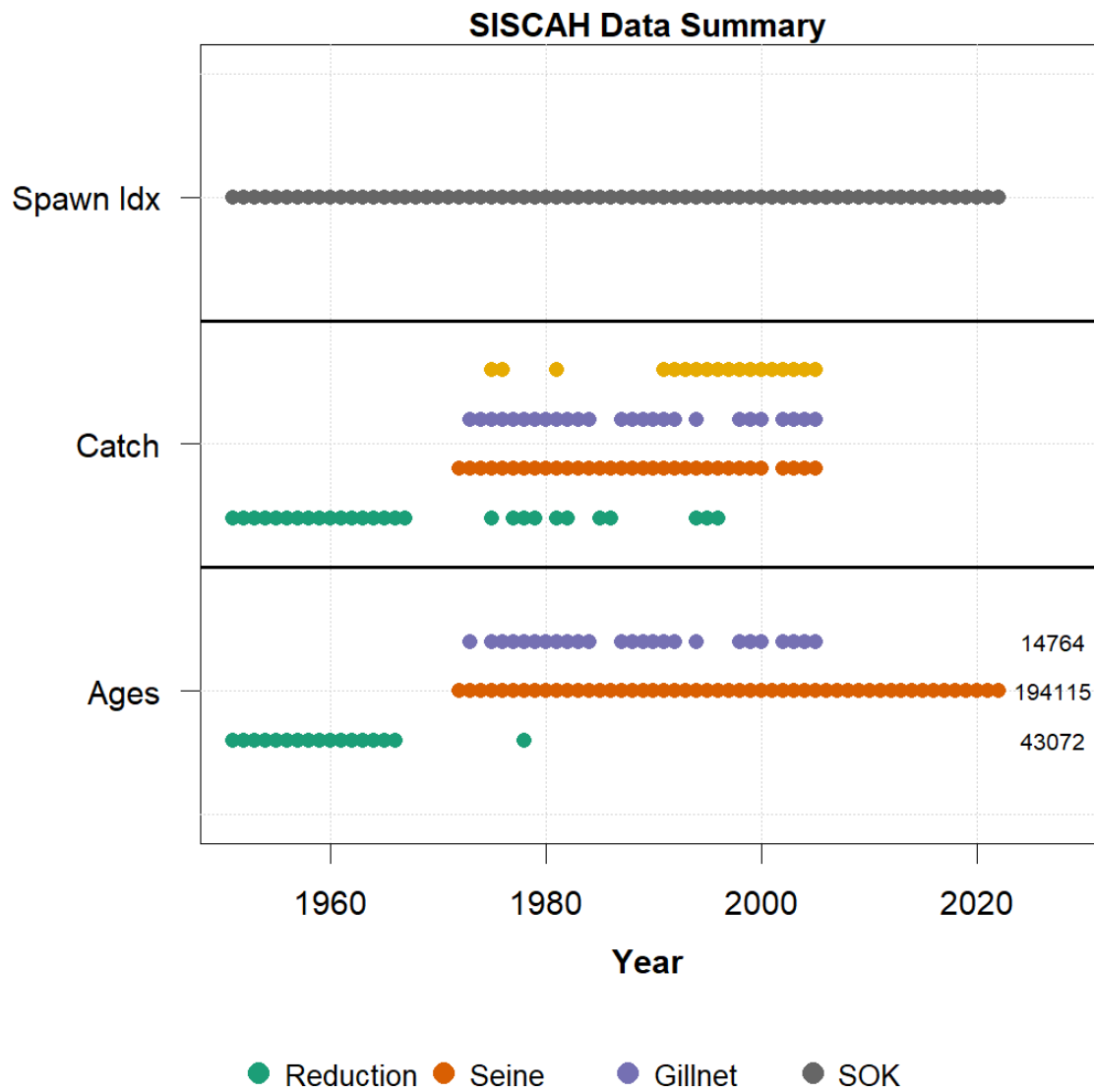


Figure D.75. Time series of West Coast of Vancouver Island herring stock assessment data. Each dot shows the existence of data, and age data shows total number of samples over all years at the right hand end.

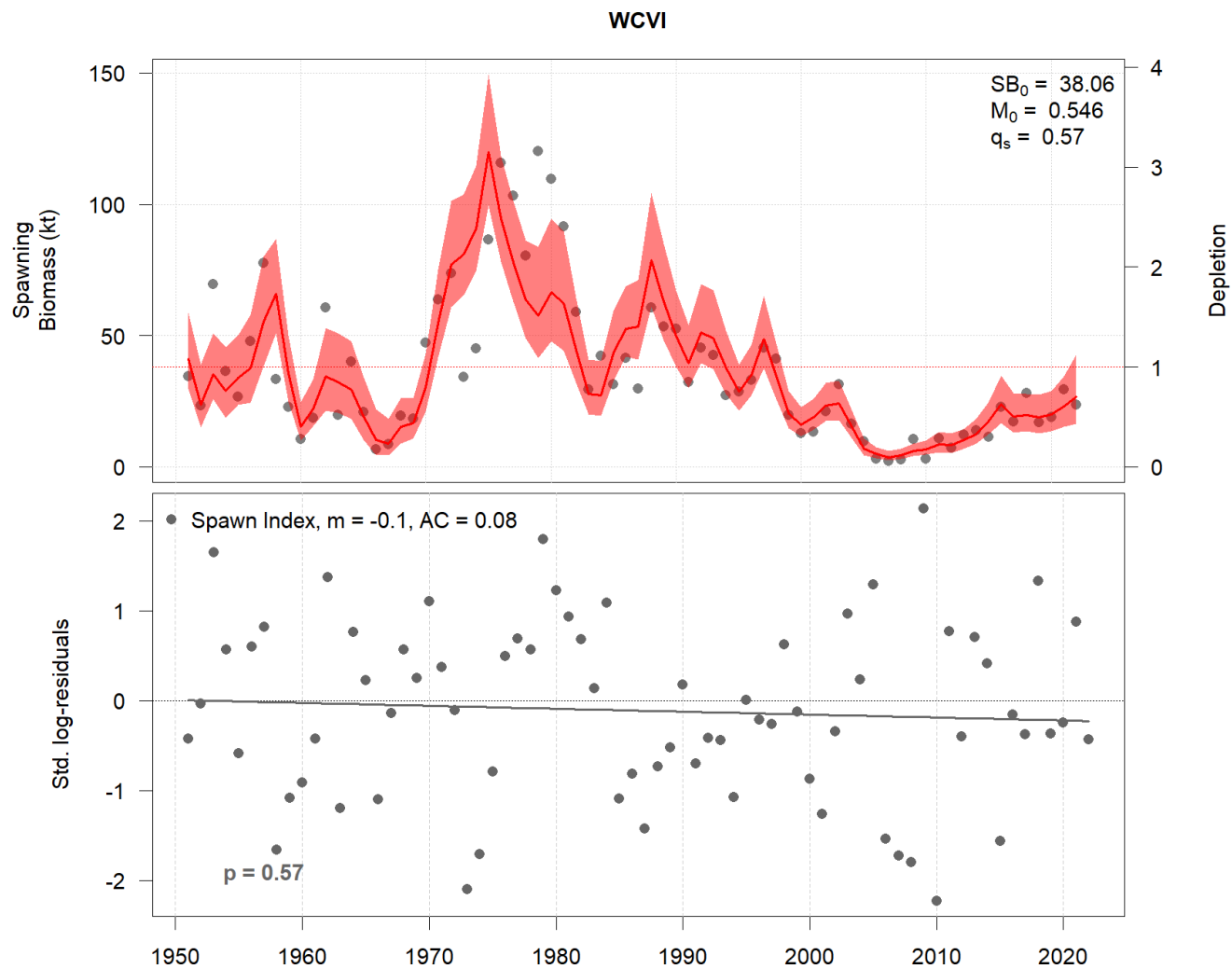


Figure D.76. West Coast of Vancouver Island blended spawn index and SISCAN spawning biomass estimates (top) and standardised observation residuals (bottom). SB_0 and M_0 are the unfished equilibrium spawning stock biomass and the natural mortality respectively, q_s is the catchability coefficient for the surface surveys, m is the mean log residual of the spawning index, and AC is the autocorrelation.

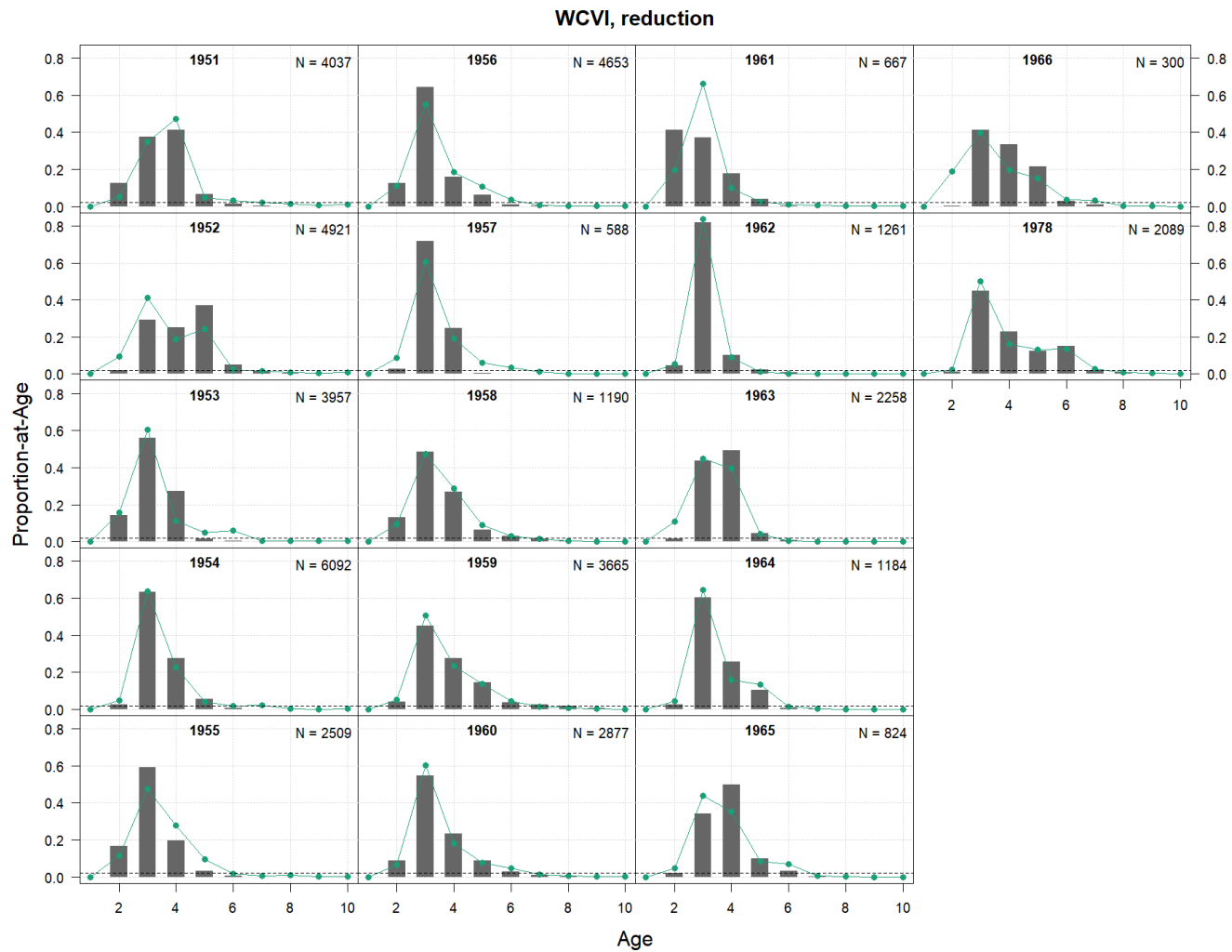


Figure D.77. SISCAH model fits to reduction age compositions collected from the West Coast of Vancouver Island region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

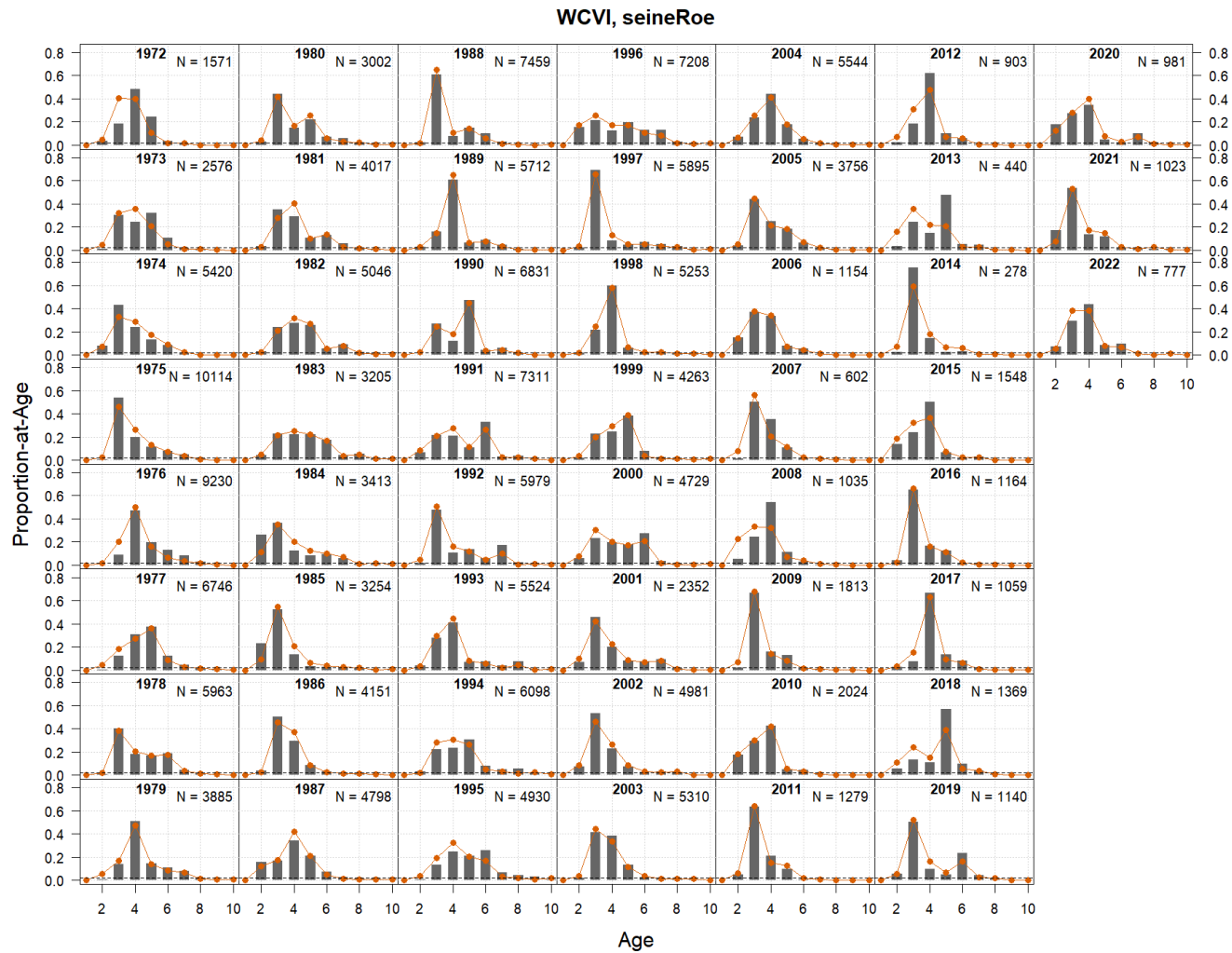


Figure D.78. SISCAH model fits to seine roe age compositions collected from the West Coast of Vancouver Island region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

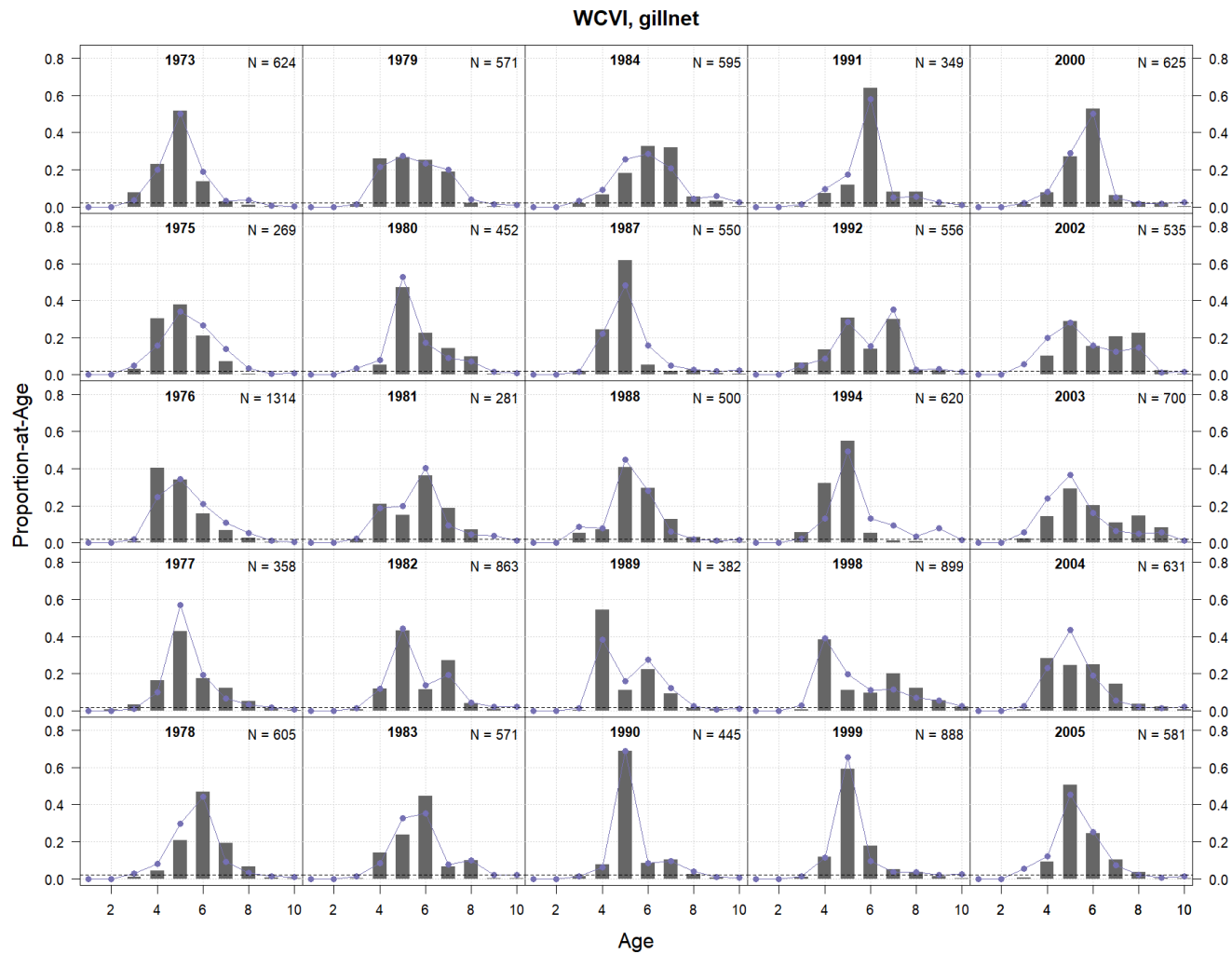


Figure D.79. SISCAN model fits to gillnet age compositions collected from the West Coast of Vancouver Island region. Data are shown as rectangles, and estimates as points connected by a line. Horizontal dashed lines show the minimum proportion required for model fitting, with data falling below that threshold subject to tail compression. N is the sample size.

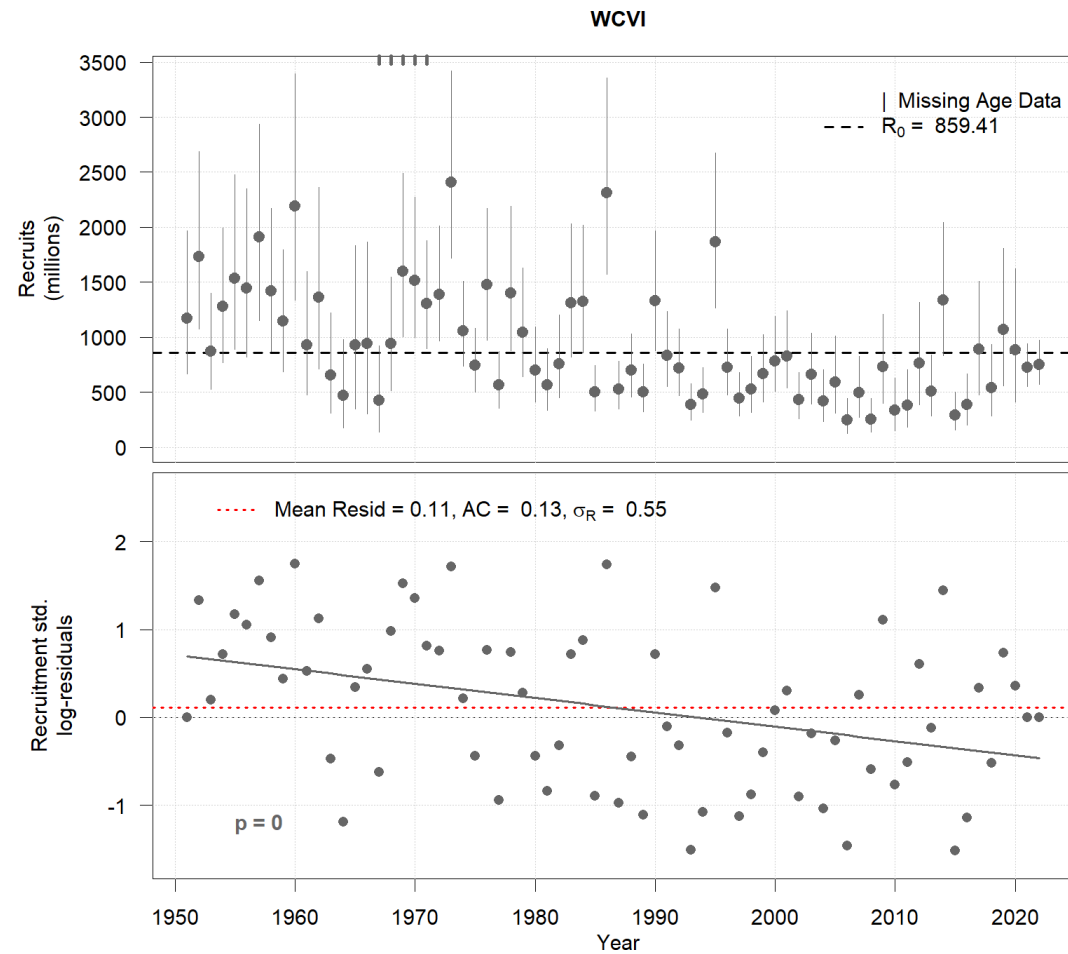


Figure D.80. West Coast of Vancouver Island age-1 recruitments (top) and standardised recruitment process errors (bottom). Equilibrium unfished recruitment R_0 is indicated by the horizontal dashed line in the top panel, and the mean process error (Mean Resid) is shown by the horizontal red dashed line in the bottom panel. AC is auto correlation and σ_R is the standard error in the log residuals.

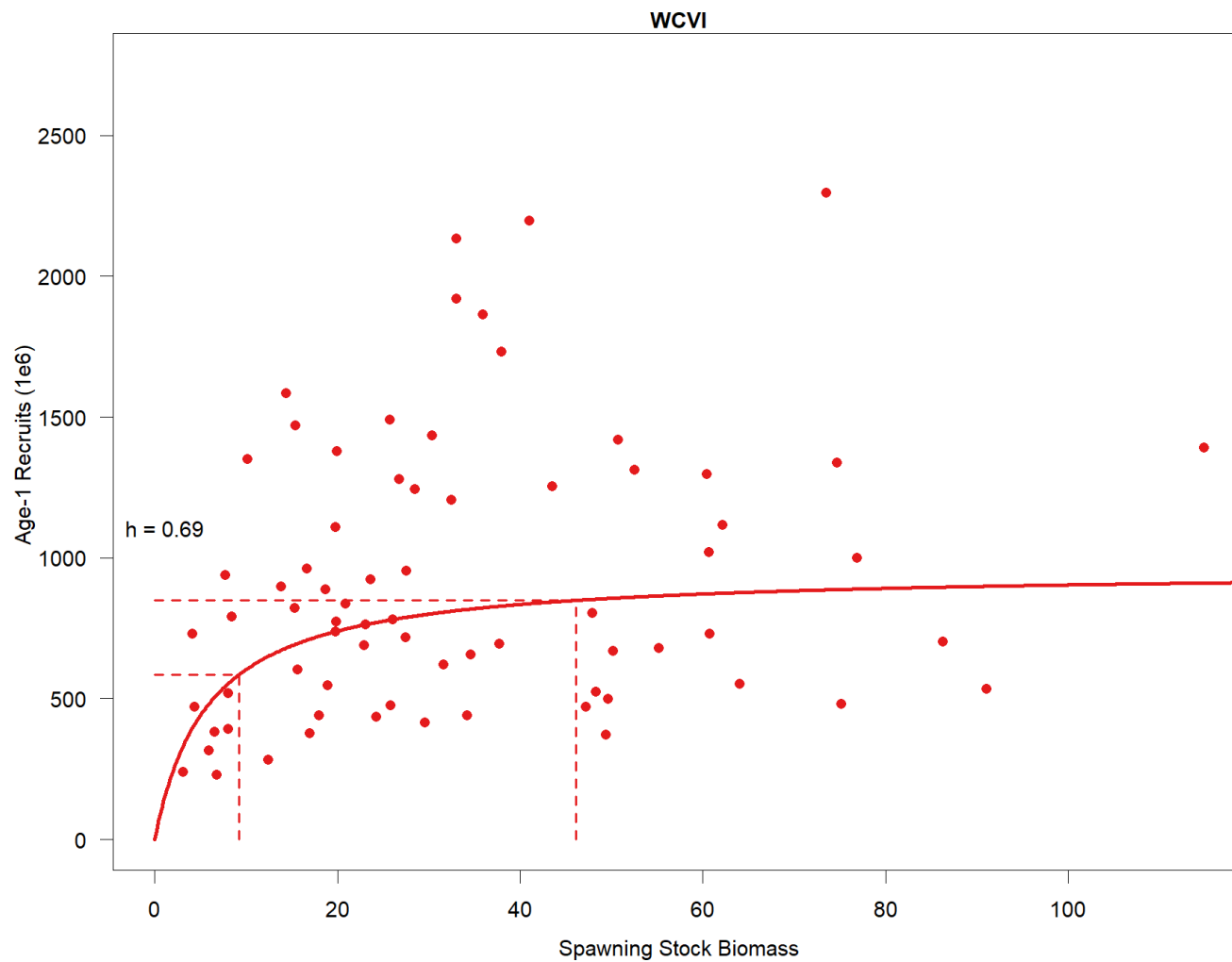


Figure D.81. West Coast of Vancouver Island stock-recruitment curves (solid lines) and age-1 estimated recruitments (points), with unfished and 20% of unfished biomass and recruitment shown as dashed lines. h is the estimated stock recruit steepness.

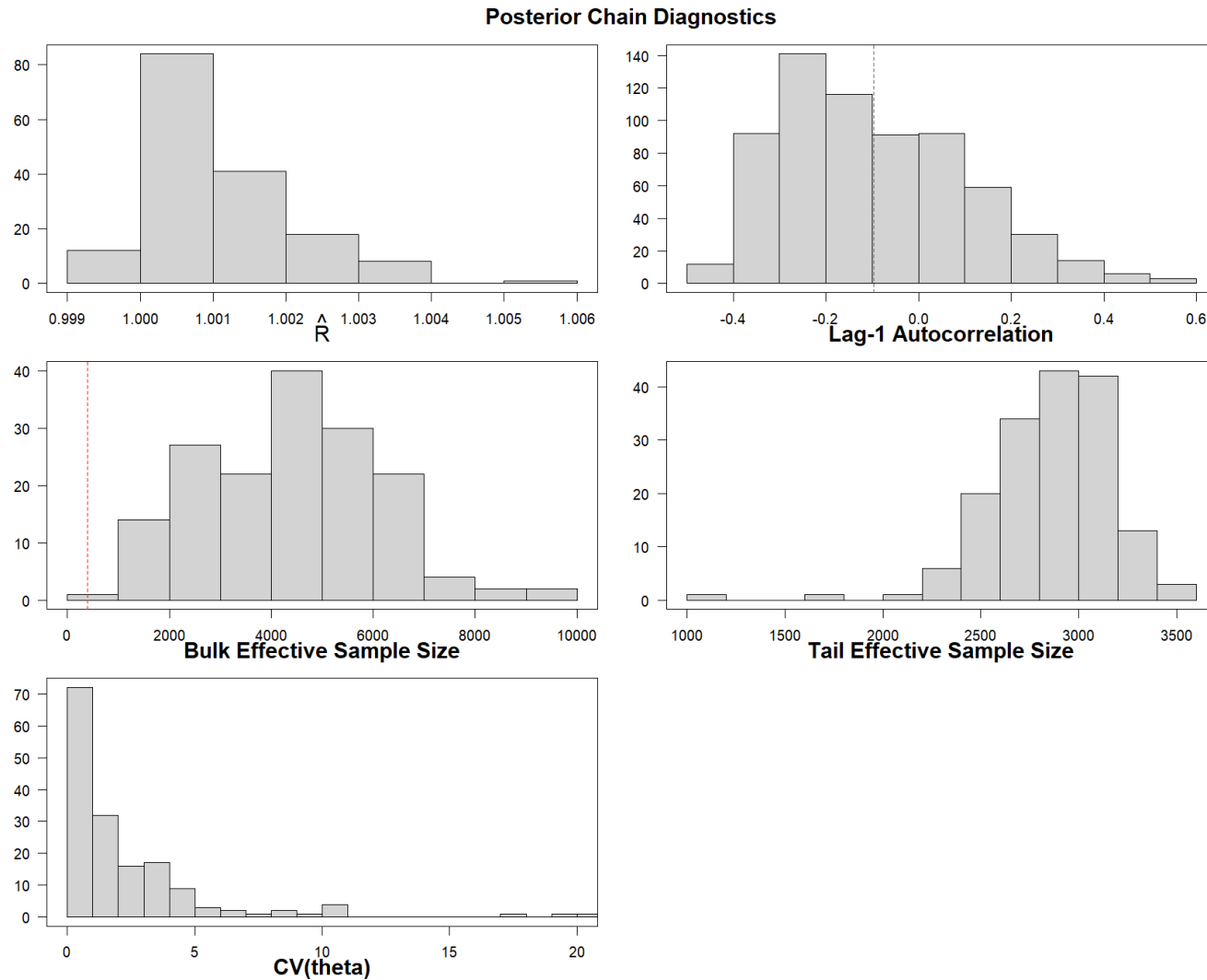


Figure D.82. Histograms of West Coast of Vancouver Island SISCAH model Bayes posterior convergence diagnostics for each leading model parameter, showing the distribution of values of each metric across all parameters. From left-to-right, starting in the top row, metrics are Gelman-Rubin scale reduction factors ($\hat{R}$), lag-1 autocorrelation factors, (bulk) effective sample size of draws in the central quantiles, (tail) effective sample size in the outer quantiles, and coefficient of variation (CV) of each parameter. Vertical red dashed lines indicate convergence thresholds, and the vertical dashed grey line indicates the median lag-1 autocorrelation.

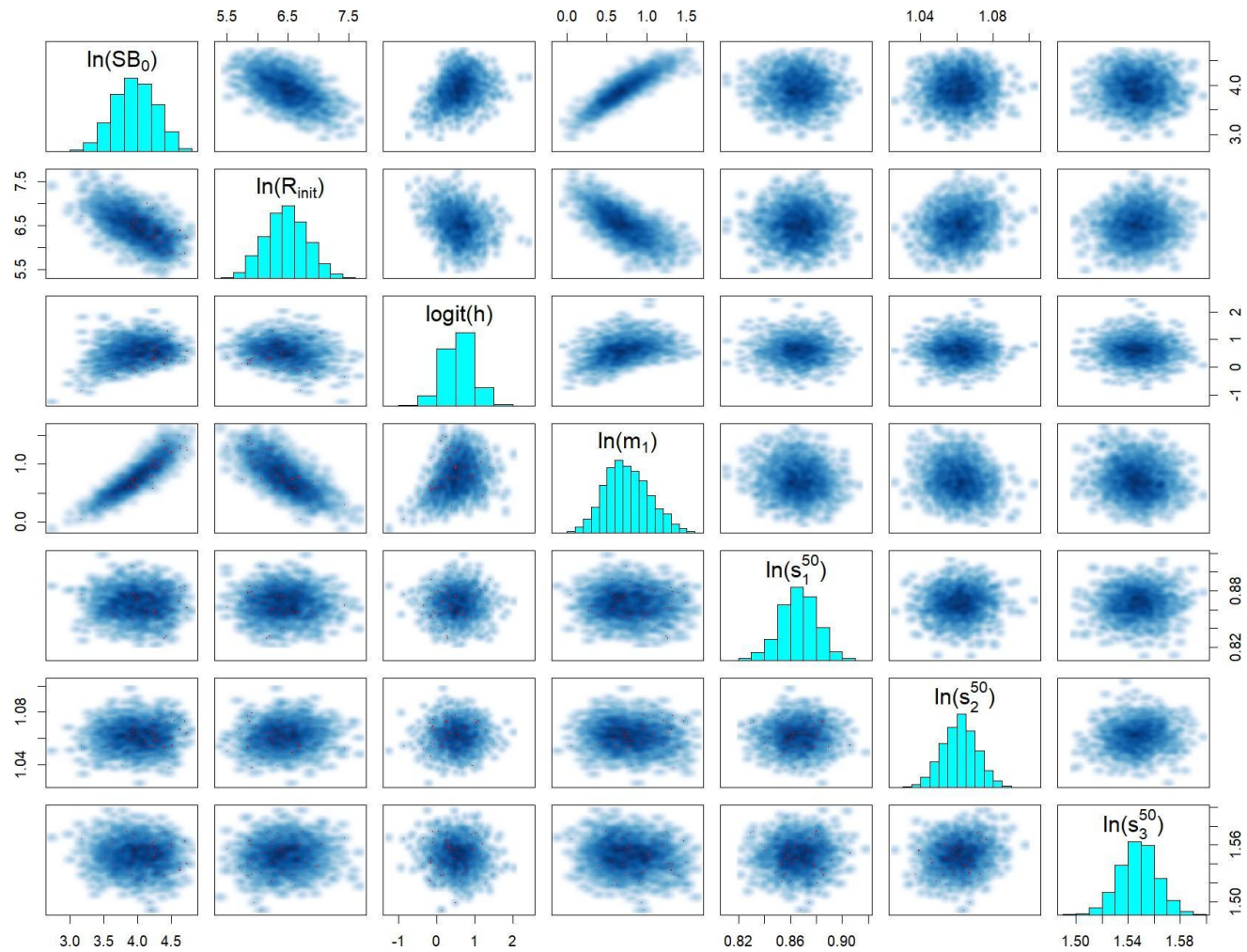


Figure D.83. West Coast of Vancouver Island SISCAH model marginal Bayes posteriors (main diagonal) and pair-wise joint-marginal Bayes posteriors (off-diagonal) for selected life-history and selectivity parameters. Red points indicate samples associated with divergent transitions.

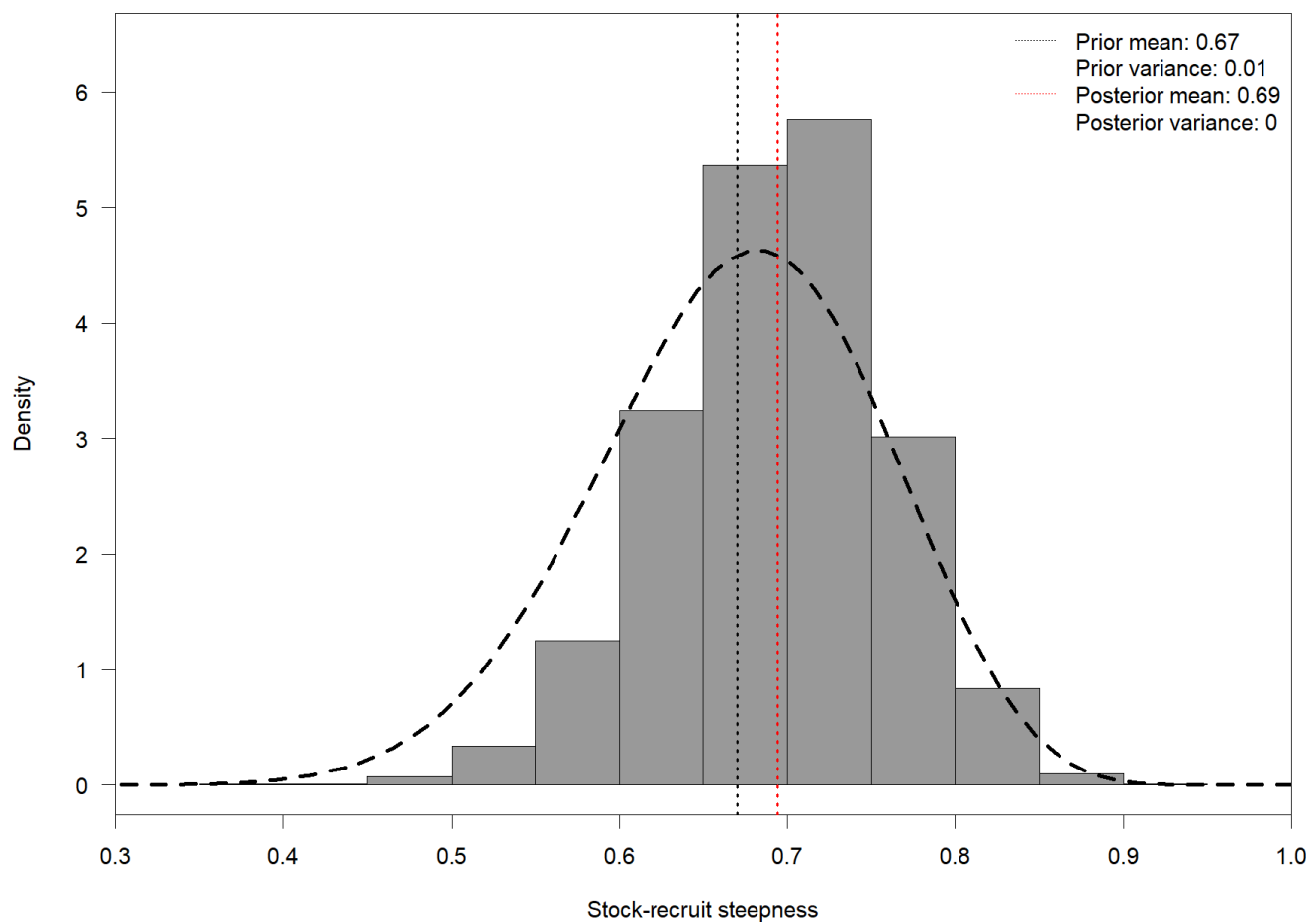


Figure D.84. West Coast of Vancouver Island SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for stock-recruitment steepness.

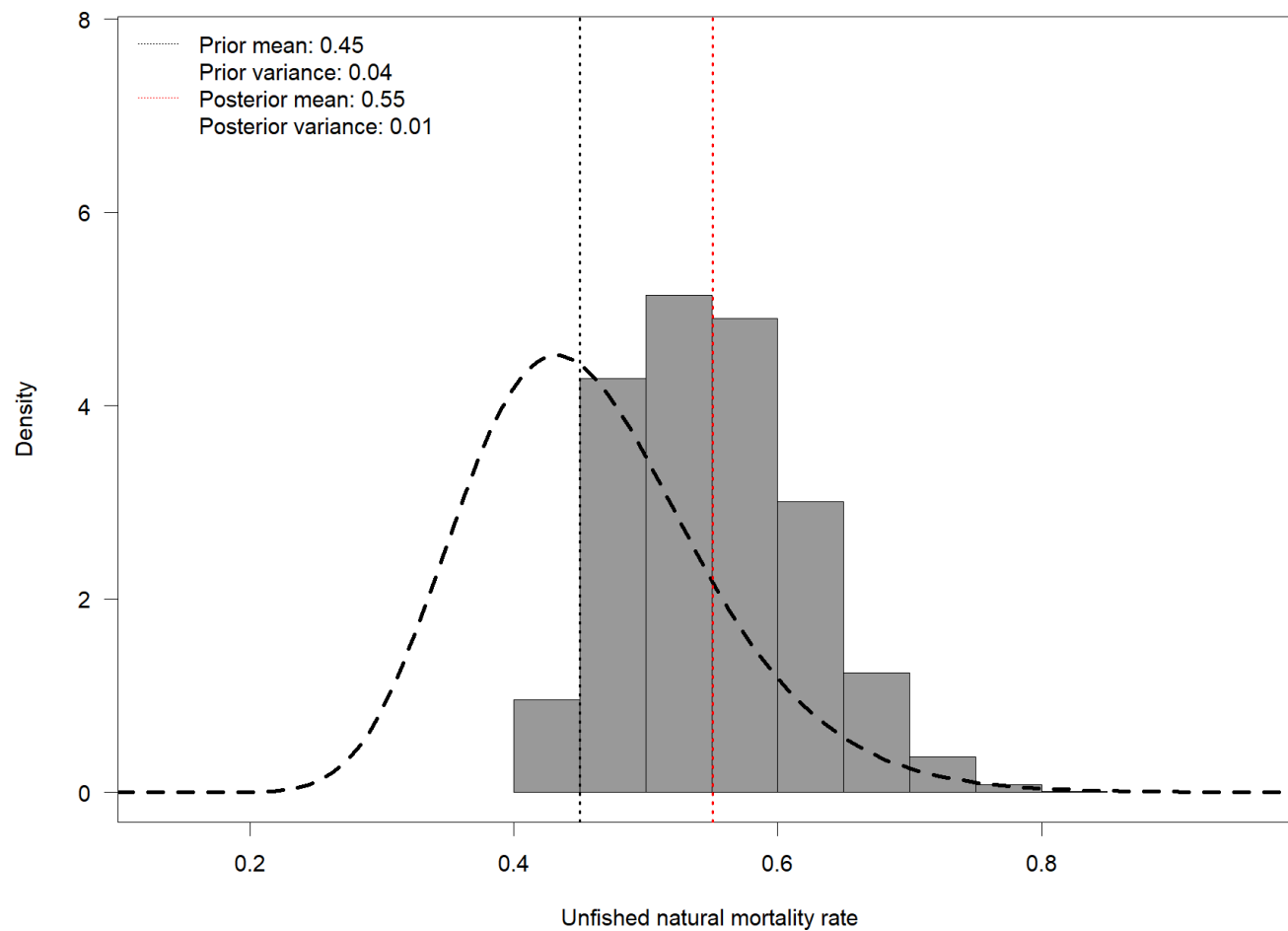


Figure D.85. West Coast of Vancouver Island SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for the unfished natural mortality rate M_0 .

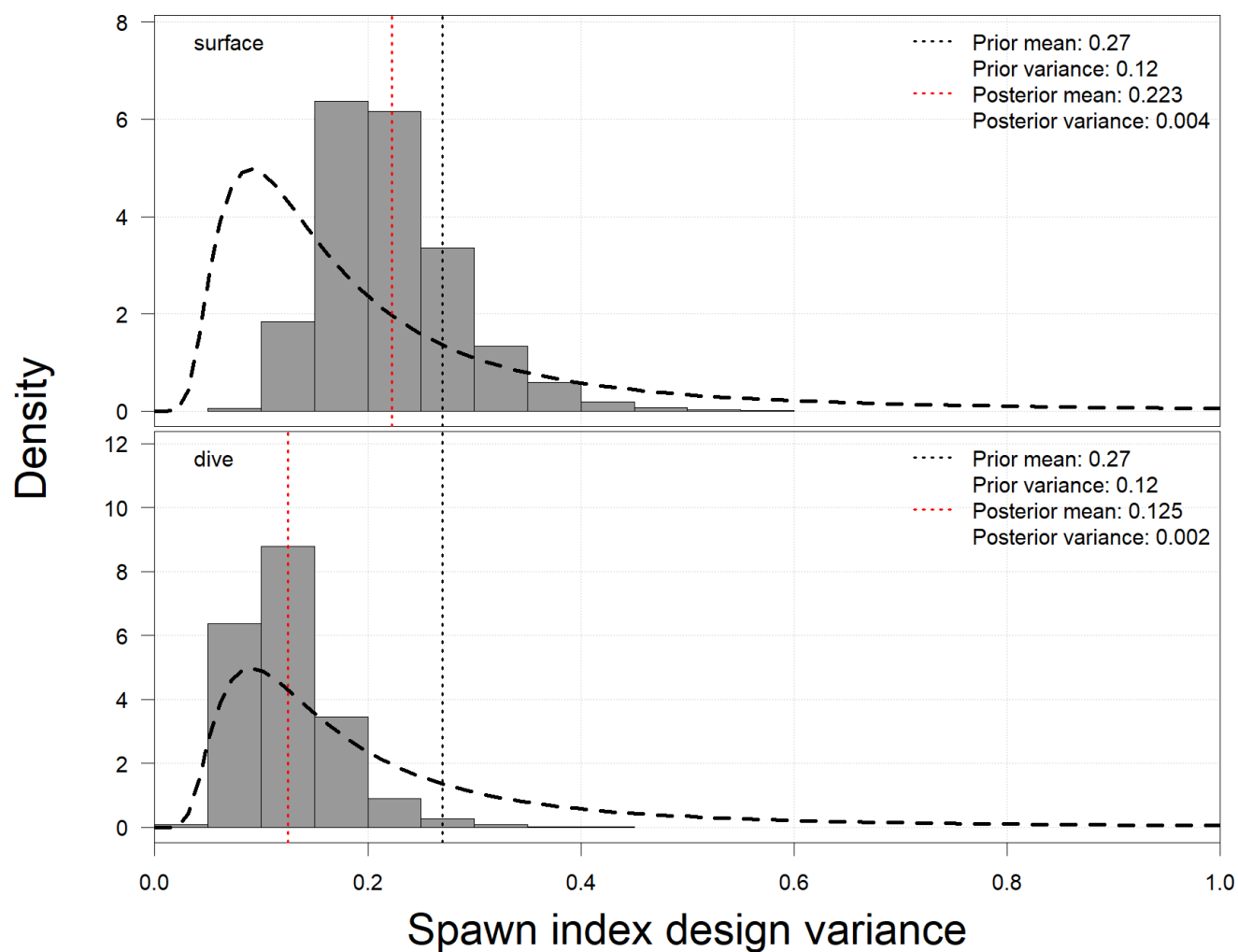


Figure D.86. West Coast of Vancouver Island SISCAH model marginal Bayes posterior (rectangles) and prior (line) distributions for spawn index observation residual standard error components from the Dive survey design (top) and surface survey design (bottom).



Figure D.87. Time series of West Coast of Vancouver Island herring spawning biomass with scaled spawn indices (top), recruitments (second row), natural mortality (third row), and harvest rates (bottom row). SB_0 , M_0 , and R_0 are unfished equilibrium spawning stock biomass, natural mortality, and recruitment respectively. q_s is the catchability coefficient for the surface surveys. SOK is spawn-on-kelp. In the recruitment panel, years with missing age data are indicated with a tick along the top axis, denoted by a 'I' in the figure legend.

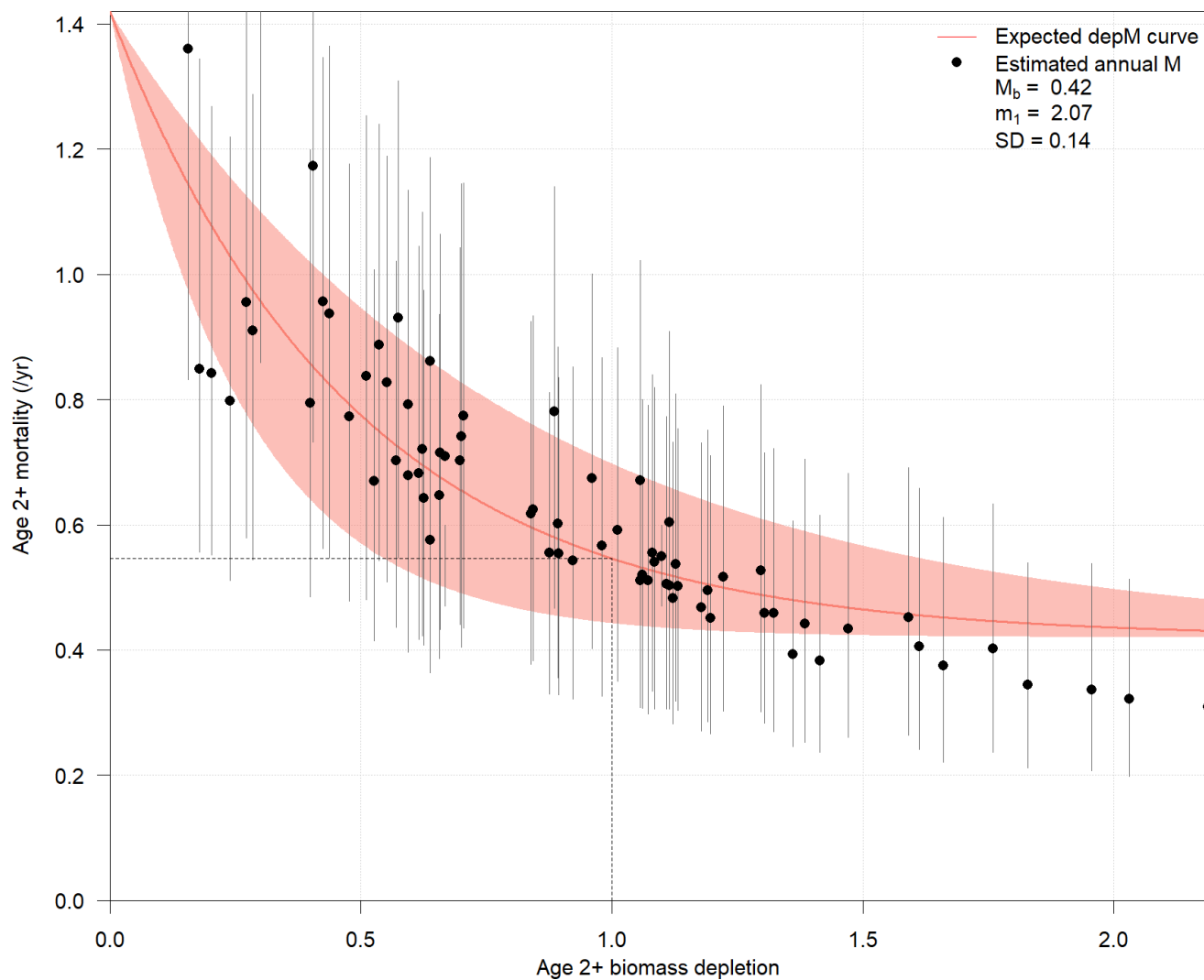


Figure D.88. West Coast of Vancouver Island SISCAH model posterior estimate of the density dependent relationship between age-2+ biomass and age-2+ natural mortality. The median relationship is shown by a thick line, with the posterior 95% credibility range shown by the shaded region. Individual points show the annual posterior median natural mortality estimates. The parameters shown are: m_1 = depensation rate; and M_b = asymptotic lower limit of density dependent mortality.

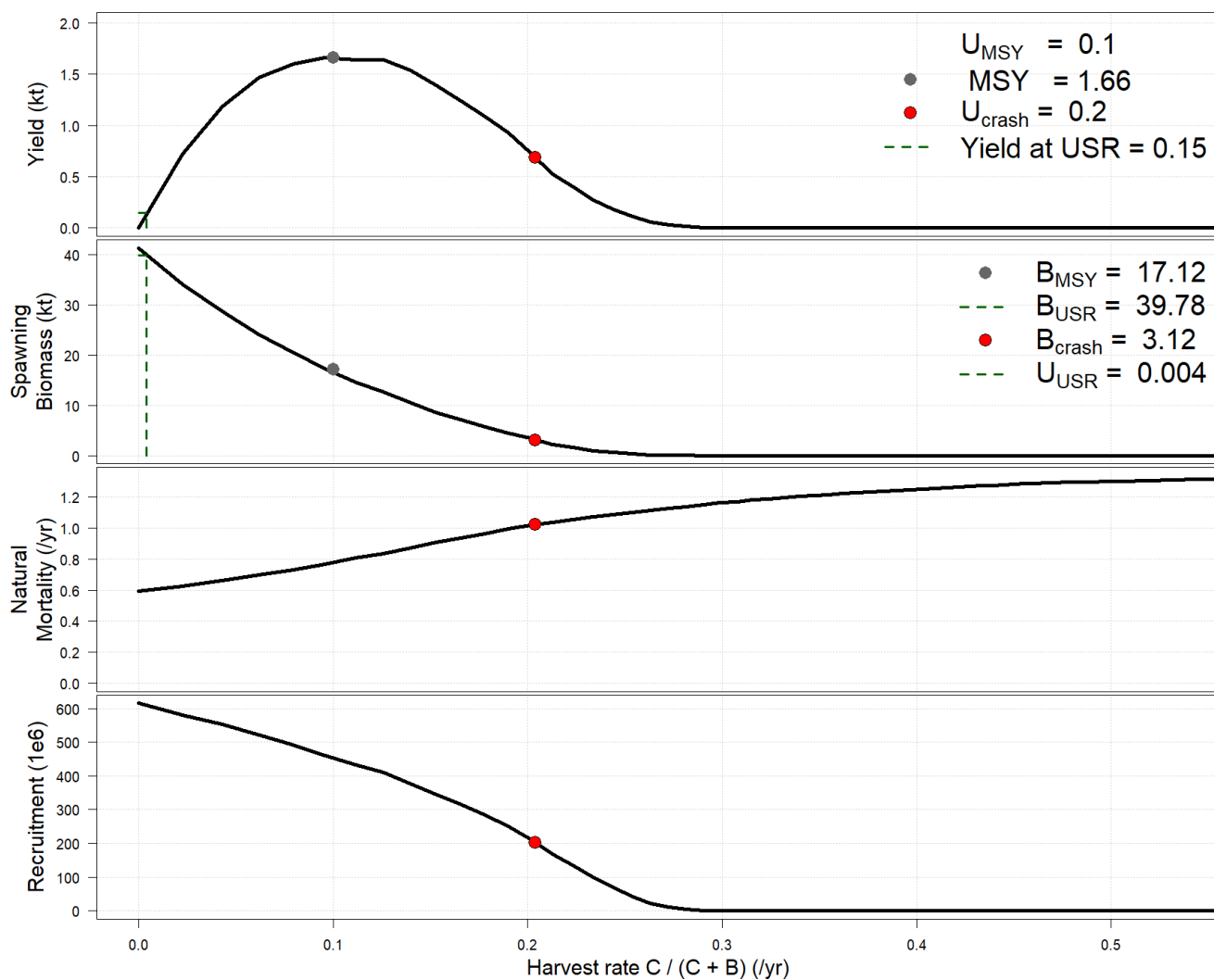


Figure D.89. West Coast of Vancouver Island reference points derived via median model equilibria of 200 year fishing mortality simulations, using the SISCAH model, with panels for yield, spawning biomass, natural mortality and recruitment. Grey points show values associated with the maximum sustainable yield (MSY). Red points show values associated with the steepest decline in yield. Green dashed lines show values associated with the upper stock reference (USR). Harvest rates are calculated as catch divided by catch plus spawning biomass.

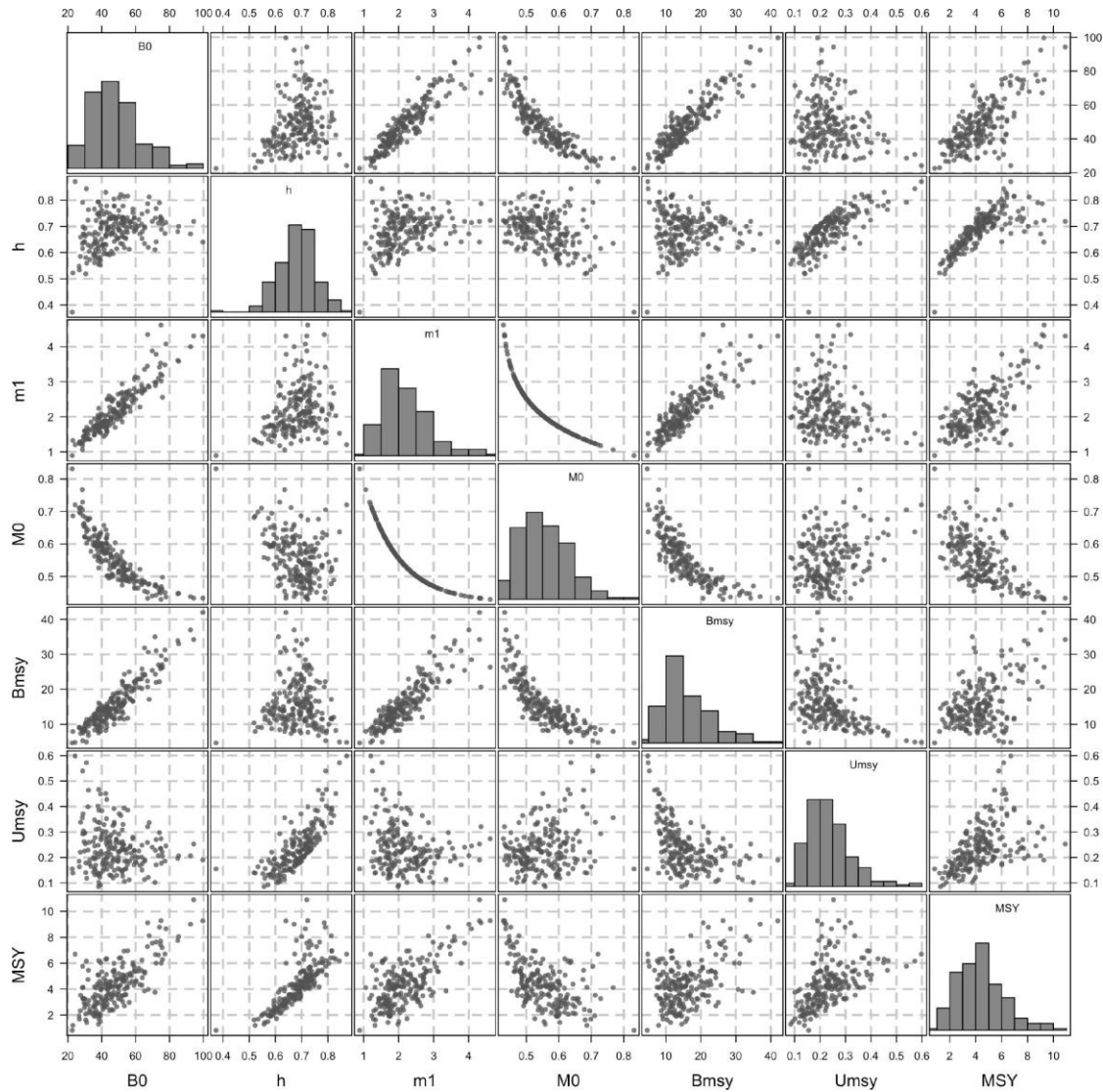


Figure D.90. West Coast of Vancouver Island: 500 random draws from joint marginal posterior distributions of selected life-history quantities and deterministic biological reference points, namely SB_0 = deterministic unfished equilibrium spawning biomass, h = stock-recruitment steepness, m_1 = depensation in density dependent mortality (if estimated), M_0 = deterministic unfished equilibrium mortality rate, B_{MSY} = deterministic optimal biomass, U_{MSY} = deterministic optimal harvest rate, MSY = deterministic maximum sustainable yield.

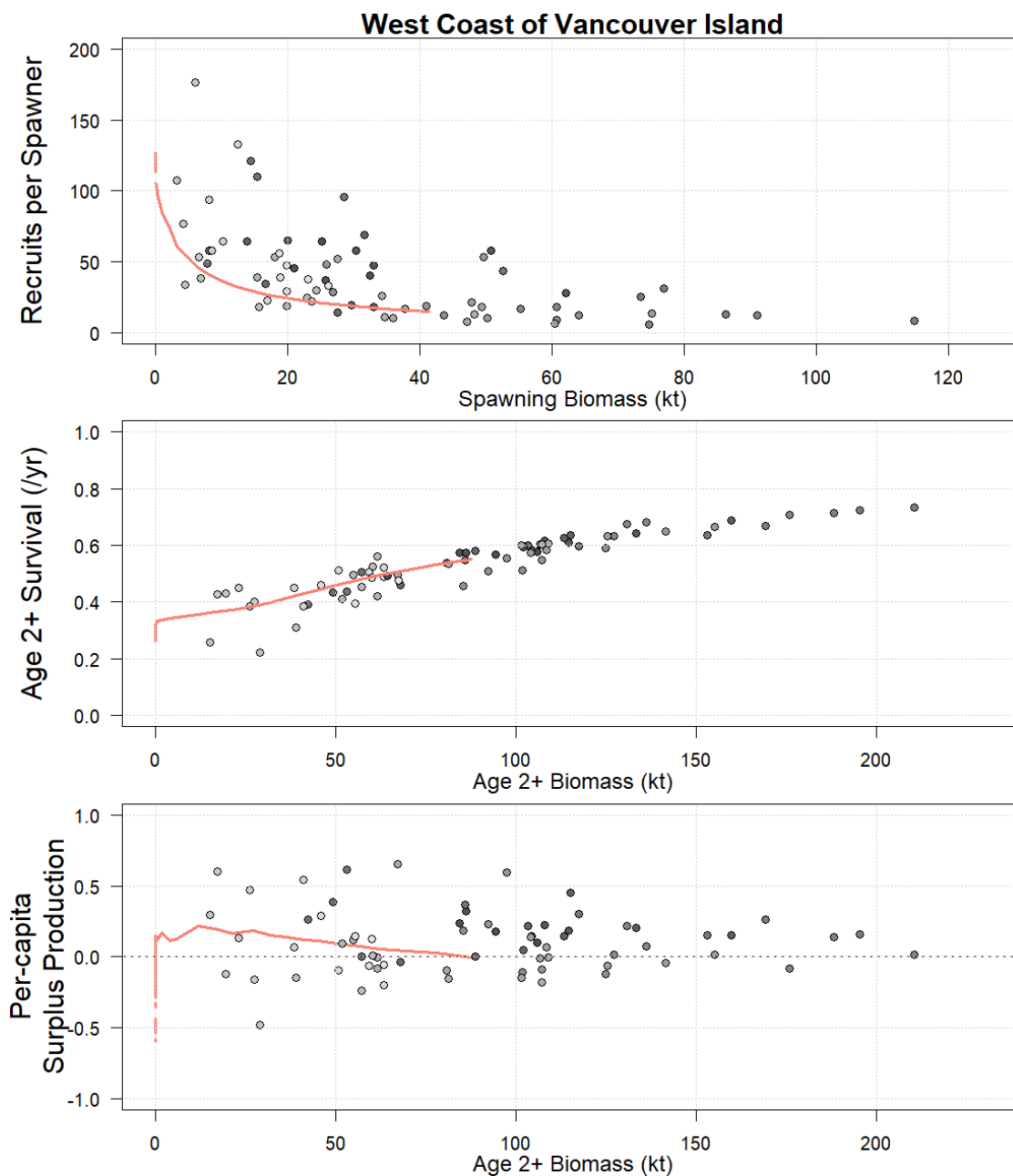


Figure D.91. West Coast of Vancouver Island SISCAN model estimates (points) and deterministic equilibria (lines) of recruits-per-spawner vs spawning biomass (top), density dependent age-2+ mortality as a function of age-2+ biomass (middle), and per-capita surplus production as a function of age-2+ biomass (bottom). Points are coloured to show phase, with light points for later years.

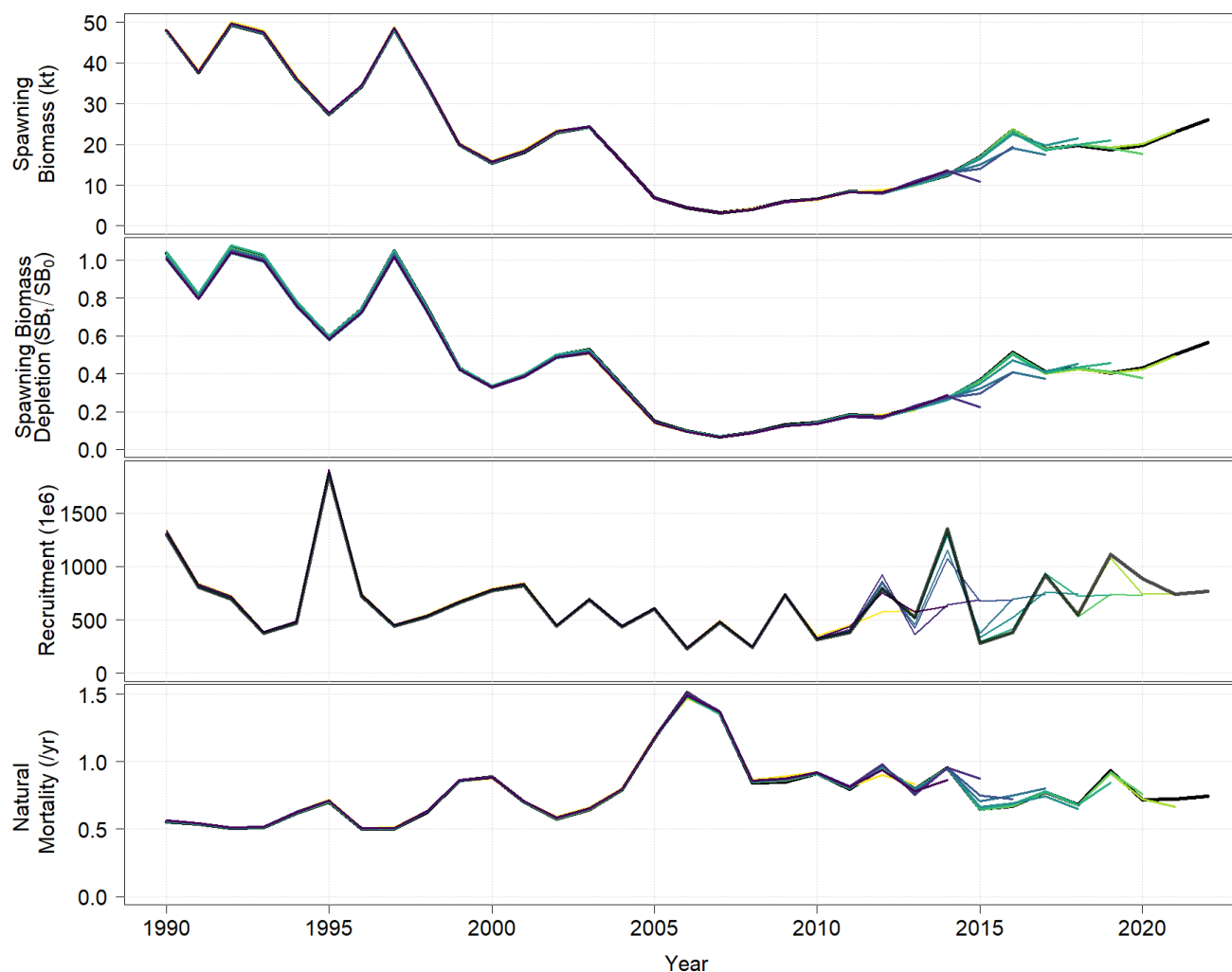


Figure D.92. West Coast of Vancouver Island SISCAN model retrospective estimates of spawning biomass (top) and spawning biomass depletion (second row), age-1 recruitment (3rd row), and natural mortality (bottom row), showing SISCAN model fits to successive data 'peels', which are truncated data sets with terminal years 2013–2022. The reference model is the largest data set in the 2022 peel, shown in black.

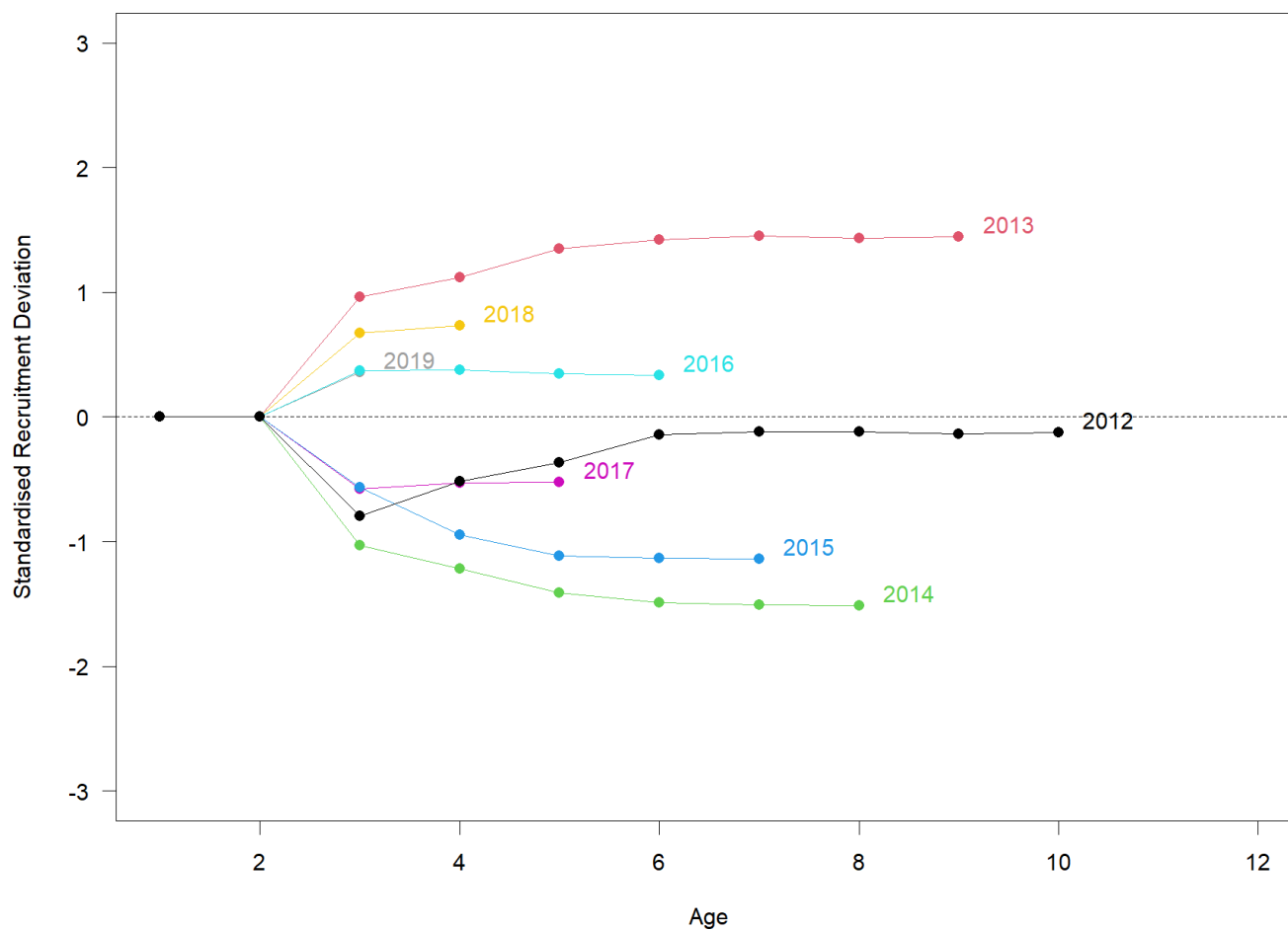


Figure D.93. West Coast of Vancouver Island SISCAH model retrospective estimates of standardised recruitment residuals, representing year class strength relative to the deterministic stock-recruitment relationship for models fit to successive data 'peels', which are truncated data sets with terminal years 2013–2022.

APPENDIX E. BIOLOGICAL REFERENCE POINTS UNDER DENSITY INDEPENDENT MORTALITY

The approach for estimating herring reference points under a density independent M formulation, such as a random walk, relies on a simplifying assumption to account for the time-variation in M . For random walk models (with or without an underlying spline), there is no mechanism explaining the variation in M , so reference point calculations for a model fit to data from 1951 to 2022 assume that the “equilibrium” natural mortality rate is the time-averaged value, i.e.,

$$M_0^{RW} = \frac{1}{T} \sum_{t=1951}^{2022} M_t, \quad (\text{E.1})$$

where $T = 2022 - 1951 + 1$ is the length of the model history. The mortality rate M_0^{RW} is then used to derive equilibrium population levels for all age-classes and all levels of fishing pressure. Any derivation of equilibrium yield starts from the assumption that at equilibrium, recruitment balances mortality and leads to replacement of the spawning stock (Quinn and Deriso 1999). In an unfished state, the replacement assumption gives

$$SB_0 = R_0 \sum_{a=1}^{A-1} e^{-(a-1)M_0^{RW}} \cdot w_a \cdot m_a + R_0 \frac{e^{-(A-1)M_0^{RW}}}{1 - e^{-M_0^{RW}}} \cdot w_A \cdot m_A$$

where w_a is mean weight-at-age over 1951–2022, m_a is the proportion of female individuals mature-at-age a , SB_0 is unfished spawning biomass, and R_0 is unfished recruitment. The unfished spawning-stock biomass-per-recruit is

$$\phi_0 = \frac{SB_0}{R_0}.$$

Equilibrium spawning-stock biomass-per-recruit can be extended assuming replacement under some amount of fishing pressure f , giving $\phi(f)$. For a multi-sector fishery, such as BC herring, the variable $f \in [0, \infty)$ parameterises a path through the space of fleet-specific fishing mortality rates as $F_g = r_g \cdot f$, where r_g is a relative fishing mortality scalar derived from the average allocation of catch among fleets over the most recent 20 years with fishing activity. Relative fishing mortality rates r_g are used to find sustainable yields, and therefore MSY, that match recent allocations among sectors for each SAR when $f = M_0$ (Table 7). For seine roe, gillnet, and reduction/food-and-bait fleets, yield is measured as catch in biomass units, while yield is measured as landed SOK product for SOK fisheries. Allocation for all fisheries is based on biomass, with landed spawn-on-kelp converted to ponded biomass equivalent via the SOK conversion model. Note that the reference points are sensitive to the choice of r_g scalars.

There is a continuum of stable population equilibria associated with a wide range of constant removal rates (i.e., fishing mortality or harvest rates) under deterministic recruitment conditions, and so the associated equilibrium yields along the yield curve are also stable. Therefore, any equilibrium yield is by definition sustainable under those same conditions. The traditional definition of MSY, in a single-sector system is the stationary point (i.e., optimum) along the equilibrium yield curve over the single-dimension decision space of fishing mortality rates. When generalising to more complex systems with multiple fleets, equilibrium yield forms a surface over that decision space. The surface has a global maximum, which may align with fishery

objectives regarding allocation, but it also may not and other considerations such as policy can define constraints.

In those cases, the maximum sustainable yield is the optimum yield over the new constrained decision space, here defined by the r_g parameterisation, rather than the global optimum.

To calculate $\phi(f)$, it is algebraically simpler to define survivorship-at-age for a given fishing mortality parameter f as

$$S_{a,f} = \begin{cases} e^{-\sum_{a'=1}^a Z_{a'}} & a < A_s \\ \frac{e^{-\sum_{a'=1}^a Z_{a'}}}{1 - e^{-\sum_{a'=1}^a Z_{a'}}} & a = A_s, \end{cases}$$

where $Z_a = M_0^{RW} + \sum_g s_{a,g} F_g$ is the total mortality for age class a , $s_{a,g}$ is fishery selectivity-at-age for gear g , and the $r_g F$ is the parameterised fishing mortality. Then, fished equilibrium spawning stock biomass-per-recruit is

$$\phi(f) = \frac{B_f}{R_f} = \sum_{a=1}^A S_{a,f} w_a \cdot m_a.$$

Similarly, equilibrium yield-per-recruit at the grid search parameter value f is calculated from total mortality via the Baranov equation

$$YPR(f) = \sum_{a=1}^A S_{a,f} \cdot w_a \cdot (1 - e^{-Z_a}) \cdot \frac{s_a F_g}{Z_a}.$$

Deriving equilibrium spawning biomass and yield from $\phi(f)$ and $YPR(f)$, and thereby establishing MSY and B_{MSY} , requires the equilibrium recruitment R_f , which until now has been unnecessary. For a Beverton-Holt stock recruitment function parameterised by stock-recruit steepness h and SB_0 , equilibrium recruitment is

$$R_f = \frac{R_0 \cdot 4h \cdot SB_f}{SB_0 \cdot (1 - h) + (5h - 1) \cdot SB_f},$$

within which spawning biomass can be substituted as $SB_f = R_f \cdot \phi(f)$, giving

$$R_f = \frac{R_0 4h \phi(f) - SB_0 (1 - h)}{5h - 1}.$$

For a given fishing mortality parameter f , equilibrium yield and spawning biomass are then derived as

$$Y(f) = R_f \cdot YPR(f), \quad (E.2)$$

$$SB_f = R_f \cdot \phi(f). \quad (E.3)$$

Standard MSY-based reference points for multi-sector fisheries are now readily derived from the above equations E.2 and E.3. First, maximum sustainable yield is

$$MSY = \max_f Y(f). \quad (E.4)$$

Then, the associated optimal fishing mortality rate that produces MSY is defined as

$$F_{MSY} = \arg \max_f Y(f), \quad (E.5)$$

and optimal biomass at which MSY is produced is

$$SB_{MSY} = R_{f=F_{MSY}} \cdot \phi(f = F_{MSY}). \quad (E.6)$$

Finally, for herring, the harvest rate achieving MSY is defined as

$$U_{MSY} = \frac{MSY}{MSY + SB_{MSY}}. \quad (E.7)$$