Guidance on when and how Science advice for Pacific salmon should account for time-varying population dynamics

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GUIDANCE ON WHEN AND HOW SCIENCE ADVICE FOR PACIFIC SALMON SHOULD ACCOUNT FOR TIME-VARYING POPULATION DYNAMICS

by

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ACKNOWLEDGEMENTS

We humbly and respectively acknowledge that this paper was written on the unceded traditional territories of Snuneymuxw, Songhees, and Esquimalt First Nations. We recognize that these Nations have been stewards of the land and water for millennia, and we honour and learn from their deep respect and understanding of the interconnection of all things.

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ABSTRACT

Holt, C.A., Connors, B., Greenberg, D., Wor, C. 2025. Guidance on when and how Science advice for Pacific salmon should account for time-varying population dynamics. Can. Tech. Rep. Fish. Aquat. Sci. 3653: xii + 90 p. https://doi.org/10.60825/002c-as40

Time-varying population dynamics are ubiquitous for Pacific salmon due to, for example, changing ocean conditions and degradation of freshwater habitats. When these changes are ignored, science advice may result in poor biological outcomes or failure to meet catch objectives. There is currently very little guidance on where, when, and how to account for them in science advice for Pacific salmon. We reviewed the literature and performed computer simulations to determine when and how stationary and time-varying assessment models should be applied to inform science advice for Pacific salmon.

When seeking to estimate population parameters from spawner-recruitment relationships, we found that models that annually track changes in productivity have better statistical reliability than stationary models or those that assume abrupt regime shifts. However, when models with time-varying parameters are applied for assessment or management purposes (e.g., as management reference points) under irreversible declines in productivity, they tend to be associated with increased biological risk relative to those that assume stationary dynamics. We recommend using time-varying models for assessment purposes only when the weight-of-evidence from multiple sources supports time-varying dynamics. Further, management actions that account for time-varying parameters should been evaluated in a risk-based, decision-making framework against those that assume stationary dynamics.

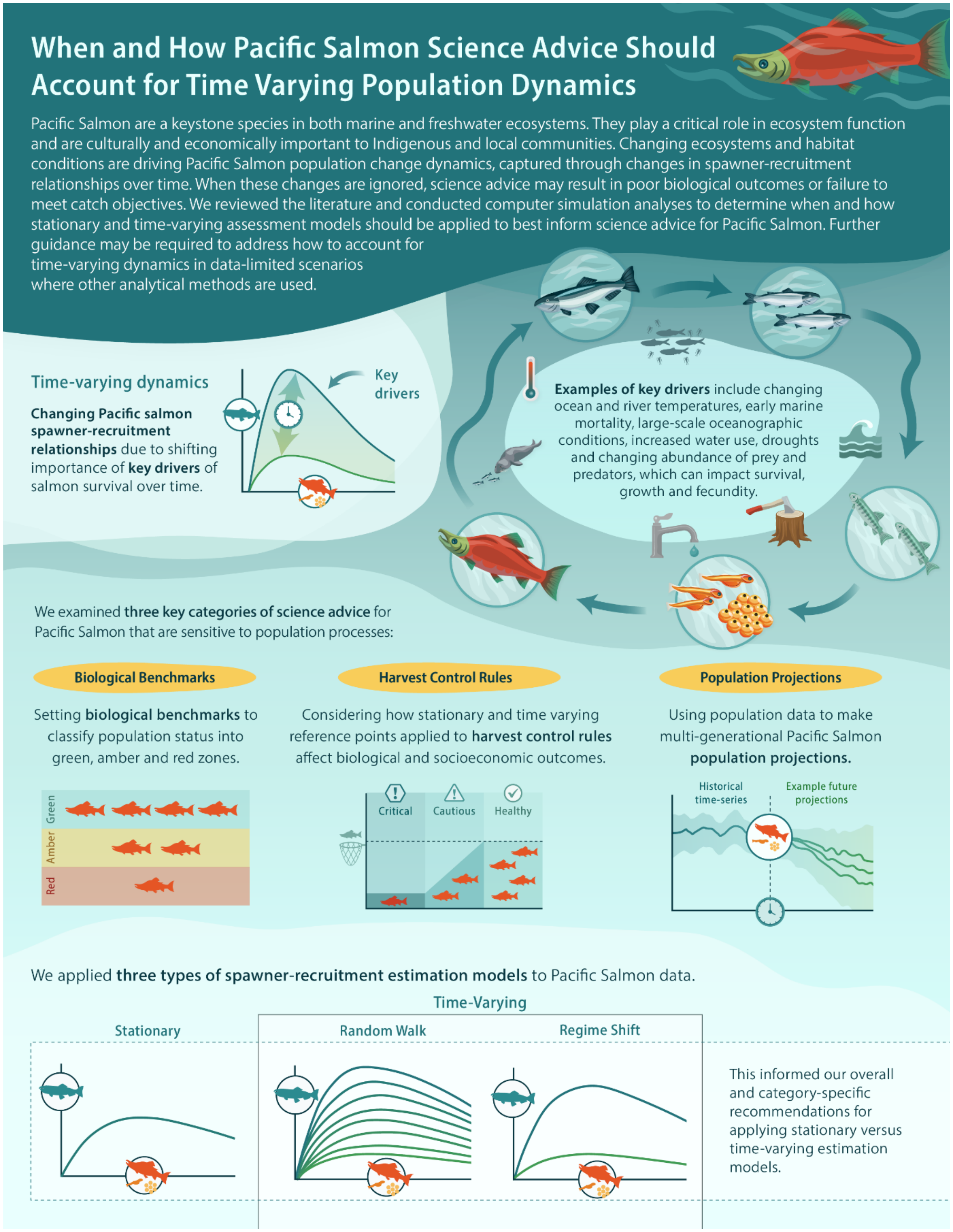
RÉSUMÉ

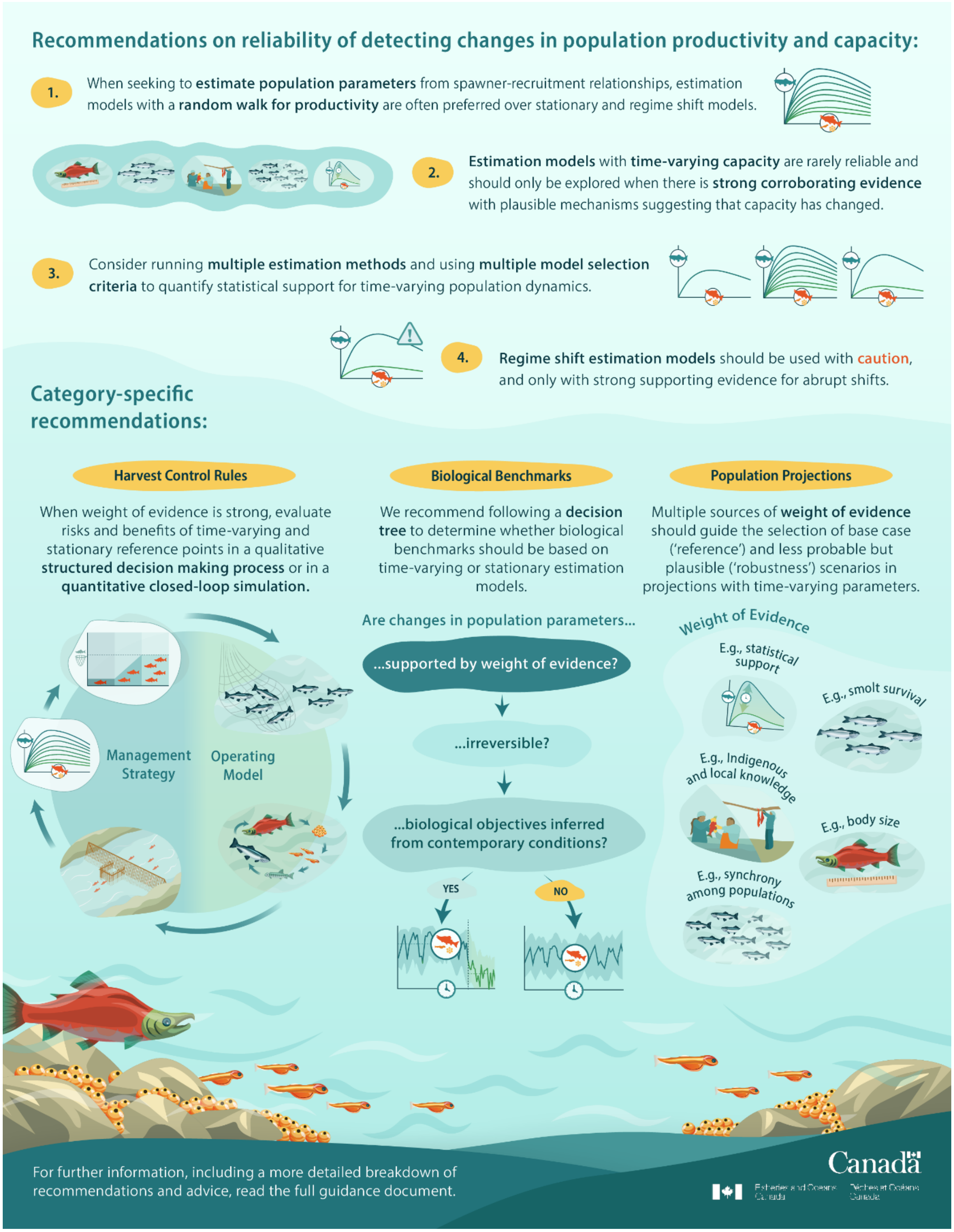
Holt, C.A., Connors, B., Greenberg, D., Wor, C. 2025. Guidance on when and how Science advice for Pacific salmon should account for time-varying population dynamics. Can. Tech. Rep. Fish. Aquat. Sci. 3653: xii + 90 p. https://doi.org/10.60825/002c-as40

La dynamique des populations qui varie dans le temps est omniprésente chez le saumon du Pacifique dus, par exemple, à l'évolution des conditions océaniques, à la dégradation des habitats en eau douce. Lorsque ces changements sont ignorés, les recommandations scientifiques peuvent aboutir à des résultats biologiques insatisfaisants ou à l'échec d'atteindre les objectifs de capture de la pêche. Il existe actuellement très peu d'indications sur où, quand et comment en tenir compte dans les avis scientifiques concernant le saumon du Pacifique. Nous avons examiné la littérature et effectué des simulations informatiques pour déterminer quand et comment des modèles d'évaluation stationnaires et variables dans le temps devraient être appliqués pour éclairer au mieux les avis scientifiques sur le saumon du Pacifique.

En cherchant à estimer les paramètres de population à partir des relations géniteurs-recrues, nous avons constaté que les modèles qui suivent les changements de productivité annuellement ont une meilleure fiabilité statistique que les modèles stationnaires ou ceux qui supposent des changements brusques de régime. Cependant, lorsque des modèles avec des paramètres variables dans le temps sont appliqués à des fins d'évaluation ou de gestion (par exemple, comme points de référence pour la gestion) dans un contexte de déclin irréversible de la productivité, ils ont tendance à être associés à un risque biologique accru par rapport à ceux qui supposent des dynamiques stationnaires. Nous recommandons d'utiliser des modèles qui permettent la variabilité temporelle à des fins d'évaluation uniquement lorsqu'il existe plusieurs preuves qui soutiennent une variation temporelle dans la dynamique des populations. De plus, les actions de gestion qui tiennent compte de paramètres variables dans le temps devraient être évaluées dans un cadre décisionnel basé sur les risques par rapport à celles qui supposent une dynamique stationnaire.

GRAPHICAL ABSTRACT





Recommendations on reliability of detecting changes in population productivity and capacity:
1.
When seeking to estimate population parameters from spawner-recruitment relationships, estimation models with a random walk for productivity are often preferred over stationary and regime shift models.
2.
Estimation models with time-varying capacity are rarely reliable and should only be explored when there is strong corroborating evidence with plausible mechanisms suggesting that capacity has changed.
3.
Consider running multiple estimation methods and using multiple model selection criteria to quantify statistical support for time-varying population dynamics.
4.
Regime shift estimation models should be used with caution, and only with strong supporting evidence for abrupt shifts.
Category-specific recommendations:
Harvest Control Rules
When weight of evidence is strong, evaluate risks and benefits of time-varying and stationary reference points in a qualitative structured decision making process or in a quantitative closed-loop simulation.
Management Strategy
Operating Model
Biological Benchmarks
We recommend following a decision tree to determine whether biological benchmarks should be based on time-varying or stationary estimation models.
Are changes in population parameters...
...supported by weight of evidence?
...irreversible?
...biological objectives inferred from contemporary conditions?
YES
NO
Population Projections
Multiple sources of weight of evidence should guide the selection of base case ('reference') and less probable but plausible ('robustness') scenarios in projections with time-varying parameters.
Weight of Evidence
E.g., statistical support
E.g., smolt survival
E.g., Indigenous and local knowledge
E.g., body size
E.g., synchrony among populations
For further information, including a more detailed breakdown of recommendations and advice, read the full guidance document.
Canada

1. INTRODUCTION

1.1. Background

The assessment and management of Pacific salmon is typically based on the premise that the longer one observes a biological system the better able they are to characterize its dynamics. This premise assumes that while a salmon population may fluctuate from year to year, it does so around some long-term average (i.e., stationary) conditions. However, time-varying (i.e., non-stationary) population dynamics are common in Pacific salmon (Dorner et al. 2008; Peterman and Dorner 2012, Malick and Cox 2016, Dorner et al. 2018, Freshwater et al. 2022), and can result from changes in survival or demographic characteristics over time due to, for example, changing ocean conditions (e.g., Malick 2020), degradation of freshwater spawning and rearing habitats (Beechie et al. 2023), and changes in ecosystem structure and function (e.g., increasing predator abundance, Couture et al. 2024). These changes are expected to become even more common and larger in magnitude as the marine and freshwater habitats salmon use rapidly change due to climate change (e.g., Crozier et al. 2021, Crozier and Siegel 2023, Litzow et al. 2024).

1.2. Legislative and policy context

While the policies and legislation guiding the management of salmon fisheries refer to changing environmental and biological conditions, robust guidance on how to address these changes is not provided. The Fish Stocks provisions (FSPs) of the *Fisheries Act* (2019) state that “the biology of the fish and environmental conditions affecting the stock” should be considered when managing the stock, providing legislative context for this guidance. The FSPs are implemented in part through DFO’s Precautionary Approach Framework (DFO 2009), which recommends considering temporal variation in population dynamics when developing reference points. Canada’s Wild Salmon Policy (DFO 2005) further states that current environmental conditions should be considered when setting biological benchmarks of population status, and DFO’s Ecosystem Approach to Fisheries Management recommends time-varying parameters in assessment models as a tool to integrate ecosystem considerations into decision-making (Pepin et al. 2023). To support implementation of the *Species At Risk Act* (SARA, 2002), Recovery Potential Assessments are developed to provide “best science advice possible” for decisions around listing species under the SARA, including projections under biologically realistic scenarios that consider uncertainties in future conditions (DFO 2007).

1.3. What’s in this document?

This document aims to help close the gap for addressing changing biological and environmental conditions by providing practical guidance to assessment analysts and managers on where, when, and how to account for time-varying dynamics in science advice for Pacific salmon. It summarizes key questions, and associated insights and recommendations for Pacific salmon when providing science advice on biological benchmarks, developing harvest control rules, and projecting population dynamics to inform decision making, e.g., through rebuilding planning and management strategy evaluations (‘closed-loop simulations’) (Figure 1). This guidance is drawn from simulation-evaluations that were undertaken specifically to inform the document, from guidance developed by other jurisdictions (summarized in Appendix Table A1) and from the peer review literature (summarized in Appendix Table A2).

This guidance is based on advice related to modelling of salmon spawner-recruitment relationships[1]. Further guidance may be required to address how to account for time-varying dynamics in data-limited scenarios where other analytical methods are used (e.g., empirical or habitat-based reference points). While some of the recommendations provided here are widely applicable across a range of data availability and analytical methods, our guidance is not specific to those alternative data-limited methods. Further guidance may also be required where alternative, more complex spawner-recruitment models are used, e.g., for cyclic populations or those with environmental or biological co-variates.

Best practice is not an absolute or fixed entity, or a guarantee of adequacy, instead it is based on experience to date. The recommendations and guidance provided here recognize that views of what is 'best' or 'recommended' will themselves be 'time-varying' and hence evolve and improve over time with experience. This document provides guidance on identifying time-varying dynamics relevant to all elements of science advice for Pacific salmon first, followed by element-specific guidance related to three overarching categories of advice: biological benchmarks, harvest control rules, and projections. Suggested audiences for each section of this guidance document are provided. We recognize that changing reference points in biological assessment and harvest control rules involves not only biological, but also other management considerations that underlie objectives. We emphasize the need to work with managers to identify frameworks to guide decisions on assessments and reference points (Zhang et al. 2021a).

Analytical tools to support the estimation of time-varying parameters in spawner-recruitment relationships and the evaluation of these methods in biological assessments and harvest control rules were developed and are publicly accessible (see links to R packages in Appendix B).

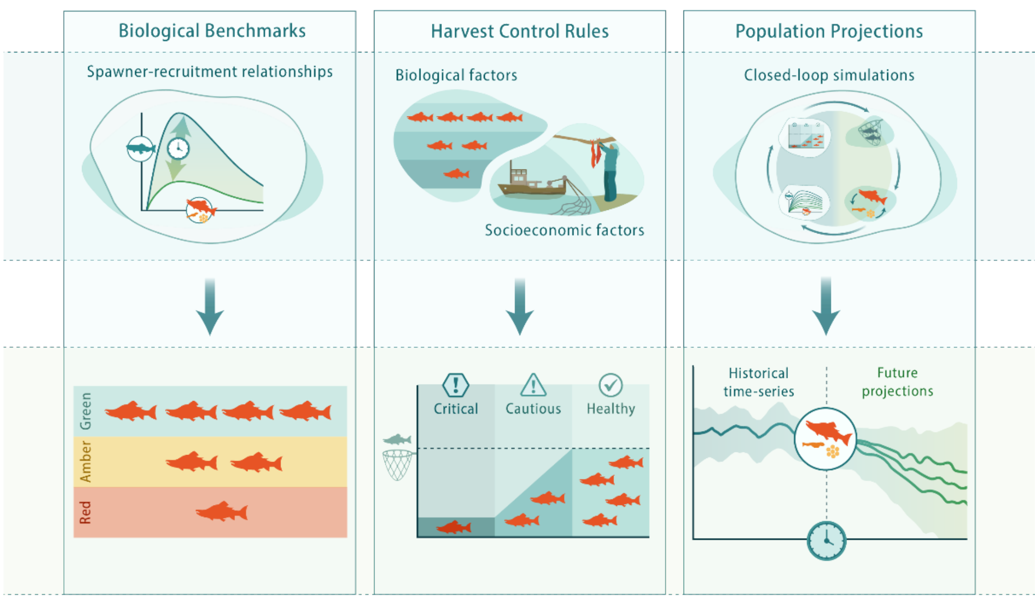


Figure 1. Simple schematic of three categories of advice (columns) addressed in this guidance document that use spawner-recruitment relationships: identifying spawner-recruitment based benchmarks for biological assessments, identifying reference points used in harvest controls rules that are informed by biological and socio-economic factors, and population projections often used in closed-loop simulations.

[1] Analyses presented here are based on Ricker spawner-recruitment relationships, but guidance is broadly applicable across spawner-recruitment models.

2. GUIDANCE ON IDENTIFYING TIME-VARYING PARAMETERS

Guidance on identifying time-varying population parameters

Goal: provide advice on ability of estimation models to detect true underlying changes in parameters from spawner-recruitment relationships

Primary Audience: stock assessment analysts

Secondary Audience: Fisheries Management, Species at Risk Program, Salmonid Enhancement Program, Fish and Fish Health Protection Program

Four key questions, **16 insights**, and **four recommendations** are derived from our simulation-evaluation and supported by a review of the literature (Figure 2, described in detail below).

2.1. Context

Providing advice on the statistical accuracy and reliability of parameter estimates is relevant for understanding population dynamics in a changing environment. Our insights and recommendations are based on results from a simulation-evaluation which compared estimates of productivity and capacity from stationary and time-varying spawner-recruitment models with known 'true' values under various scenarios of changes in these parameters (Appendix Figure C1). Estimation models that annually track parameters (using 'random walk models') and those that identify abrupt regime shifts in parameters (using 'hidden Markov models') are considered[2] (Figure 3). These analyses further evaluated the ability of statistical model selection criteria (i.e., AIC, BIC, and leave-future-out cross validation, LFO-CV) to detect time-varying dynamics. The goal of these analyses was to evaluate our ability to detect time-varying dynamics and estimate parameters, and not on biological assessments of stock status or harvest control rules, which are explored in later sections. Data truncation (removing data that pertains to time-periods before or after a regime shift) may be relevant once those changes have been identified, and is discussed in the next section on benchmarks; this section focuses on the statistical accuracy and reliability of parameter estimation approaches.

2.2. Questions and insights

2.2.1. Question 1: Statistical performance

Guidance on Identifying Time-varying Population Parameters, Question 1: How does the magnitude and type of population process affect the statistical performance (i.e., bias and precision[3]) of both stationary and time-varying spawner-recruitment estimation models?

[2] Spawner-recruitment models used here capture variability in recruitment due to mortality prior to adult return to freshwater, but do not include mortality that occurs after recruitment prior to spawning during return migration.

[3] Throughout this question and associated insights "bias" is median absolute bias in parameter estimates, "precision" is the coefficient of variation (CV) in parameter estimates across all time steps, "stationary" refers to scenarios and estimation models that have autocorrelated recruitment deviations, and all estimation models are fit in a Maximum Likelihood framework.

Guidance on Identifying Time-varying Population Parameters: Insights and Recommendations

Q1: How does the magnitude and type of time-varying population process affect the statistical performance (i.e., precision and bias) of both stationary and non-stationary spawner-recruitment estimation models?

1. When there are no underlying changes in productivity or capacity over time, all classes of models tend to have similar statistical performance
2. When there are true underlying changes in productivity over time, models that allow productivity to vary continuously over time tend to yield the most precise and least biased parameter estimates
3. The same is true for models that allow capacity to vary continuously over time when there are true underlying changes in capacity, but the improvements are more modest.
4. The type of change in population processes (e.g., abrupt vs gradual, increasing vs. decreasing) also impacts performance.
5. When both productivity and capacity change over time the performance of all model classes is relatively poor.
6. When large and abrupt declines in productivity occur, random walk models take on average up to 10 years of observations post change for estimates to approach the new long-term dynamics.

Q2: How well and under which conditions do alternative model selection criteria correctly classify different types of time-varying dynamics?

1. When there are no underlying changes in productivity or capacity over time, likelihood-based model selection criteria tend to correctly detect stationary dynamics. However, it is difficult to differentiate autocorrelated variation in recruitment from persistent changes in productivity
2. Standard model selection criteria are not able to consistently detect true underlying time-varying dynamics, though performance is variable
3. Likelihood based model selection criteria are better at detecting true underlying changes in productivity over time than changes in capacity
4. The reliability of likelihood-based model selection criteria depends on the direction and type of underlying change and improves as the magnitude of change increases.
5. Likelihood-based model selection criteria tend to select models with gradually changing parameters over those with abrupt changes, even when the true underlying dynamics include regime shifts.
6. When both productivity and capacity vary, model selection is less reliable than when either one varies alone.
7. The leave-future-out-cross-validation (LFO-CV) model selection criterion has poor reliability over a range of underlying time-varying dynamics.

Q3: How does variability in recruitment and exploitation rate history impact statistical performance of estimation models and ability to detect time-varying dynamics using model selection criteria?

1. Reducing the standard deviation in recruitment residuals within plausible ranges can improve ability to detect time-varying dynamics but these improvements are relatively minor given inherent natural variability in recruitment and limitations on accuracy of sampling methods
2. High exploitation rates increase bias and reduce precision in estimates of capacity but not productivity when there is a linear decline in productivity

Q4: What are the costs (in terms of bias and precision) of fitting an incorrect estimation model?

1. The costs of fitting an incorrect estimation model are highly asymmetric. On the one hand, fitting a time varying estimation model to stationary dynamics comes with little cost to statistical performance of parameter estimates, but on the other hand, fitting a stationary estimation model to data from a population that exhibits time varying dynamics results in more biased and less precise parameter estimates.

<u>Recommendation 1</u>
When seeking to estimate population parameters from spawner-recruitment relationships, estimation models with a random walk for productivity are preferred over stationary and regime shift models.

<u>Recommendation 2</u>
Estimation models with time-varying capacity are rarely reliable and should only be explored when there is strong corroborating evidence with plausible mechanisms suggesting that capacity has changed

<u>Recommendation 3</u>
Consider running multiple model selection criteria and estimation frameworks (frequentist and Bayesian) to assess evidence for time-varying population dynamics

<u>Recommendation 4</u>
Regime shift estimation models should be used with caution, and only with supporting evidence for abrupt shifts

Figure 2. Schematic of four key questions, 16 insights, and four recommendations to support guidance on identifying time-varying population parameters estimated from spawner-recruitment relationships.

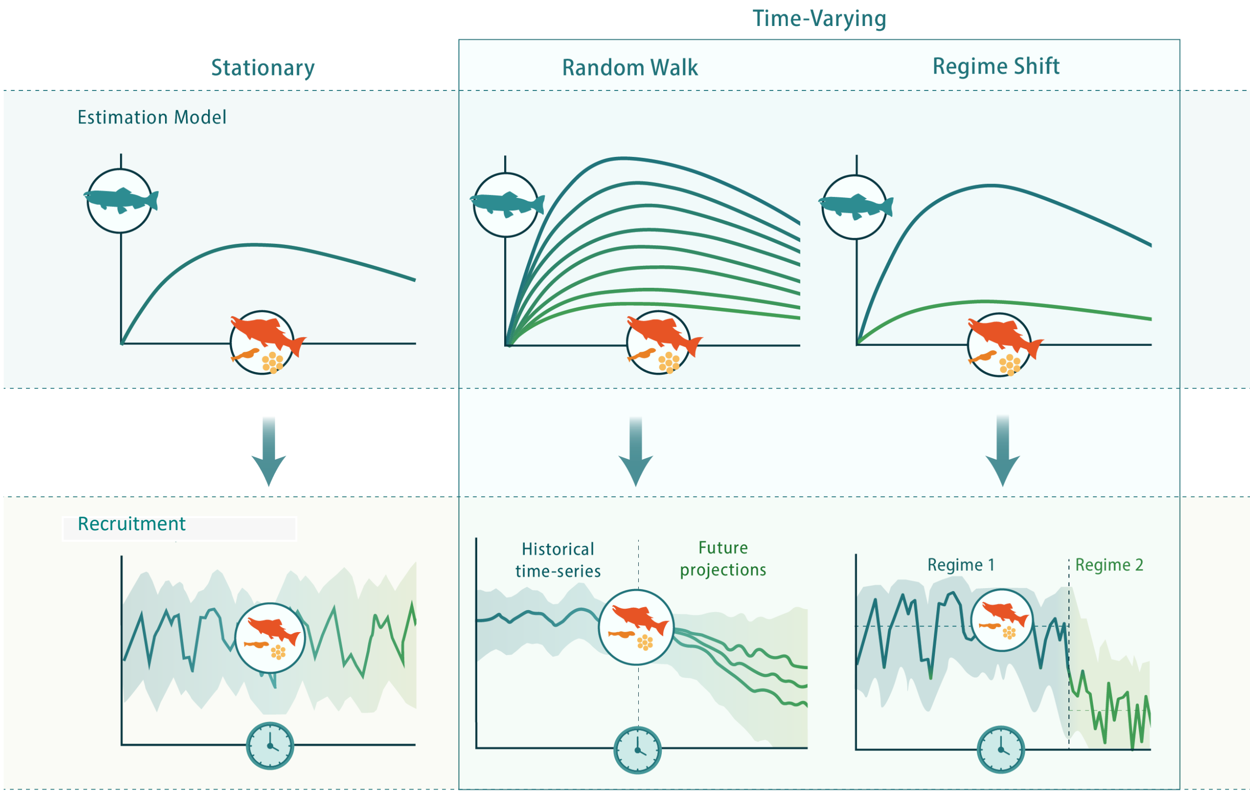


Figure 3. Simple schematic of spawner-recruitment estimation models considered in this guidance document (top row) that assume parameters are stationary (left column), time-varying annually according to a random walk (middle column), or time-varying according to a regime shift (right column). Corresponding hypothetical time series in recruitment are illustrated in the bottom row.

2.2.1.1. Insight 1

When there are no underlying changes in productivity or capacity over time, all classes of spawner-recruitment estimation models (i.e., stationary, random walk, and regime shift) tend to have relatively similar statistical performance (Appendix Figure C2 and Figure C3), though parameter estimates from time-varying estimation models are slightly less precise (coefficient of variation, CV, for the random walk and regime shift estimation models were similar or higher than for stationary estimation model (Appendix Figure C4 and Figure C5)). The one exception to the above is estimation models that allow capacity to vary as a regime shift which have much poorer performance than other estimation models.

2.2.1.2. Insight 2

When there are true underlying changes in productivity over time, estimation models that allow productivity to vary continuously over time as a random walk tend to yield the least biased estimates of productivity, compared to both stationary or regime shift models (Figure 4), and these models have an intermediate level of precision (Appendix Figure C4 and Figure C5). This insight is consistent with the findings in the literature (e.g., Peterman et al. 2000).

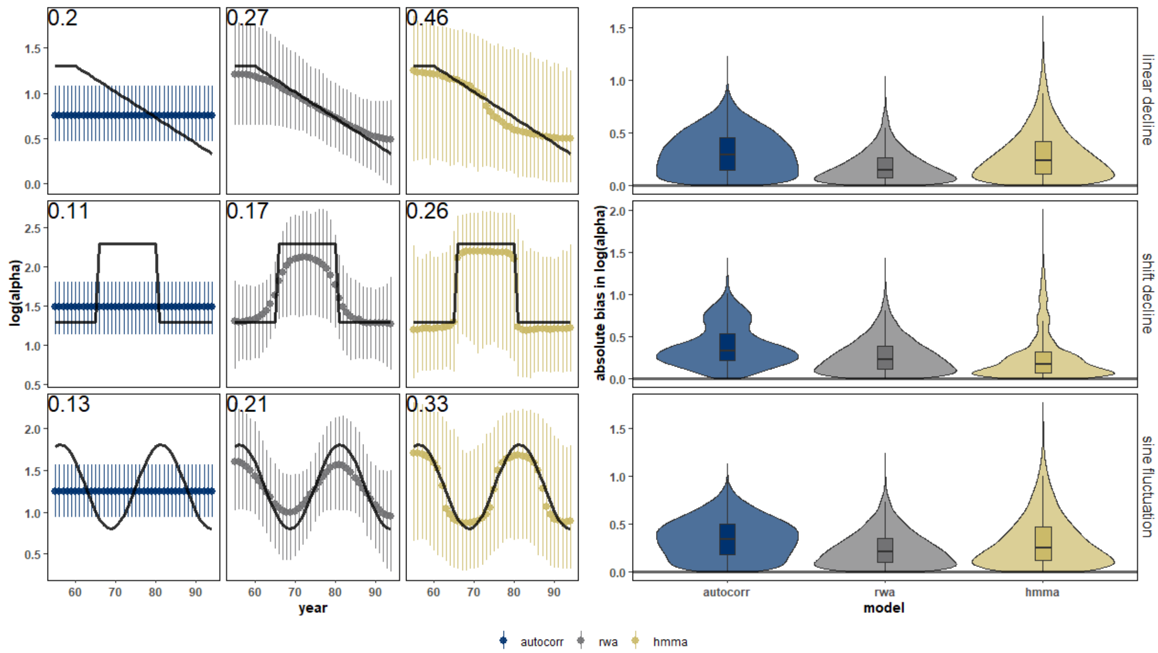


Figure 4. Statistical performance of alternative estimation models. Rows indicate different simulation scenarios of true change in productivity (labelled log(alpha), as parameterized in the Ricker spawner recruitment model) and columns and colors indicate estimation models ("autocorr" denotes stationary with lag-1 year autocorration in residual variation, "rwa" denotes random walk on productivity, and "hmma" denotes regmine shift on productivity). Left panels show simulated trajectory of log(alpha) (black lines) and median and 95% quantiles of estimates (color range plots) as well as mean CV in parameter estimates in top left corner. Right panels show absolute % bias violin plots combined over the entire time series, where the best performance results in highest mass closer to zero (wider base and low peak).

2.2.1.3. Insight 3

When there are true underlying changes in capacity over time, estimation models that allow capacity to vary continuously over time as a random walk tend to yield similar or slightly less biased and similarly precise estimates of capacity, compared to both stationary or regime shift models (Appendix Figure C3 and Figure C5, respectively). However, these improvements in statistical performance are small to negligible compared to cases where productivity varied over time (Appendix Figure C2 and Figure C4).

2.2.1.4. Insight 4

When both productivity and capacity change over time, the statistical performance of all estimation models is relatively poor, though models that allow productivity to vary over time as a random walk tend to produce the least biased and similarly precise parameter estimates (Appendix Figure C2-Figure C5).

2.2.1.5. Insight 5

The type of change in population processes (e.g., abrupt vs gradual and increasing vs. decreasing) also matters. **Parameter estimates are generally less biased and more precise when derived from models fit to time series with gradual change over abrupt change** (Figure 5).

2.2.1.6. Insight 6

When large and abrupt declines in productivity occur, **random walk models take on average up to 10 years of observations post change for estimates to approach the new long-term dynamics.** It takes around five years for the estimation models to capture the regime shift dynamics, however, the data for the run-reconstruction only becomes available after one generation (~5 years in this case), which further increases the delay in detecting the shift in spawner-recruit dynamics.

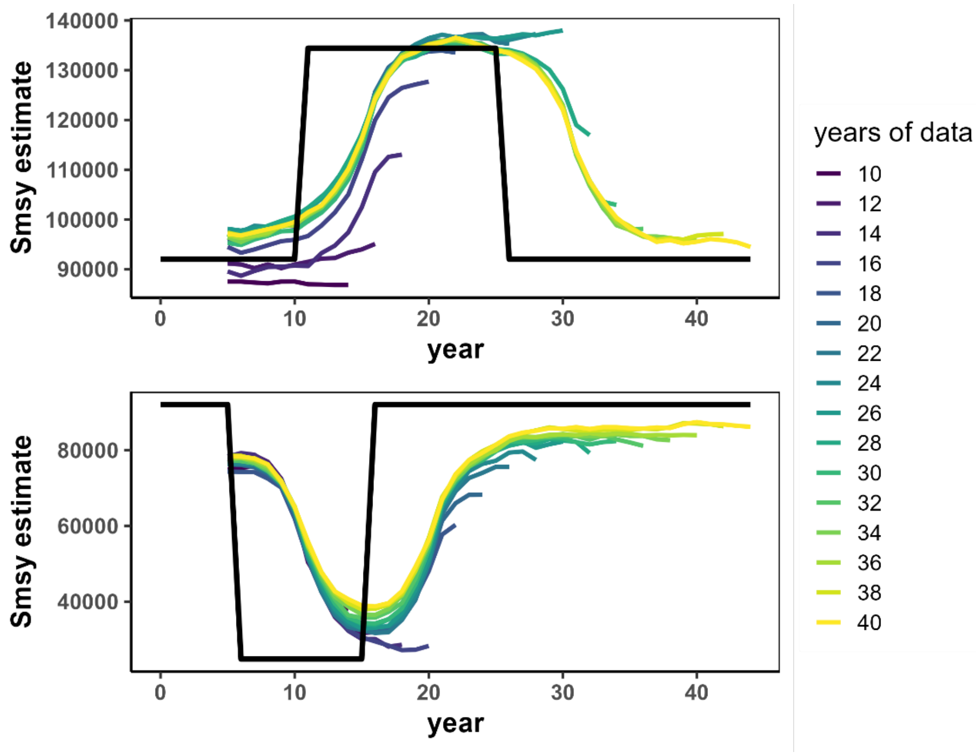


Figure 5. Results of retrospective analyses showing median estimates of the spawners for maximum sustainable yield (S_{MSY}) from a Ricker model with time-varying productivity with different lengths of the full time-series (colour-scale) relative to the true simulated time-series of S_{MSY} (black). Estimates of SMSY in a given brood cohort will lag assessment by ~10 years based on both the delay in data for run-reconstructions (5 years in this case) and the identifiability of parameter shifts in the model (~5 years).

2.2.2. Question 2: Model performance

Guidance on Identifying Time-varying Population Parameters, Question 2: How well and under which conditions do alternative model selection criteria (AIC, BIC and leave-future-out cross validation, LFO-CV) correctly classify different types of dynamics?

2.2.2.1. Insight 1

When there are no underlying changes in productivity or capacity over time, likelihood-based model selection criteria tend to correctly detect stationary dynamics. However, it is **difficult to differentiate autocorrelated variation in recruitment from persistent changes in productivity** using model selection. For populations that exhibit temporal autocorrelation in recruitment variability due to, for example variability in age at maturity that spread the impacts of episodic events over multiple age classes, models with time-varying productivity are often selected even when underlying parameters are stationary (Figure 6, left two columns).

Likelihood-based model selection criteria AIC and BIC perform similarly, with slight improvements under BIC, which has a steeper penalty on model complexity than AIC.

2.2.2.2. Insight 2

Standard model selection criteria **are not able to consistently detect true underlying dynamics** in spawner-recruitment models, though performance of criteria is variable. For likelihood-based selection criteria, the ability to detect dynamics depends on the type and magnitude of underlying dynamics (Figure 6). Similarly, in a simulation-evaluation, Holt and Michielsens (2020) found that likelihood-based criteria were unreliable for model selection when underlying spawner-recruitment parameters were time-varying.

2.2.2.3. Insight 3

Likelihood-based model selection criteria are better at detecting true underlying changes in productivity over time than changes in capacity (Figure 6). The statistical signature of changes in these two parameters is similar and so it is often difficult to differentiate them. In addition, capacity is often mis-identified as stationary dynamics.

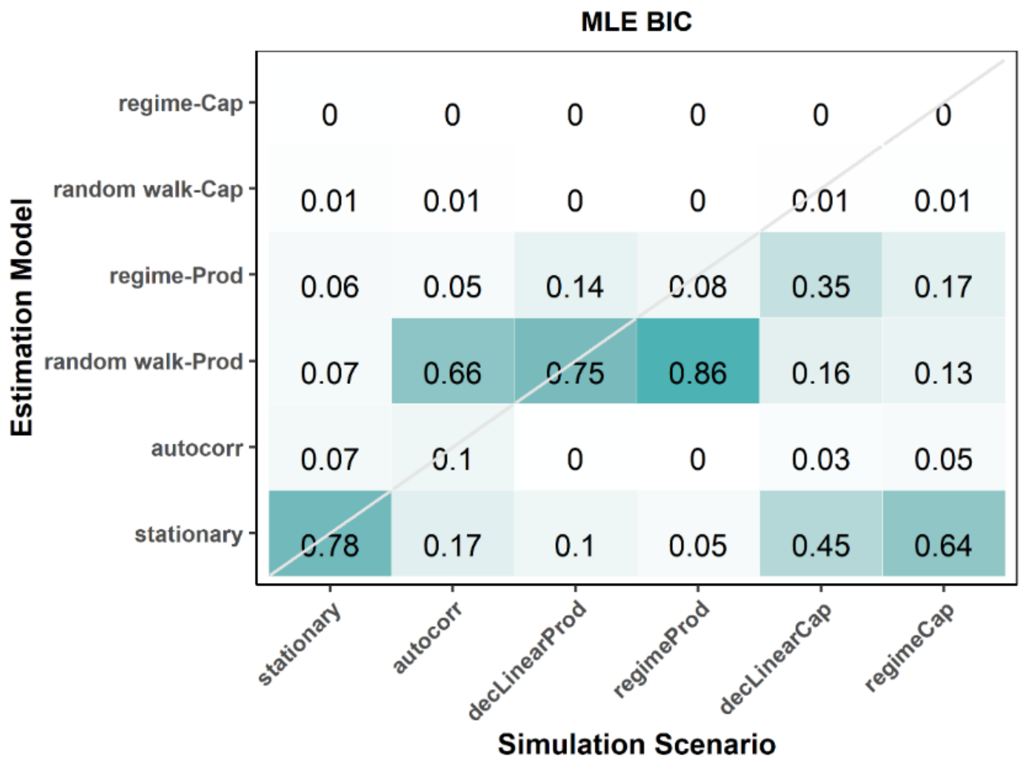


Figure 6. Probabilities of each estimation model (rows) being selected as the best-fit model using BIC selection criterion for each simulation scenario (column) aggregated over years and Monte Carlo trials of the simulation. Models are estimated using likelihood estimation methods using the following forms: stationary Ricker model ('stationary'), stationary Ricker model with lag-1 year autocorrelation in residuals ('autocorr'), random walk model that allows the productivity parameter to vary annually ('random walk-Prod'), hidden Markov model that allows the productivity parameter to vary in abrupt regime-type shifts ('regime-Prod'), random walk model with capacity allowed to vary annually ('random walk-Cap'), and hidden Markov model that allows the capacity parameter to vary in abrupt regime-type shifts ('regime-Cap'). Simulation scenarios are as described in Appendix Figure C1. Darker shading represents higher probabilities. The diagonal line represents the estimation model that best matches the simulation scenario.

2.2.2.4. Insight 4

Likelihood-based model selection criteria tend to select models with gradually changing parameters over those with abrupt changes, even when the true underlying dynamics include regime shifts (Figure 6). When using likelihood-based selection criteria, models with annually varying parameters have an analytical advantage over those that explicitly include regime shifts[4] which is a known shortcoming of using likelihood-based selection criteria to evaluate random walk models (Szuwalski et al. 2019, Holt and Michielsens 2020). Further, it is often difficult to achieve model convergence with regime shift models[5] when estimated in a maximum likelihood framework (Zucchini et al. 2016), potentially limiting their applicability and requiring careful scrutiny of initial values and outputs.

The statistical signal of a complete shift and reversal in parameters is stronger than a linear decline. As a result, the detection of dynamics is more reliable for estimation models with annually varying parameters when the underlying 'true' parameters exhibit an abrupt regime shift followed by an abrupt reversal to initial values compared with when conditions change gradually.

2.2.2.5. Insight 5

The reliability of likelihood-based model selection criteria depends on the direction and type of underlying change and improves as the magnitude of change increases (Figure 7). Reliability of model selection is greater than 70% when the underlying productivity change is linear and **greater than 1 (in log space)**, with higher reliability when underlying changes are abrupt. However, the reliability of detecting changes in capacity remains relatively poor and variable (25-75%) even with large (≥ 3-fold) changes in capacity.

Also, likelihood-based model selection criteria tend to correctly detect linear declines in productivity and capacity slightly better than increases, though reliability depends on whether the changes are gradual or abrupt (Figure 7). Abrupt changes in productivity and capacity are easier to detect than gradual linear changes, with linear increases in capacity being especially difficult to detect. This insight is further supported by findings from another simulation evaluation study parameterized for Fraser Sockeye Salmon, where linear declines in productivity were more accurately detected than increases (Holt and Michielsens 2020).

[4] This is because for models with annually varying parameters, the annual deviations are not explicitly included in the likelihood calculations thereby increasing the overall likelihood of the model.
[5] Using hidden Markov models that estimate the frequency and magnitude of regime-type shifts in parameters.

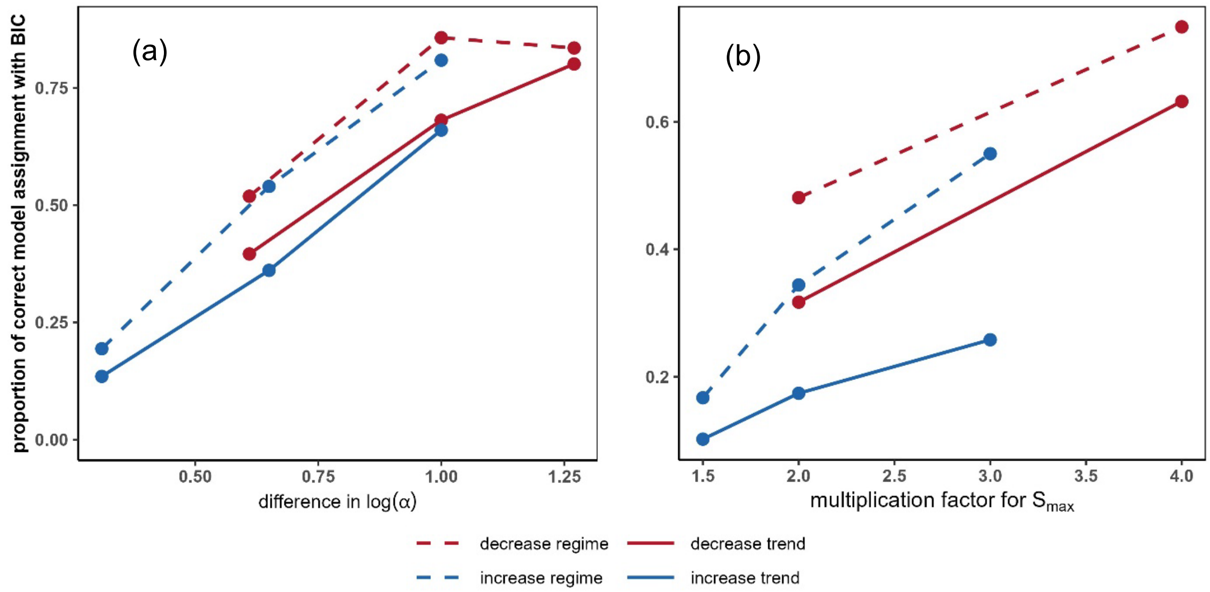


Figure 7. Percentage of correct model assignments using BIC selection criterion for various magnitudes of 'true' underlying changes in (a) productivity, labelled log(α) and (b) capacity, labelled S_{MAX}, spawners required for maximum recruitment. Dashed lines represent abrupt, regime-type changes; solid lines represent gradual, linear changes. Red lines represent declines and blue lines, increases, though for regime shifts 'decrease regime' represents an abrupt decline followed by an abrupt increase 20 year later, and 'increase regime' represents an abrupt increase followed by an abrupt decline 20 years later. Dots represent scenarios examined in simulation. The 'correct' models are those that identify the correct parameter changing, regardless of whether the random walk or regime shift estimation model was selected.

2.2.2.6. Insight 6

When both productivity and capacity vary over time, model selection is less reliable than when either one varies alone (Figure 8, right two columns). Likelihood-based selection criteria tend to favour stationary models when parameters change in different directions, and models with time-varying productivity are selected when that dynamic is dominant. In general, it is difficult to distinguish the statistical signatures of the two processes (productivity and capacity).

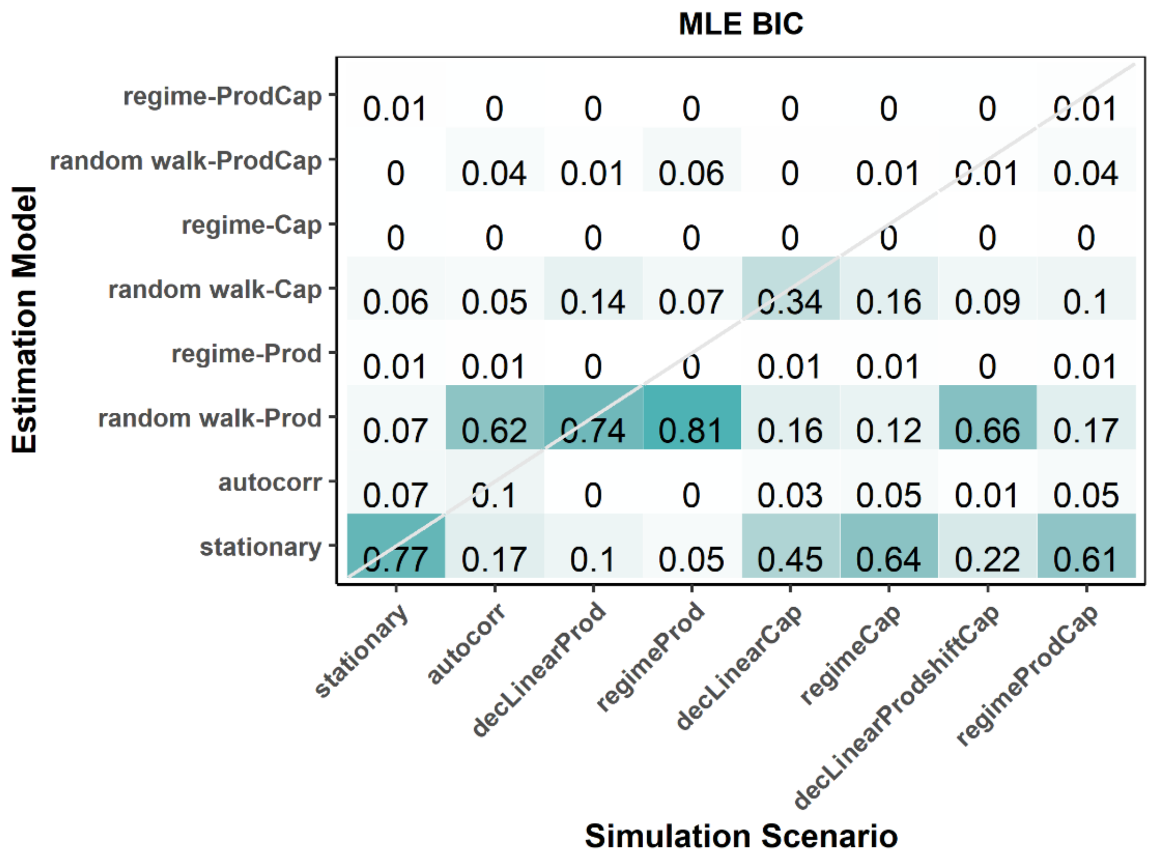


Figure 8. Probabilities of each estimation model (rows) being selected as the best-fit model using BIC selection criterion for each simulation scenario (column) over all years and Monte Carlo trials of the simulation. Estimation models are those described in the caption to Figure 6, with the addition of a random walk model with both productivity and capacity parameters allowed to vary annually in a random walk ('random walk-ProdCap'), and a hidden Markov model that allows both productivity and capacity parameters to vary in abrupt regime-type shifts ('regime-ProdCap'). Simulation scenarios are described in Appendix Figure C1. Darker shading represents higher probabilities. Diagonal grey lines represent the estimation model that best matches each simulation scenario.

2.2.2.7. Insight 7

The **leave-future-out-cross-validation (LFO-CV)** model selection criterion, a test of predictive accuracy one-year ahead usually applied to Bayesian estimation, **has poor reliability** over a range of underlying dynamics (Figure 9). When recruitment residuals are autocorrelated, LFO-CV tends to have better performance at correctly selecting the stationary model with autocorrelation than likelihood-based selection criteria, though performance is still marginal, only selecting the correct model just over half of the time.

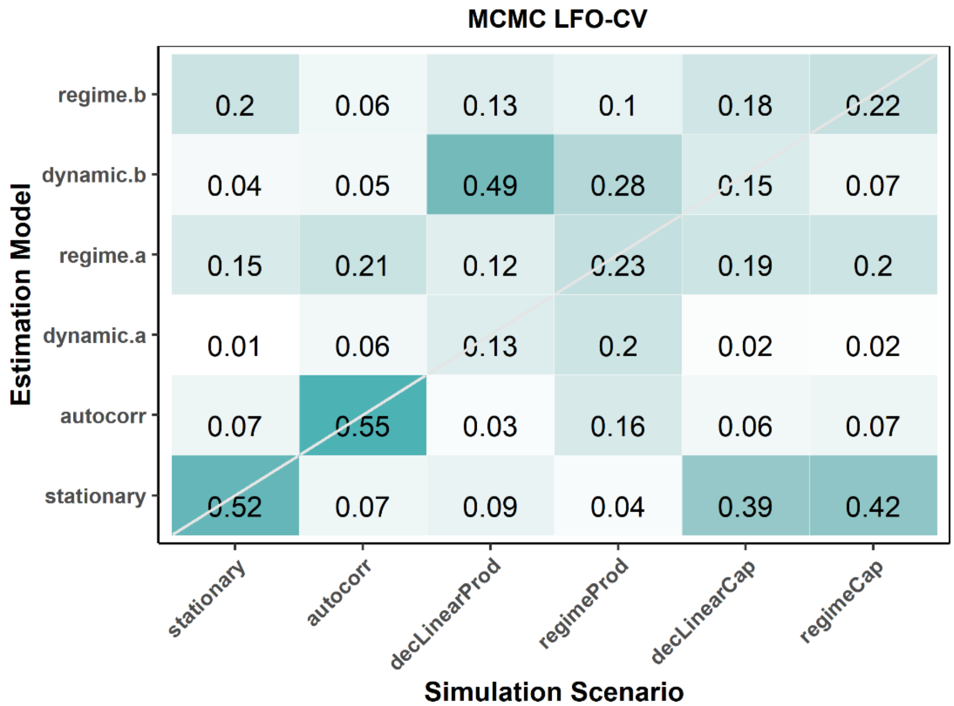


Figure 9. Probabilities of each estimation model (rows) being selected as the best-fit model using leave-future-out cross-validation criterion for each simulation scenario (column) over all years and Monte Carlo trials of the simulation. Models are estimated using Bayesian methods and are as described in the caption to Figure 6. Simulation scenarios are the same as in Figure 6. Darker shading represents higher probabilities. Diagonal grey lines represent the estimation model that best matches each simulation scenario.

2.2.3. Question 3: Variability in recruitment and exploitation rate

Guidance on Identifying Time-varying Population Parameters, Question 3: How does variability in recruitment and exploitation rate history impact statistical performance of estimation models and ability to detect time-varying dynamics using model selection criteria?[6]

2.2.3.1. Insight 1

Reducing the standard deviation in recruitment residuals within plausible ranges, as might occur with improved monitoring, **reduces biases** in estimates of productivity **and increases precision** for the random walk estimation model when productivity declines linearly. Similar patterns are observed for other estimation models and scenarios (Appendix Figure C6 and Figure C7 compared with Figure C2 and Figure C4).

Reducing variance in recruitment residuals can also improve reliability for detecting time-varying dynamics using likelihood-based model selection, to greater than 90% for productivity when

[6] This question can address, in part, how information content in spawner-recruitment observations influence statistical reliability in model selection since recruitment residuals capture the combined impacts of process and observation errors. Future work can investigate impacts of varying the magnitude of observation errors in spawners and recruitment (and associated sampling designs) on statistical reliability and ability to correctly detect underlying changes in parameters.

changes are linear and at least 1 unit (in log scale) in magnitude, with smaller improvements in reliability for detecting changes in capacity (Figure 10 vs. Figure 6)[7].

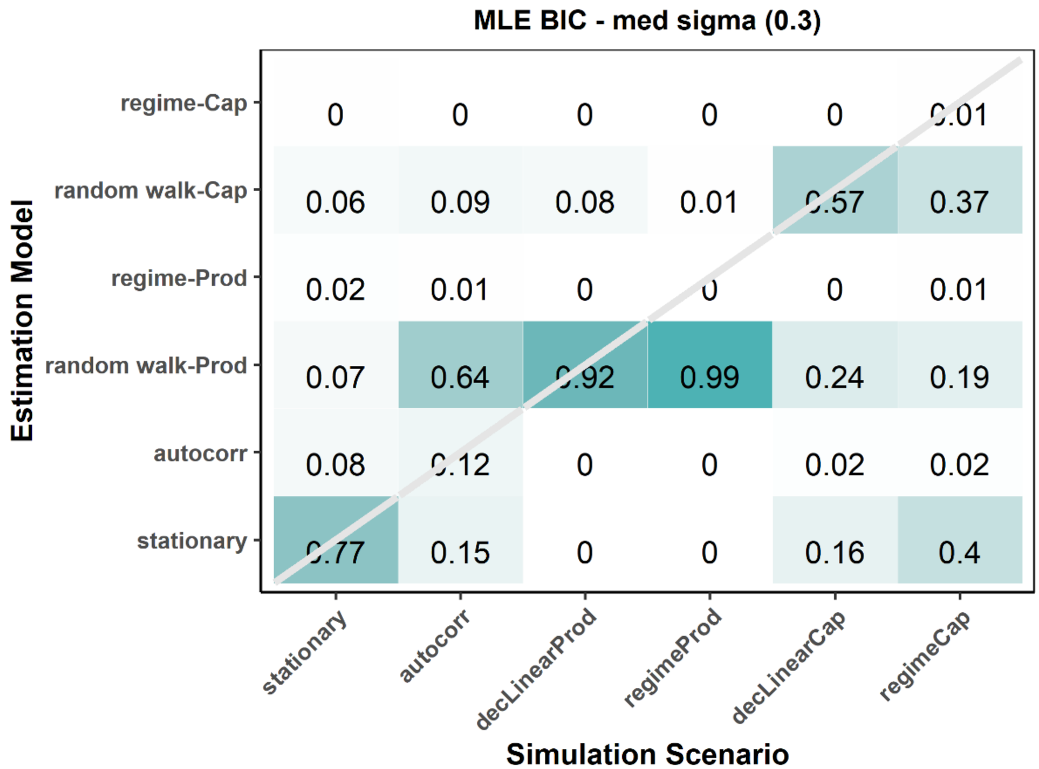


Figure 10. Probabilities of each estimation model (rows) being selected as the best-fit using BIC selection criterion for each simulation scenario (column) over all years and Monte Carlo trials of the simulation with smaller recruitment residual variation at 0.3 (instead of 0.7 for the base case). Estimation models are as described in the caption to Figure 6. Simulation scenarios are the same as in Appendix Figure C1. Darker shading represents higher probabilities. Diagonal grey lines represent the estimation model that best matches each simulation scenario.

2.2.3.2. Insight 2

High exploitation rates increase bias and reduce precision in estimates of capacity but not productivity when there is a linear decline in productivity. Biases in capacity tend to increase and precision decrease for scenarios with high vs. low exploitation, while estimates of productivity have similar biases and precision under both exploitation rate scenarios (Appendix Figure C8-Figure C11). Contrast in spawner and recruitment data tends to be low for highly exploited populations, which increases parameter uncertainty. Similarly, in a simulation-evaluation of models for Fraser River Sockeye Salmon Holt and Michielsens (2020) identified higher uncertainty in estimates of management-relevant parameters under heavy exploitation.

[7] Estimates of model reliability may be pessimist relative to the approach where process and observation errors in recruitment are simulated separately. In our simulation-evaluation framework, all variability in recruitment was assumed to propagate into variability in spawner abundances in the subsequent generation (e.g., as if it were 100% process error and 0% observation error). Future model iterations could derive simulated 'true' spawner abundances from the recruitment estimate with process error only.

The magnitude of exploitation did not significantly impact reliability of model detection among the scenarios considered here.

2.2.4. Question 4: Costs of incorrect estimation model

Overall Guidance, Question 4: What are the costs (in terms of bias and precision) of fitting an incorrect estimation model (e.g., model fit to stationary dynamics and vice versa)?

2.2.4.1. Insight 1

The costs of fitting an incorrect estimation model are highly asymmetric. On the one hand, **fitting a time-varying estimation model to stationary dynamics comes with relatively little cost to statistical reliability** of parameter estimates (i.e., slight increase in bias and some reduction in precision; Appendix Figure C2-Figure C5).

On the other hand, **fitting a stationary estimation model to data from a population that exhibits time-varying dynamics results in more biased and less precise parameter estimates**. These costs in terms of bias are most pronounced for situations where productivity or capacity decline abruptly over time (Appendix Figure C2-Figure C5).

2.3. Recommendations

2.3.1. Recommendation 1: Random walk models

When seeking to estimate population parameters from spawner-recruitment relationships, **estimation models with a random walk for productivity are more statistically reliable and are preferred** over stationary and regime shift models.

2.3.2. Recommendation 2: Time-varying capacity models

Estimation models with time-varying capacity are rarely reliable and should only be explored when there is strong corroborating evidence with plausible mechanisms suggesting that capacity has changed. This evidence can include habitat or ecosystem changes that impact density-dependent survival, and should be documented alongside spawner-recruitment analyses. When evidence is conflicting, time-varying capacity models should not be used.

2.3.3. Recommendation 3: Model selection criteria

Consider running multiple model selection criteria (AIC, BIC, and LFO-CV), and multiple estimation methods (maximum likelihood and Bayesian estimation), to quantify statistical support for time-varying population dynamics. Convergence of parameter estimates among analytical approaches provides additional support for underlying trends. Divergences in models selected among criteria (likelihood- vs. cross-validation based) may be expected in some cases because their reliability varies among underlying scenarios. While likelihood-based selection criteria are more reliable for detecting stationary uncorrelated parameters, LFO-CV has higher reliability for detecting autocorrelation in recruitment when underlying parameters are stationary.

2.3.4. Recommendation 4: Regime shift estimation models

Regime shift estimation models fit using hidden Markov models should be used cautiously and only when there is supporting evidence for abrupt shifts and rigorous review of model convergence. Random walk models with annually varying parameters will usually be preferred over regime shift models due to their improved statistical reliability over a range of underlying true changes in population dynamics.

3. GUIDANCE ON ESTIMATING BIOLOGICAL BENCHMARKS USING TIME-VARYING MODELS

Guidance on estimating biological benchmarks using time-varying models to classify stock status

Goal: provide advice on the use of time-varying models to estimate spawner-recruitment benchmarks within biological status assessments

Primary Audience: stock assessment analysts, including Species at Risk Program and Salmonid Enhancement Program

Secondary Audience: Fisheries Management, Fish and Fish Habitat Protection Program

Two key questions, **five insights**, and **one recommendation** derived from our simulation-evaluation and supported by a review of the literature (see Figure 11, described in more detail in the text below).

3.1. Context

Spawner-recruitment based biological benchmarks are used to delineate three zones of biological status for Pacific salmon Conservation Units (CUs) under Canada's Wild Salmon Policy (WSP): green, amber and red. These benchmarks can also be used to inform survival or recovery targets under the Species at Risk Act (e.g., as in Recovery potential assessments for Fraser Sockeye Salmon DFO 2020, Huang et al. 2021, and southern BC Chinook Weir et al. 2022, DFO 2021a), and may be considered targets within rebuilding plans under the Fish Stocks provisions of the *Fisheries Act*. They can also be used to measure performance of management strategies relative to conservation objectives when used to infer lower limits to avoid or targets to achieve.

Similar to biological benchmarks, reference points define the boundaries between critical, cautious, and healthy zones under DFO's Precautionary Approach framework (or 'PA Policy'; DFO 2009). These reference points are also commonly used to inform decision points in harvest control rules, as 'management reference points', which are considered further in the following section on 'Harvest Control Rules'.

Fishing mortality relative to maximum population productivity can be considered a metric of biological status (Holt et al. 2009). However, benchmarks related to fishing mortality (or removals) are more directly linked to management decisions than biological assessment, and so are also considered under the 'Harvest Control Rule' advice in subsequent sections of this guidance document.

Guidance on estimating biological benchmarks: Insights and Recommendations

Q1: What are the consequences when classifying biological status, e.g., misclassifications, of assuming stationary (time varying) productivity and capacity when one or both population parameters change (do not change) over time, and how does the magnitude of change in productivity and/or capacity influence misclassifications?

1. Changes in productivity impact abundance based biological benchmarks in counterintuitive ways when S_{gen} increases under small to moderate declines in productivity, but S_{MSY} declines.
2. When productivity declines irreversibly , time-varying estimation models result in fewer misclassifications of biological status than stationary ones and these misclassifications are overwhelmingly biologically pessimistic.
3. When productivity changes are transient, time-varying estimation models tend to have similar, low misclassification rates as stationary ones
4. Given an irreversible decline in capacity, the choice of estimation model has minimal influence on misclassification rates

Q2: How does the frequency of biological status assessments affect misclassifications when productivity and/or capacity does (does not) change over time?

1. More frequent updates of biological benchmarks (i.e., every 5 instead of 10 years) reduce misclassification rates when changes in productivity are irreversible and time-varying estimation models are used to assess status

<u>Recommendation 1</u>
When deciding whether or not benchmarks for biological status assessments should be based on time-varying estimation models, we recommend following a step-wise decision-making process that considers
(1) the strength of evidence for changes based on a 'weight of evidence approach',
(2) if the changes are irreversible with high certainty, and
(3) the underlying biological population and/or ecosystem objectives

<u>Recommendation 2</u>
In general, we recommend that biological benchmarks be re-estimated every one to two generations so that they capture contemporary fishery and biological process, though the risk of mis-specifying benchmarks using historical data will need to be weighed against the costs of implementing an assessment.

Figure 11. Schematic of two key questions, five insights, and two recommendations to support guidance on estimating biological benchmarks from spawner-recruitment relationships within assessments.

Here, we report on the consequences of classifying biological status into red, amber or green, when using either stationary or time-varying spawner-recruitment based benchmarks when one or both population parameters changes. Our recommendations are based in part on results from a simulation-evaluation analysis which compared the annual classification performance (i.e., the probability of correct or incorrect determination of status, red, amber or green) using biological benchmarks from stationary and time-varying estimation models under various scenarios of changing population productivity or capacity. As in the previous section, we considered estimation approaches that annually track parameters using 'random walk models' and those that identify abrupt regime shifts in parameters using 'hidden Markov models'. The time-varying estimation approaches provide benchmarks that vary annually or by regimes. Data truncation can also be applied with stationary estimation models to approximate the impacts of time-varying parameters on benchmark estimation for a specified time period (Adams et al. 2021; Eddy et al. 2023). Although not explicitly included in the simulation-evaluation, this alternative is considered in the recommendations below. The simulation-evaluation analyses included a constant harvest rate strategy that was not responsive to changes in status. The focus of this category of advice is on classification accuracy; the next section evaluates harvest control rules that are responsive to time-varying population parameters.

The key questions and insights identified here focus on scenarios where productivity or capacity have declined over time or are stationary, as these are common across Pacific salmon populations and can provide important insights on biological risks of misclassification. However, the recommendations provided below can be generalized across a diversity of types and directions of change.

3.2. Questions and Insights

3.2.1. Question 1: Classification accuracy

Guidance on estimating biological benchmarks using time-varying models to assess stock status, Question 1: What are the consequences when classifying biological status, e.g., misclassifications, of assuming stationary (time-varying) productivity and capacity when one or both population parameters change (do not change) over time, and how does the magnitude of change in productivity and/or capacity influence misclassifications?

3.2.1.1. Insight 1

Changes in productivity impact abundance based biological benchmarks in counterintuitive ways. For example, as productivity declines so too does the spawner abundance associated with Maximum Sustainable Yield (S_{MSY}) and hence the upper WSP biological benchmark (Figure 12). In contrast, the lower WSP biological benchmark S_{GEN}, the spawner abundance required to rebuild to S_{MSY} in one generation under equilibrium conditions, increases under small to moderate declines in productivity (Figure 12) since higher abundances are required to rebuild to S_{MSY} (Holt and Bradford 2011; Holt and Folkes 2015). Under large reductions in productivity, S_{GEN} declines in a similar fashion to S_{MSY}.

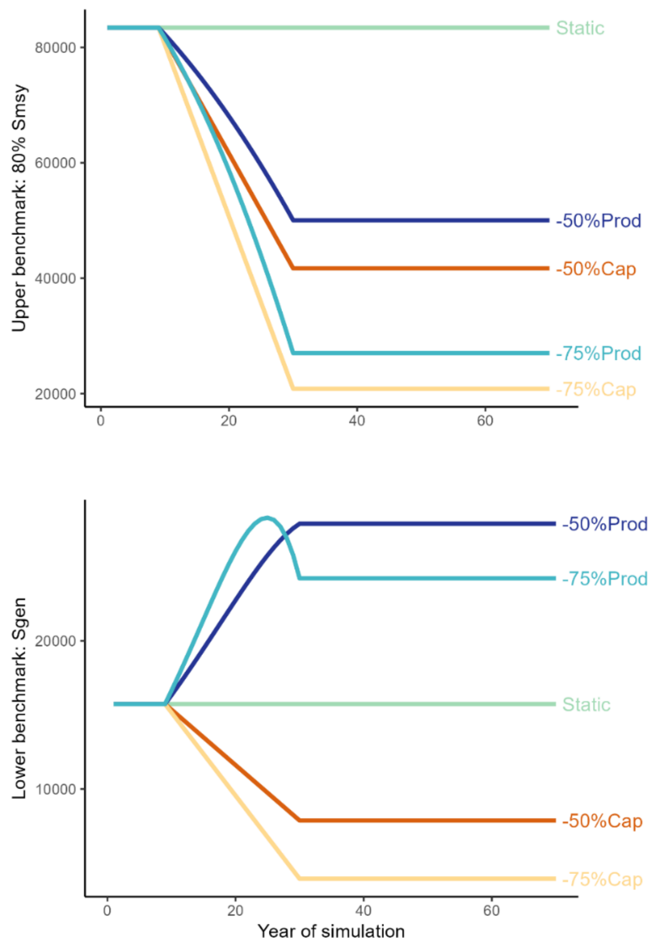


Figure 12. Illustration of how two biological benchmarks, S_{GEN} and S_{MSY}, change over time as productivity and capacity decline (in years 10-30), and how the magnitude of decline influences them. The stationary scenario is labelled 'static'. Scenarios for time-varying productivity are labeled by the precent change over time and whether productivity or capacity changes.

3.2.1.2. Insight 2

When productivity declines irreversibly[8], time-varying estimation models[9] result in fewer misclassifications of biological status than stationary ones and these misclassifications are overwhelmingly biologically pessimistic (i.e., estimated status lower than 'true' status) (Figure 13). Optimistic misclassifications are rare for both estimation models. The magnitude of declines in productivity influences these misclassifications with larger magnitude declines to very low productivity levels resulting in larger differences in misclassification rates between time-varying and stationary estimation models (Figure 13). The improved performance of time-varying estimation models is in part because they tend to

[8] Defined here as persistent declines over the time-period investigated.
[9] For the purpose of this section, 'time-varying estimation models' refer to estimation models that allow productivity to vary over time according to a random walk and 'stationary estimation models' refer to models that do not allow productivity to vary over time but that do allow for autocorrelated recruitment deviations.

track ‘true’ benchmark values better than stationary models when productivity declines (Appendix Figure D1 and Figure D2).

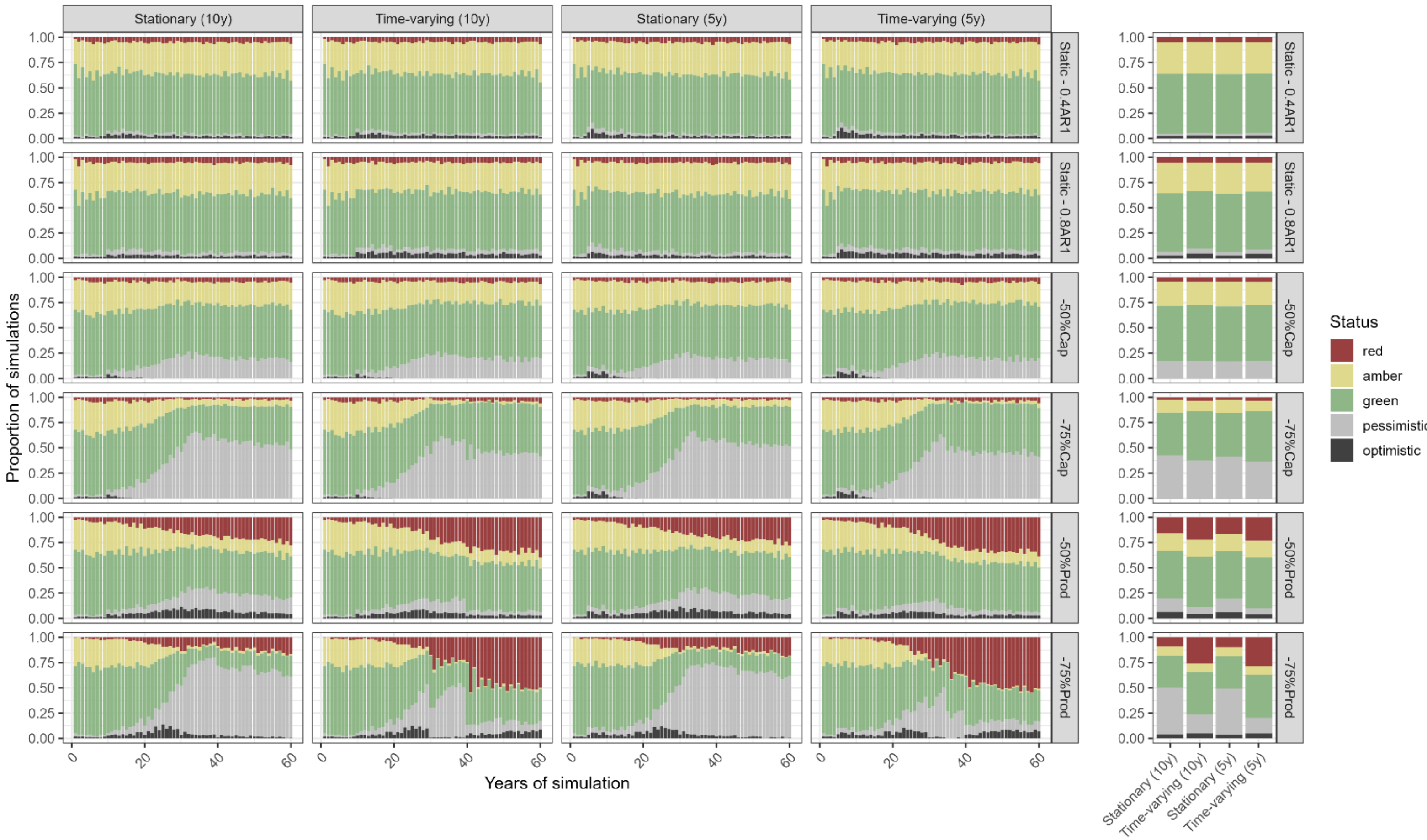


Figure 13. Proportion of simulations with correct green, amber, or red status, or biologically pessimistic (grey) or optimistic (black) misclassifications of biological status, based on either stationary (first and third column) or time-varying (second and fourth column) estimation models that are updated every 10 years (first and second columns) or 5 years (third and fourth columns) under scenarios with either true declines in capacity or productivity, or static dynamics with transient "apparent" changes in productivity due to autocorrelation in recruitment (rows). Base case autocorrelation is labeled 'Static-0.4AR1' (0.4 is the average autocorrelation coefficient across salmon in the NE Pacific) and high autocorrelation, 'Static-0.8AR1'. Row labels show which parameter declined and the % decline that occurred. In all scenarios with true underlying declines, those changes occur between year 10 and 30. Individual bars in the first four columns represent annual status over the 60-year simulation. The fifth column summarizes classifications across the last 50 years of simulations.

3.2.1.3. Insight 3

When productivity changes are transient, time-varying estimation models tend to have similar, low misclassification rates as stationary ones. In this case, misclassifications tend to be split between those that are pessimistic and those that are optimistic. The larger the degree of autocorrelation in recruitment from year to year, the larger and longer transient changes in productivity are, the worse the classification of time-varying estimation models relative to stationary models (Figure 13, 'AR1 high' scenario). The absolute magnitude of misclassifications, however, are smaller for all types of estimation models when productivity changes are transient compared to when they irreversibly decline.

3.2.1.4. Insight 4

Given an irreversible decline in capacity, the choice of estimation model has minimal influence on misclassification rates. Similar to when productivity irreversibly declines, misclassifications tend to be biologically pessimistic when capacity declines, and greater with larger magnitude declines (Figure 13). Pessimistic classifications arise from the estimation model interpreting capacity change as productivity changes and underestimating benchmarks. These insights are further supported by the work of Peacock et al. (2019) who also found that large declines in capacity resulted in increases in biologically pessimistic misclassifications and suggested that the ability to correctly classify status depends on escapement enumeration and run-reconstruction methods.

3.2.2. Question 2: Frequency of status assessments

Guidance on estimating biological benchmarks using time-varying models to assess stock status, Question 2: How does the frequency of biological status assessments affect misclassifications when productivity and/or capacity does (does not) change over time?

3.2.2.1. Insight 1

More frequent updates of biological benchmarks (i.e., every 5 instead of 10 years) reduce misclassification rates when changes in productivity are irreversible and time-varying estimation models are used to assess status but these improvements are small relative to the total variability in classification accuracy (Figure 13). This occurs because more frequent updates better track true underlying change in benchmarks and status, and the benefits of more frequent updates using time-varying estimation models are greatest when declines are large.

3.3. Recommendations

3.3.1. Recommendation 1: Step-wise approach

We recommend a **step-wise approach when deciding whether benchmarks for biological status assessments should be based on time-varying estimation models**. These recommendations are drawn from insights on detecting underlying changes in population parameters, and associated misclassification rates. The steps include considering (1) the strength of evidence for changes based on a 'weight of evidence approach' that considers data limitations, (2) if the changes are reversible over the short to medium term with high certainty, and (3) the underlying biological population and/or ecosystem objectives (Figure 14). These steps provide structure to guide the decision making process and are not meant to be prescriptive. Although these steps are illustrated in a dichotomous tree of yes-no questions, in reality the answers may not be clearcut, and estimating benchmarks using both stationary and time-varying parameters, and evaluating risks of both, will often be appropriate

(Figure 14, bottom middle box). Analytical tools for evaluating risks within simulation-evaluations are provided in Appendix B, and guidance on developing projections given uncertainty in time-varying population parameters is provided in the Category of Advice on Projections.

(1) Are changes in population parameters over time supported by weight of evidence from multiple sources?**:** The first step is to evaluate the 'weight of evidence' in support of time-varying population dynamics (Klaer et al. 2015), which considers multiple types of information concurrently. At a minimum the following information should be compiled to inform the weight of evidence:

- statistical model selection criteria from models with stationary and time-varying parameters, and time series of estimated parameter values, spawner-recruitment residuals, and $\log_e$(recruits/spawner); and
- empirical evidence supporting mechanistic drivers of survival or recruitment (e.g., habitat disturbance limiting spawning or rearing habitat, climate impacts across life stages, predation, marine ocean conditions, estimates of effect sizes based on lab and field studies)

Additional lines of evidence that should be compiled when available include, but are not limited to:

- time series data on the dynamics of salmon at life-stages considered to be bottlenecks in production (e.g., early marine survival, egg-fry survival);
- qualitative knowledge (including local), simulation-based evidence, and frameworks that combine these types of evidence with empirical quantitative data to quantify evidence for changes over time (Goethel et al. 2023) (e.g., within Bayesian Belief Networks Pihlajamäki et al. 2023, Araujo et al. 2013); and
- synchronous trends among neighboring populations or salmon species impacted by similar drivers. Changes in productivity or capacity may be inferred from meta-analyses that document synchronous trends across regions. This is similar to the recommendation in other fisheries to share information on cohort-strength in recruitment among stocks when identifying time-varying patterns in recruitment (Maunder and Thorson 2019).

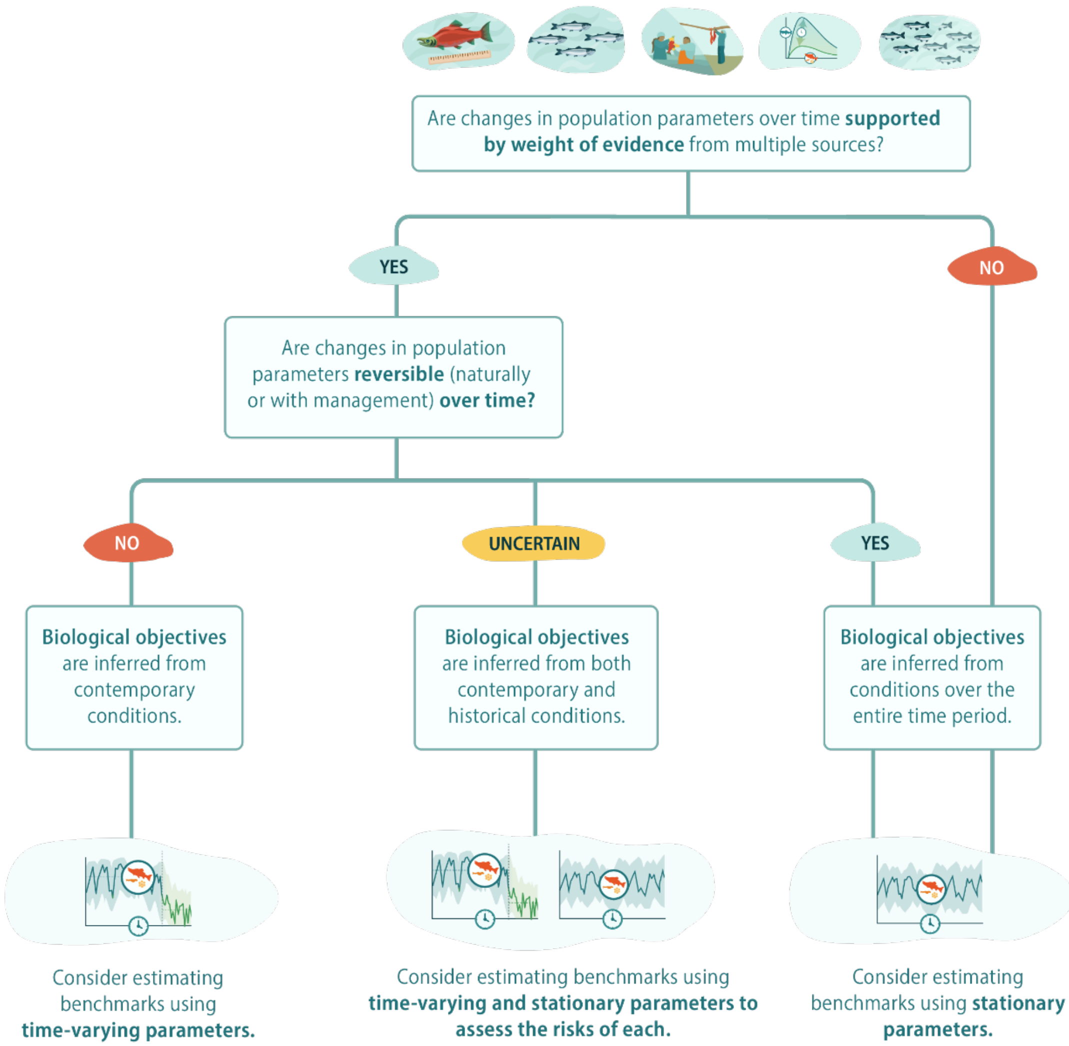


Figure 14. Decision tree addressing when benchmarks for classification of biological status should be estimated with time-varying population parameters in spawner-recruitment models.

With this information compiled, along with documentation on underlying uncertainties, one can then ask, "***Is temporal variability in population parameters supported by the weight of evidence from multiple sources?***" (Figure 14). For example, if model selection criteria favor a non-stationary model of relatively large magnitude (e.g., >1 $\log_e$(recruits/spawner) for productivity) , and plausible ecological mechanisms that coincide with the timing of changes are identified, this may be considered strong support for using time-varying estimation models to estimate biological benchmarks. Further, if time-varying models are not selected with statistical selection criteria, but trends are observed and other lines of evidence strongly supports underlying changes such as declines in marine survival or degradation of freshwater habitat capacity which is poorly detected with standard model selection criteria, then time-varying models may also be considered. This may occur when spawner-recruitment data are limited or noisy but there is compelling evidence from life-history changes, ecological indicators and/or population parameter changes in neighbouring populations. In contrast, we caution against considering time-varying models without empirical evidence supporting plausible mechanisms of change that are irreversible over the long term. Where evidence is contradictory, confidence in time-varying dynamics can also be assigned using schemes such as those used for IPCC that combine agreement among lines of evidence and the type, quality, and consistency of the evidence (Mastrandrea et al. 2010).

(2) Are changes in population parameters reversible (naturally or with management) over time? The second step is to evaluate whether or not observed changes are reversible or not. Mechanisms associated with reversible processes over management-relevant time frames (e.g., a specified number of salmon generations) should be discriminated from more persistent, less reversible mechanisms (DFO 2013), which can again be evaluated in a weight of evidence framework. Reversible changes in productivity may be associated with natural environmental variation, or variability in fish behaviour, migration or movement leading to greater or lesser vulnerability to sampling or fishing gear, or depensation at low abundance related to difficulty find mates or increased predation. In contrast, changes that are irreversible over long time periods (e.g., a human life span) may be associated with climate change, permanent loss of freshwater rearing or spawning habitat, or reduced marine survival due to recovered marine mammal predator populations. In general, evidence should support a change that has persisted and is expected to last over the relatively long term (DFO 2013).

We recommend that the burden of proof be on demonstrating evidence for irreversible time-varying dynamics, not that conditions have remained constant. This burden of proof is consistent with DFO's PA policy recommendation that reference points be based on long-term average dynamics estimated using "as long of a time series as possible" except in the rare circumstances where changes are irreversible (DFO 2009). While time-varying dynamics are pervasive in fisheries, evidence for irreversible rather than transient, reversible changes is central to this burden of proof. While the *Fisheries Act* (2019) requires that current environmental conditions be considered when developing management measures that promote sustainability of the stock, it is less clear on whether current or long-term average conditions be used to develop reference points.

Similar to DFO's PA policy, ICES (2017) technical guidelines for estimation of reference points for data-rich stocks states "unless strong evidence exists that a consistent change has occurred, the full time series of stock and recruitment should be used. Be careful not to mistake periodicity in recruitment success, induced by e.g. cyclic climate conditions, with prolonged shifts." In addition, Australia's Commonwealth Fisheries Guidelines recommend that "assessment and management consider environmental variability, regime shifts and persistent trends, e.g., related to climate change, but these perceived changes should have high confidence with mechanistic understanding of impacts on stock" (DAWR 2018).

(3) Are biological objectives inferred from contemporary or historical conditions? Identifying biological benchmarks includes implicit assumptions about population and ecosystem objectives (Zhang et al. 2021a), which we recommend be explicitly described when deciding whether to use time-varying estimation models to derive biological benchmarks. Advice on reference points and rebuilding targets may be mis-specified if changes in underlying parameters are not considered and biological objectives are implicitly intended to capture current conditions (Zhang et al. 2021a). Time-varying biological benchmarks based on maximum sustainable yield (MSY) that track irreversible changes in productivity and capacity imply objectives for maximizing fishing opportunities assuming contemporary conditions will persist. However, biological objectives may deviate from those related to MSY. For example, when there are declines in productivity or capacity, benchmarks derived from historical productive, high-capacity conditions above MSY levels may provide added precaution to buffer against uncertainties in climate change impacts (Szuwalski et al. 2023). In addition, high values for benchmarks estimated with stationary models under declines in productivity or capacity may be aligned with ecosystem-based objectives even if not easily reversible in the short-to-medium term within the scope of current management actions.

When biological objectives extend beyond maximization of sustainable yield, estimating benchmarks from stationary and time-varying models and evaluating risks and trade-offs of each may be prudent. As an example, the U.S. Magnuson Stevens Act specifies that optimal yields be assessed by specifying the present and probable future MSY values for U.S. fisheries (MSA, 2007), which requires estimating a regime representative of current conditions. This approach implies a yield maximizing assessment and management framework. However, Szuwalski et al. (2023) suggest an alternative approach based on stationary reference points that are aligned with broader ecosystem objectives under climate-driven declines in habitat capacity, akin to extending the timeframe for assessing 'irreversibility' to a longer time frame. The evaluation of risks and benefits from assessing and managing according to yield maximizing versus broader ecosystem objectives highlight trade-offs in these decisions for management (Szuwalski et al. 2023). Indeed, Zhang et al. 2021a suggest that "changing reference points is both a scientific and a political question, and for these reasons, it is important that scientists develop clear messaging around dynamic reference points" and emphasize the need to work with managers to identify frameworks such as this one to guide decisions on approaches for estimating reference points.

Outcomes of decision tree

When changes in population parameters are supported by the weight of evidence from multiple sources and are irreversible naturally or with management intervention over the long-term (e.g., a human generation), and biological objectives are inferred from contemporary instead of historical conditions, then models with time-varying parameters can be considered in the estimation of benchmarks (left branch of decision tree, Figure 14). These benchmarks capture contemporary expectations for population dynamics, as benchmarks based on historical conditions may no longer be relevant. This recommendation is aligned with DFO's PA policy, which states "the only circumstances when reference points should be estimated using only information from a period of low productivity is when there is no expectation that the conditions consistent with higher productivity will ever recur naturally or be achievable through management" (DFO 2009).

When changes in parameters are supported by the weight of evidence but these changes are reversible over management-relevant time-sales (e.g., a specified number of salmon generations), or changes are not supported by the weight of evidence, then benchmarks estimated using stationary parameters that integrate population dynamics over the available time series can be considered (right branch of decision tree, Figure 14).

When changes in population parameters are supported by the weight of evidence but reversibility is uncertain (e.g., possibly reversible over the medium-to-long term but not in the short term), then biological objectives may be identified from both contemporary and historical conditions. Here, we recommend considering benchmarks using both time-varying and stationary parameters and assessing the risks of each. In practice, the weight of evidence for changes in population parameters and their reversibility is rarely clear cut, and in many cases it will be prudent to evaluate both benchmarks and assess risks of each. This schematic outlines key considerations for identifying when efforts should be placed on identifying time-varying benchmarks.

While time series are sometimes truncated to account for time-varying population dynamics (e.g., removing data before or after a regime shift), this approach introduces additional uncertainty into analyses by shortening time series and requiring setting the specific time period to include (van Deurs et al. 2020). We recommend this method only be applied when there is overwhelming evidence for an abrupt regime shift such that historical data are no longer relevant, following the same decision criteria shown in Figure 14 for time-varying parameters. This situation would be the exception and not the rule.

3.3.2. Recommendation 2: Frequency of status assessments

While there is currently no formal DFO guidance on how often biological benchmarks for WSP status assessments should be updated, past assessments have recommended re-assessments should occur if one or more of the following apply: after one salmon generation, when salmon productivity and/or abundance changes significantly, and/or when new methods not previously peer reviewed are developed (Grant et al. 2020), the latter of which is also consistent with more general DFO guidance that LRPs be re-considered when a new advisory framework or management paradigm are adopted (DFO 2023). Other jurisdictions recommend re-estimating reference points periodically, typically every 5-10 years depending on the species life span and stock assessment cycle (e.g., ICES 2021, DAWR 2018). This is intended to ensure re-estimation incorporates relevant fishery and biological processes including expected population dynamics.

Accordingly, **we recommend that biological benchmarks (stationary and/or time-varying) be re-estimated every one to two generations to capture contemporary fishery and biological process including expected population dynamics. In practice, the risk of mis-specifying benchmarks using historical data will need to be weighed against the costs of implementing an assessment.** We also recommend that biological benchmarks be updated when new advisory framework or management paradigms are adopted regardless of the time that has passed since biological benchmarks were last updated.

4. GUIDANCE ON ACCOUNTING FOR TIME-VARYING PARAMETERS IN HARVEST CONTROL RULES

Guidance on accounting for time-varying population dynamics in harvest control rules

Goal: provide advice on the use of time-varying estimation models to inform reference points in harvest control rules

Primary Audience: stock assessment analysts, Fisheries Management

Secondary Audience: Species at Risk Program, Salmonid Enhancement Program, Fish and Fish Habitat Protection Program

Two key questions, **five insights**, and **one recommendation** derived from our simulation-evaluation and supported by a review of the literature (Figure 15, see text for more details).

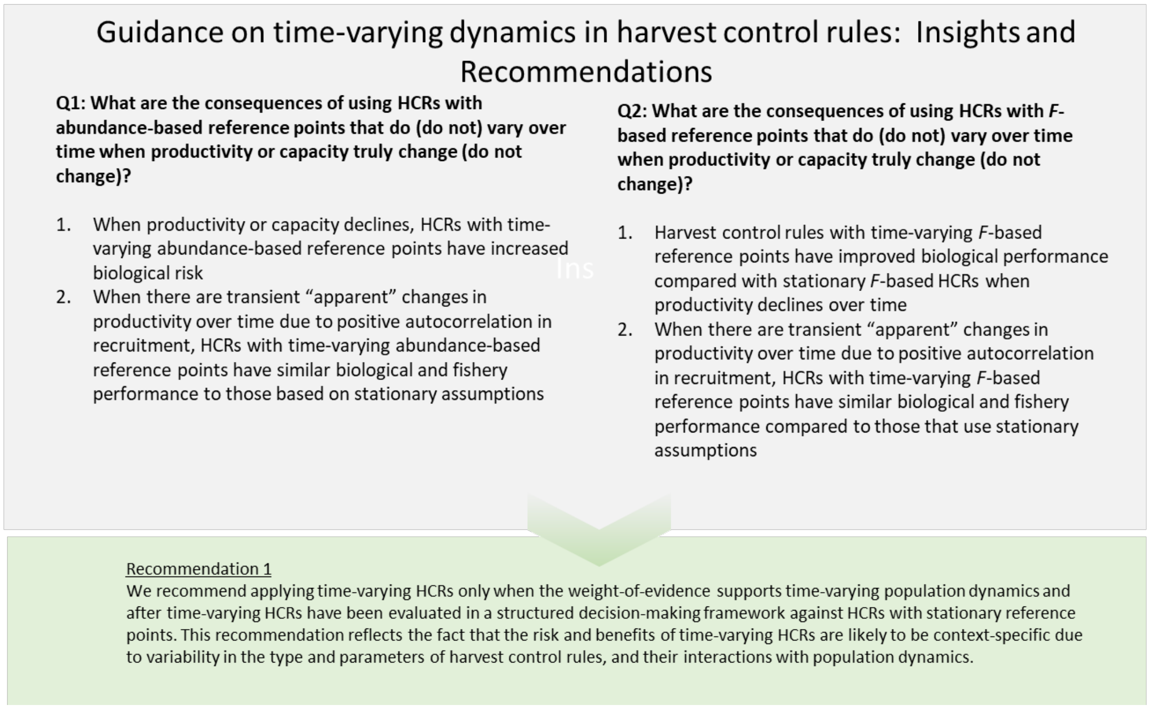


Figure 15. Schematic of two key questions, four insights, and one recommendation to support guidance on accounting for time-varying dynamics in reference points used for harvest control rules.

4.1. Context

Harvest control rules (HCRs) are a key fisheries management tool that describe how harvest rates should vary as a function of adult abundance or biomass (Free et al. 2022). For Pacific salmon, HCRs generally range from those that have fixed harvest rates across all run-sizes to those that have stepped or ramped harvest rates as run-sizes increase. These latter rules incorporate feedback control, often considered an important characteristic of sustainable fishery management, whereby harvest rates are progressively reduced as run-sizes and associated spawning escapements decline so as to promote stock growth and limit biological risks. The points at which harvest rates change in these HCRs, and the harvest rates associated with them, are typically based on estimated or inferred characteristics of the stock such as intrinsic productivity and carrying capacity and associated reference points (e.g., S_{MSY} and U_{MSY}, exploitation rate at maximum sustainable yield).

Harvest control rules with feedback control can partially compensate for changing population dynamics, even if the HCR is time invariant (Kritzer et al. 2019; Collie et al. 2021). However, modifications to HCRs may be the most direct and impactful strategy available for fisheries management to respond to the impacts of varying population dynamics, and the processes that create them (e.g., changing climate). These modifications can include uncertainty buffers (Roux et al. 2022), and temporal changes in abundances at which harvest rates change, and/or in maximum allowable harvest rates.

Scientific advice on when and how to use time-varying HCRs will depend on the type and parametrization of the HCR. Our guidance is scoped to HCRs with a single escapement goal (abundance based reference point) and target exploitation rate above the goal (*F*-based reference point) and a low exploitation below the goal (Figure 16). This relatively simple rule is intended to illustrate the direction and possible magnitude of biological and fishery impacts of having the escapement goal or target exploitation rate vary over time. We focused on this simple, albeit unrealistic, rule to isolate the specific impacts of time-varying escapement goals and target exploitation rates. More complex and realistic rules with multiple steps and ramps may dampen these impacts, and should be evaluated on a case-by-case basis.

Our guidance is further scoped to HCRs that rely on parameter estimates from spawner-recruitment relationships. Harvest control rules developed from habitat, empirical, or other sources of information can be evaluated for robustness to time-varying population dynamics (see Category of Advice on Projections) but advice on adapting those rules in response to time-varying population dynamics directly, as well as multi-stock HCRs, is beyond scope here.

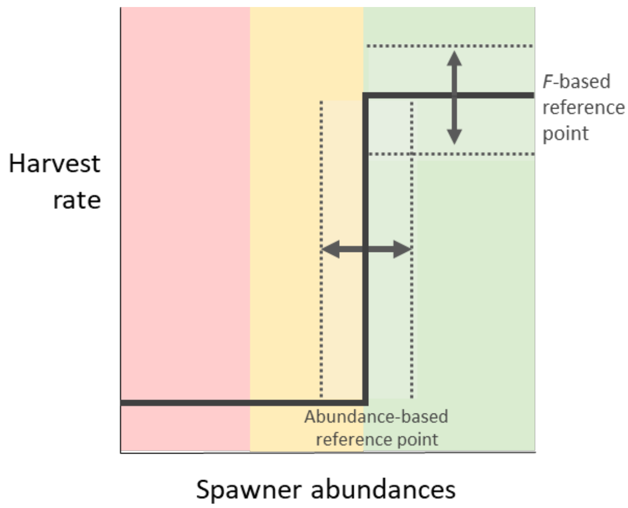


Figure 16. Illustration of simple stepped harvest control rule and both abundance and fishing mortality based reference points (thick black vertical and horizontal line, respectively). The dashed lines and arrows illustrate instances where either reference point varies over time. Shading illustrates hypothetical status zones of increasing conservation concern from right to left.

Our recommendations in this section are based, in part, on results from a simulation analysis that evaluated the biological and fishery performance of HCRs derived from stationary and time-varying estimation models under various scenarios of changing productivity or capacity[10]. For illustrative purposes, a stepped harvest control rule was used, with an abundance-based reference point at 80% of S_{MSY}, an *F*-based target reference point near U_{MSY} (when above the abundance-based reference point) and a lower exploitation rate of 10% of the target exploitation rate (when below the abundance-based reference point). These reference points were re-estimated every 5 years using either stationary or time-varying estimation models. Time-varying estimation models were applied to either the abundance-based reference point in the HCR (Question 1 below) or *F*-based reference point in the HCR (Question 2 below). Future analyses could consider a scenario where both vary over time. Candidate performance metrics that reflect biological and fishery objectives were evaluated: annual probability of dropping below the ‘true’ lower benchmark into the red status zone, average spawner abundances, and average annual catch. These were selected to demonstrate key trade-offs between biological and fishery objectives.

[10] Two scenarios in declines of productivity were considered: log(α) 2 to 0.5 (75% decline) and 2 to 1 (50% decline) over a 20-year period, and one scenario of declines in capacity by 75% of spawner abundances at maximum recruitment, S_{max}. Increases in productivity and capacity were evaluated in sensitivity analyses.

4.2. Questions and Insights

4.2.1. Question 1: Abundance-based reference points in HCRs

Guidance on accounting for time-varying dynamics in harvest control rules, Question 1: What are the consequences of using HCRs with abundance-based reference points that do (do not) vary over time when productivity or capacity truly change (do not change), and how does the magnitude of these changes influence HCR performance?

4.2.1.1. Insight 1

When productivity or capacity declines, HCRs with time-varying abundance-based reference points have increased biological risk (Figure 17 and Figure 18), and the magnitude of these impacts increases with the severity of the declines in productivity. Stationary models tend to provide more pessimistic estimates of status as productivity declines (see Category of Advice on Estimating Biological Benchmarks), hence reference points that rely on stationary assumptions are associated with more precautionary management than those that track time-varying population parameters. Fisheries yield either increases or declines when time-varying abundance-based reference points are used in the HCR, depending on the specification of HCR (e.g., the allowable harvest below and above the escapement goal) and the magnitude of decline. For an example HCR with relatively precautionary exploitation rate (10% of the target) below the escapement goal, time-varying abundance-based reference points resulted in similar or higher catch (Figure 17 and Figure 18), though the opposite was true with a more permissive exploitation rate (30% of the target) below the escapement goal (Appendix Figure E1 and E2). When productivity increases over time, performance of HCRs are generally not sensitive to the assumptions about stationary or time-varying dynamics (Appendix Figure E3).

These findings are similar to findings from a global simulation evaluation of hundreds of stocks which found that adjusting abundance-based reference points to reflect the productivity of current environmental conditions (a so called 'climate-adaptive strategy') resulted in higher fishing pressure and associated conservation risks on populations relative to only small gains in harvest (Szuwalski et al. 2023). Further, in an evaluation of harvest strategies for four pelagic stocks in Australia, Bessell-Browne et al. (2024) found when productivity declined, HCRs with time-varying biomass-based reference points had higher overall catches but lower biomass than those with stationary reference points, which may result in failure to meet conservation and ecosystem objectives. In contrast, Collie et al. (2012), who used closed-loop simulations to investigate the outcomes of time-varying management policies in which abundance-based reference points changed in response to changes in productivity, found that time-varying HCRs yielded improved biological and fishery performance relative to time invariant ones. A key difference, however, between our simulations and those of Collie et al. (2012) is their performance was averaged over scenarios where dynamics of productivity were transient without persistent trends whereas we focused on declines in productivity given their ubiquity in salmon populations across the Pacific region.

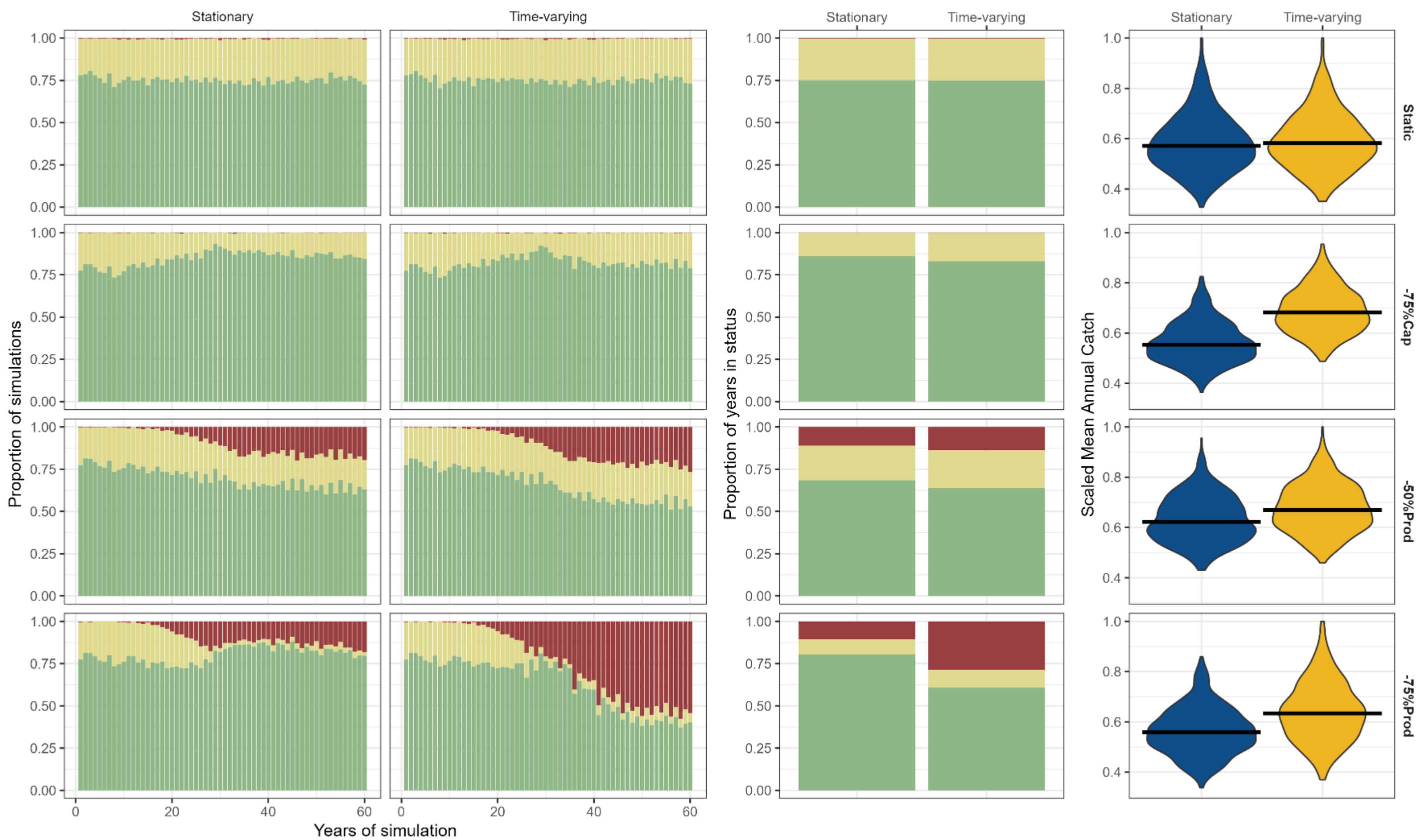


Figure 17. Biological and fishery performance of harvest control rules with and without time-varying abundance-based reference points, where the harvest control rules includes a time-varying or stationary abundance-based reference point ('escapement goal') at 80% of S_{MSY}, a fixed target exploitation rate near U_{MSY} (65%) above the escapement goal, and fixed exploitation rate at 10% of the target below the escapement goal. Left panels show proportion of simulations where the population falls into true green, amber, or red status zones over time for harvest control rules with abundance based reference points that do ('time-varying') or do not ('stationary') vary over time based on either time-varying or stationary estimation models (columns) that are updated every 5 years under scenarios (rows) with either true declines in capacity, productivity, or transient "apparent" changes in productivity due to autocorrelation in recruitment ('static'). The middle panel summarizes the proportion of simulation years the population falls into each status zone and the right panel summarizes mean annual catch scaled to the maximum for that scenario over the 60 years of simulations.

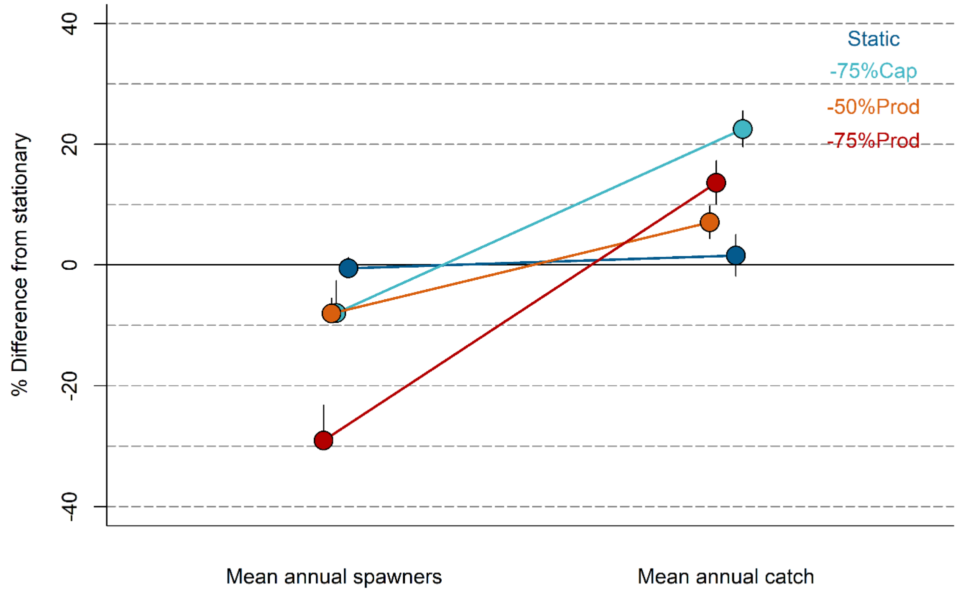


Figure 18. Biological and fishery performance of harvest control rules with time-varying abundance based reference points ('escapement goals') relative to a stationary reference points, where the harvest control rule includes a time-varying or stationary escapement goal at 80% of S_{MSY}, a fixed target exploitation rate near U_{MSY} (65%) above the escapement goal, and fixed exploitation rate at 10% of the target below the escapement goal. Each point is the percent difference in either mean annual spawner abundances or mean annual catch for a harvest control rule with time-varying abundance based reference point, under a given scenario (shading), relative to a harvest control rule based on a stationary abundance based reference point. Points below (above) the horizontal line at zero indicate worse (better) biological or fishery performance of the harvest control rule with time-varying reference points. Error bars represent 95% confidence intervals.

4.2.1.2. Insight 2

When there are transient "apparent" changes in productivity over time due to positive autocorrelation in recruitment, HCRs with time-varying abundance-based reference points have similar biological and fishery performance to those based on stationary assumptions (Figure 17 and Figure 18). Stationary and time-varying estimation models estimate similar statuses under this scenario (see Category of Advice on Estimating Biological Benchmarks), and hence performance of HCRs is similar. When capacity declines over time the biological performance of time-varying and stationary HCRs is similar but average catch tends to be greater for time-varying HCRs. In contrast, in a simulation study of age- and length-structured assessment models for pelagic species, Szuwalski et al. (2018) found that reference points and associated management advice were inaccurate and misleading when a process other than the true time-varying process was allowed to vary, highlighting value in evaluating HCRs with time-varying reference points under a range of hypothetical operating models prior to implementation.

4.2.2. Question 2: Fishing mortality-based reference points in HCRs

Guidance on accounting for time-varying dynamics in harvest control rules, Question 2: What are the consequences of using HCRs with *F*-based reference points that do (do not) vary over time when productivity or capacity truly change (do not change), and how does the magnitude of these changes influence HCR performance?

4.2.2.1. Insight 1

Harvest control rules with time-varying *F*-based reference points have improved biological performance compared with stationary *F*-based HCRs when productivity declines over time (Figure 19 and Figure 20). For HCRs with time-varying *F*-based reference points, target exploitation rates estimated relative to U_{MSY} decline with productivity, resulting in more precautionary management and improved biological status. Similar to HCRs with time-varying escapement goals, fisheries yields depend on the specification of HCR and the magnitude of decline. For an example with a relatively precautionary exploitation rate (10% of the target) below a fixed escapement goal, time-varying *F*-based reference points resulted in similar catches compared with stationary reference points (Figure 19 and Figure 20), though yield can be lower for time-varying *F*-based reference points when a more permissive exploitation rate (30% of the target) is applied below the escapement goal (Appendix Figure E4 and E5). This later scenario reflects a reduction in target exploitation rate over time with declines in productivity, and those impacts on yield are diminished when a more precautionary stepped HCR is used, as in Figures 19 and 20.

Under certain conditions fishery yields can be slightly higher when using time-varying models to derive exploitation rate targets based on U_{MSY} (e.g., 50% decline in productivity in Figure 19 and Figure 20) which is consistent with a case study on Gulf of Maine Atlantic cod that found fishery yields were similar or higher over the long term when fishing mortality was reduced under periods of high natural mortality (low population productivity) (Legault and Palmer 2016). However, the exact shape and parameters of the harvest control rule, as well as the magnitude and rate of productivity decline, will determine whether fishery yields are similar or lower when adopting a time-varying *F*-based reference points.

When productivity increases over time, performance of HCRs with *F*-based reference points are generally not sensitive to the assumptions about stationary or time-varying dynamics (Appendix Figure E6).

4.2.2.2. Insight 2

When there are transient "apparent" changes in productivity over time due to positive autocorrelation in recruitment, HCRs with time-varying *F*-based reference points have similar biological and fishery performance compared to those that use stationary assumptions (Figure 19 and Figure 20). When capacity declines over time the biological performance of time-varying HCRs was similar to that of stationary HCRs, and yields vary according to the HCR.

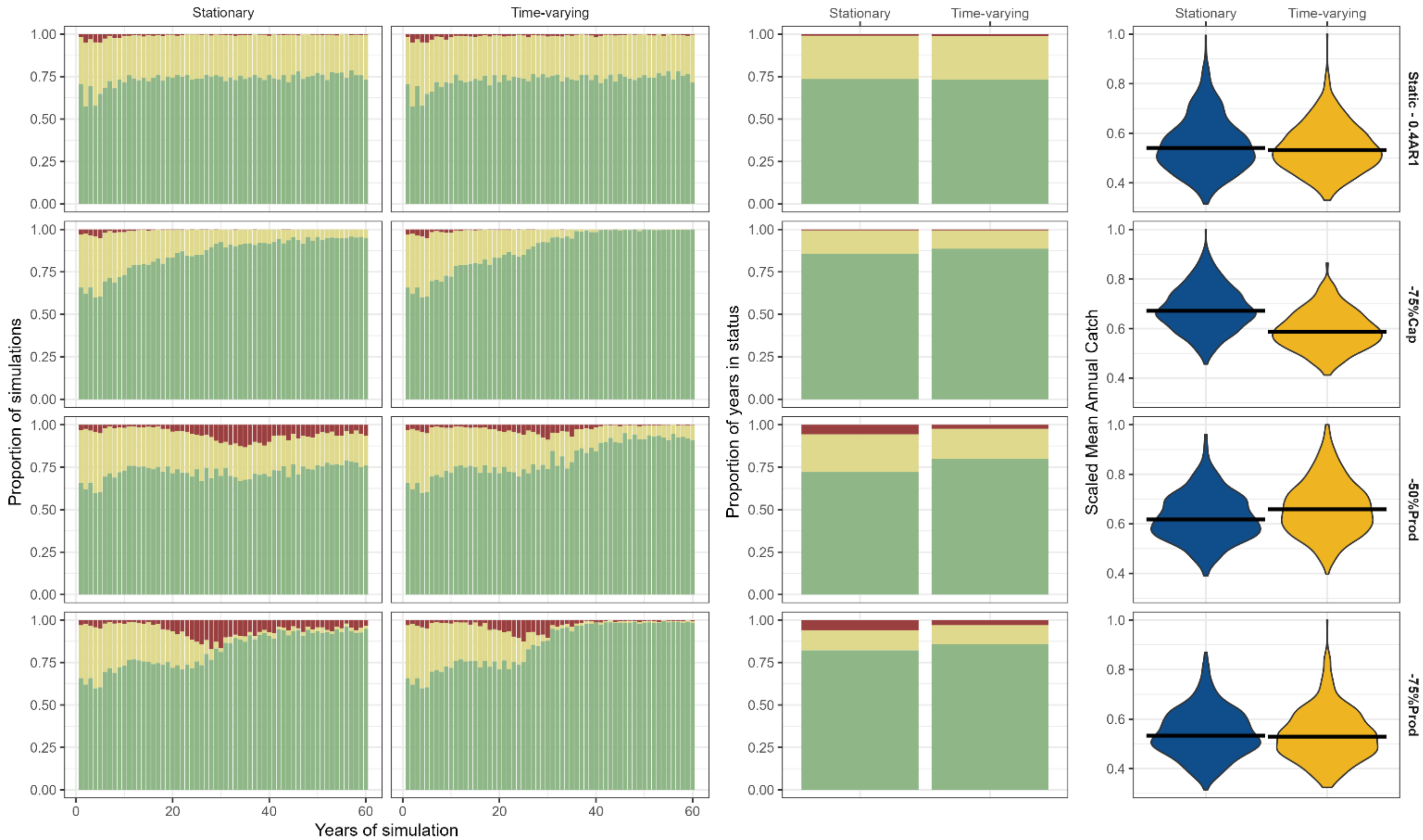


Figure 19. Biological and fishery performance of harvest control rules with and without time-varying F-based reference points, where the harvest control rule includes a fixed abundance-based reference point ('escapement goal'), a time-varying or stationary target exploitation rate near U_{MSY} (x0.9) above the escapement goal, and time-varying or stationary exploitation rate of 10% of the target below the escapement goal. Left panels show proportion of simulations where the populations falls into true green, amber, or red status zones over time for harvest control rules with F-based reference point that do ('time-varying') or do not ('stationary') vary over time based on either time-varying or stationary estimation models (columns) that are updated every 5 years under scenarios (rows) with either true declines in capacity, productivity, or transient "apparent" changes in productivity due to autocorrelation in recruitment ('Static'). Middle panel summarizes the proportion of simulation years the population falls into each status zone and right panel summarizes mean annual catch scaled to the maximum for that scenario, both based on all 60 years of the simulation.

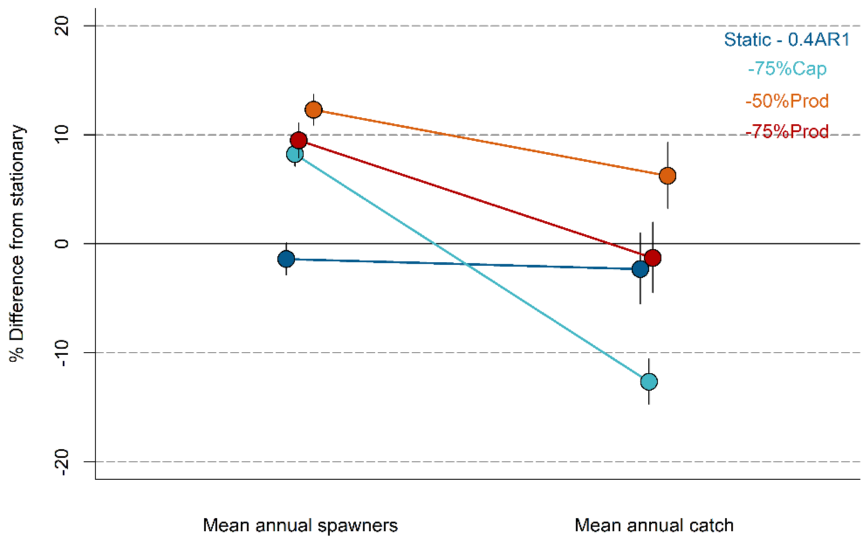


Figure 20. Biological and fishery performance of harvest control rules with time-varying F-based reference points relative to stationary reference points ('escapement goals'), where the harvest control rule includes a fixed escapement goal, a time-varying or stationary target exploitation rate near U_{MSY} (x0.9) above the escapement goal, and time-varying or stationary exploitation rate of 10% of target below the escapement goal. Each point is the percent difference in either mean annual spawner abundance or mean annual catch for a harvest control rule with time-varying F-based reference point, under a given scenario (shading), relative to a harvest control rule based on a stationary abundance based reference point. Points below (above) the horizontal line at zero indicate worse (better) biological or fishery performance of the harvest control rule with time-varying reference points. Error bars represent 95% confidence intervals.

4.3. Recommendation: Structured decision-making process

We recommend **applying time-varying HCRs only when the weight of evidence supports time-varying population dynamics and time-varying HCRs have been evaluated in a structured decision-making framework against a range of HCRs with stationary reference points**. Structured decision making can be defined as "the collaborative and facilitated application of multiple objective decision making and group deliberation method to environmental management and public policy" (Gregory et al. 2012). This approach allows analysts and decision makers to understand risks and trade-offs associated with time-varying abundance and *F*-based reference points in HCRs. This recommendation also reflects the fact that the risk and benefits of time-varying HCRs are likely to be context-specific due to variability in the type and parameters of harvest control rules, and their interactions with population dynamics and performance against biological and socio-economic objectives. In addition, they will depend on information content in the spawner-recruitment relationship, determined in part by the escapement enumeration methods and sampling design both of which can be accounted for in simulation evaluation. This recommendation is generally consistent with the recommendations in DFO 2013.

While quantitative decision analyses (e.g., closed-loop simulations) are widely used for structured decision making in fisheries, and are considered a good practice for fisheries internationally (Punt and Hilborn 1997; Punt et al. 2016), qualitative approaches may be more appropriate when data and resources are limited and/or uncertainties cannot be quantified (Dorn and Zador 2020; Fletcher 2004; Gregory et al. 2012). In instances where simulation-evaluation is impractical (Walter et al. 2023), we recommend qualitative decision-analytic approaches such as scenario planning (Gammage and Jarre 2021; Star et al. 2016) that consider expert-derived risks and benefits of various future scenarios for HCRs with either stationary or time-varying reference points.

We acknowledge the promising performance and appeal of HCRs with time-varying *F*-based (instead of abundance-based) reference points and hence suggest a less stringent evaluation may be needed relative to time-varying abundance-based reference points. However, we note that even in instances where time-varying reference points in HCRs may improve management performance, the loss of management stability associated with frequent changes to reference points could undermine the credibility of managers. In such cases, management may "prefer to sacrifice a bit of performance to gain more stability" (Zhang et al. 2021a). In addition, there is broad recognition that communication of the justification for changes in reference points, when they are proposed or implemented, is crucial to the acceptance of management advice by stakeholders (Sivar-Viladomiu et al. 2021; Zhang et al. 2021a).

As described for the category of advice for biological benchmarks, an alternative to explicitly incorporating time-varying estimation models when deriving reference points for HCRs is truncating the underlying data used to be representative of current (or historical) conditions. As above, we suggest considering data truncation only when there is overwhelming evidence for an abrupt regime shift, and only when the impact of this HCR can be evaluated in a structured decision making framework (e.g., Gregory et al. 2012; Punt et al. 2016) against those that use reference points based on the entire time series.

Lastly, we note that rather than developing HCRs that respond dynamically to changing environmental conditions Punt et al. (2014) recommend considering "the implications of plausible broad forecasts related to how biological parameters may change in the future as a way to assess the robustness of management strategies". Within Management Strategy Evaluations (MSE), stationary reference points that are robust to uncertainty can be identified, where HCRs can be evaluated against a range of projected scenarios (Punt et al. 2014, and as described in the next section on Guidance on Population Projections below).

5. GUIDANCE ON ACCOUNTING FOR TIME-VARYING PARAMETERS IN POPULATION PROJECTIONS

Guidance on accounting for time-varying population dynamics in projections

Goal: Provide advice on when and how time-varying population processes be accounted for when projecting population dynamics

Primary Audience: stock assessment analysts, Species at Risk Program

Secondary Audience: Fisheries Management, Salmonid Enhancement Program, Fish and Fish Habitat Protection Program

One key question and **3 recommendations** derived from a review of the literature (Figure 21, see text for more details).

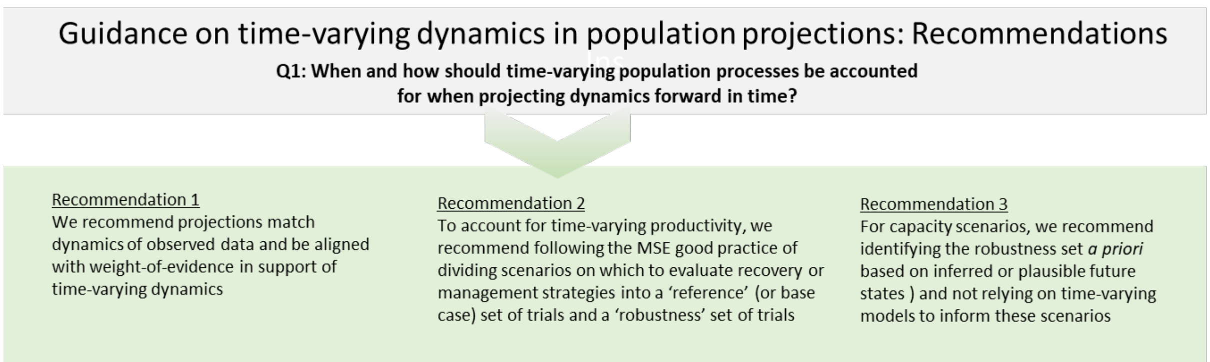


Figure 21. Schematic of one key question and three recommendations to support guidance on accounting for time-varying dynamics in population projections.

5.1. Context

Population projections are an important component of Recovery Potential Assessments within DFO's Species at Risk Program and the evaluation of management strategies within closed-loop simulations for fisheries management (MSE) as they define the nature and magnitude of how population dynamics are expected to change over time. Also, when identifying management actions within rebuilding plans under the *Fisheries Act* DFO Science recommends "when possible, closed-loop simulation modelling should be used to design feedback control rules demonstrated to avoid undesirable outcomes under hypotheses about future dynamics" (DFO 2021c)[11]. More broadly, simulation evaluation "is widely considered to be the most appropriate way to evaluate the trade-offs achieved by alternative management strategies and to assess the consequences of uncertainty for achieving management goals." (Punt et al. 2016), and is increasingly being applied to Pacific salmon fisheries (e.g., Pestal et al. 2011, Cunningham et al. 2018).

Population projections can also be used to identify management procedures (e.g., HCRs or management strategies within rebuilding plans) that are robust to uncertainties in time-varying dynamics, aligned with our recommendation in Category of Advice on HCRs to

[11] Here we refer to projections synonymously with simulations of population dynamics that are initiated from observed population data. The evaluation of projections used in short-term (annual) forecasting models is outside the scope of this guidance.

evaluate a range of stationary and time-varying HCRs in simulation. The expected time required to meet rebuilding targets is another requirement of rebuilding plans under the Fish Stocks provisions which projections can inform. In particular, projections are used to estimate the minimum time to reach the rebuilding target with zero fishing mortality, $T_{\min}$, accounting for the current estimates of stock depletion, generation time, and population parameters such as productivity (DFO 2021c). However, there is little guidance on how to consider time-varying parameters in projections, limiting the rigor of the resulting Science advice.

5.2. Question: Time-varying processes in projections

Guidance on accounting for time-varying models in population projections, Question 1: When and how should time-varying population processes be accounted for when projecting dynamics forward in time?

5.3. Recommendations

5.3.1. Recommendation 1: Weight-of-evidence

We recommend **projections match dynamics of observed data and be aligned with weight-of-evidence in support of time-varying dynamics**, as described for the category of advice on estimating biological benchmarks. This includes careful accounting of the magnitude of autocorrelation in recruitment (Zhang et al. 2021b; Maunder and Thorson 2019) as well as directional trends. “Care should be taken to include all relevant processes in the simulation with stochastic errors that match the observed patterns“ (ICES 2021).

5.3.2. Recommendation 2: ‘Reference’ and ‘robustness’ scenarios

To account for time-varying productivity, we recommend following the MSE good practice of **dividing scenarios on which to evaluate recovery or management strategies into a ‘reference’ (or base case) set of trials and a ‘robustness’ set of trials**. “The reference trials are considered to reflect the most plausible hypotheses…and hence form the primary basis for identifying the ‘best’ management strategy, while the robustness trials are used to determine whether the management strategy behaves as intended in scenarios that are fairly unlikely, even though they are still plausible” (Punt et al. 2016). In this context, the ‘reference set’ can include current and future dynamics of productivity best supported by the weight-of-evidence, and ‘robustness set’ can include those also moderately supported, but with less weight. We recommend explicitly identifying within which set each plausible scenario of current and future time-varying dynamics belongs according to their supporting evidence, with dynamics with low plausibility being excluded from consideration. When considering scenarios in the ‘robustness set’, we recommend projections be based on productivity estimates from a range of supported models, including their lower and upper uncertainty intervals. While a preferred management strategy may not be robust to all projection scenarios in the ‘robustness set’, this analyses will make the magnitude and type of risks transparent. Similar approaches have been adopted internationally, such as within the International Whaling Commission which assigns high, medium and low plausibility to future scenarios when evaluating management strategies in simulation (cited in Punt at al. 2016).

In addition, where life-cycle and/or climate-linked models are available, we recommend using this mechanistic understanding to support plausibility of various scenarios and including empirical or mechanistic forcing of population dynamics in projections if possible, as illustrated in a DFO review of ecosystem-approaches for fisheries management (Pepin et al. 2023).

5.3.3. Recommendation 3: Scenarios of changing capacity

For capacity scenarios, we recommend identifying the robustness set *a priori* based on inferred or plausible future states (e.g., increases or declines of a specified proportion from current estimates of capacity), and not necessarily relying on time-varying models to inform these scenarios given poor statistical reliability of models with time-varying capacity.

6. FUTURE RESEARCH

Future research could identify key data uncertainties that most impact the reliability of time-varying estimation models. In particular, the consequences of alternative data collection methods and designs on the statistical reliability of time-varying estimation methods can be evaluated by incorporating sampling and monitoring design components into the simulation models described above. Value-of-information analyses could be used to identify how extreme changes in population parameters need to be before changes in sampling designs are warranted to achieve acceptable reliability of assessments and performance of management decisions.

We also recommend continued research on the mechanistic underpinnings of time-varying population dynamics, including impacts of climate and species interactions on productivity and capacity. When placed within a salmon life-cycle framework, these mechanisms can inform an ecosystem-approach for fisheries management (DFO 2023) and help identify spatial and temporal scales of diversity across populations relevant for long-term sustainability (e.g., Thorson et al. 2014). The Risk Assessment Method for Salmon, RAMS, (DFO 2018), Salmon Management Decision Support Tool, DST, within the Likely Suspects Framework (Bull et al. 2022), and Cumulative Effects Model for Prioritizing Recovery Actions, CEMPRA (Bayley et al. 2023) are three examples of such life-cycle approaches.

We further recommend exploring the application of estimation methods with time-varying parameters that relate environmental covariates to population dynamics (Ovando et al. 2022), include cyclic population dynamics (White et al. 2014), and are applicable to data-limited contexts (e.g., benchmarks based on habitat capacity, Parken et al. 2006). Further consideration of time-varying estimation models in forecasts of adult recruitment and buffers to account for bias and uncertainty in forecasts (Satterthwaite and Shelton 2023) may be warranted. Accounting for the spatial as well as temporal covariation in ocean survival among neighbouring populations within spatiotemporal models is another area of future research (DeFilippo et al. 2021).

Using climate-linked population models to inform management advice is a growing area of research. Where quantitative climate projections are lacking, a risk-based approach can be applied using risk-equivalency to identify management actions that are robust to uncertainties in future climate conditions (Roux et al. 2022). This approach can be a powerful tool for combining quantitative assessment outputs with qualitative and semi-quantitative information of hypothesized climate impacts to provide climate-informed advice.

Lastly, we recommend development of consistent reporting templates and tools to aid in the communication and documentation on if and how time-varying dynamics are considered in biological assessments, estimation of reference points within HCRs, and projections. The analytical tools developed here (Appendix B) can be used to support the development of such reporting templates and tools, which could be part of regular reporting in Fisheries Science Advisory Reports.

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8. GLOSSARY OF TERMS

AIC: Akaike information criterion, a likelihood-based approach for model selection

BIC: Bayesian information criterion, a likelihood-based approach for model selection that is closely related to AIC but includes a larger penalty on the number of additional parameters

Biological Benchmark: thresholds that distinguishes biological zones of status, Red, Amber, and Green, under Canada's Wild Salmon Policy (DFO 2005)

Capacity: spawner abundances where adult recruitment is maximized, parameterized as $1/\beta$ in the Ricker spawner-recruitment model

Hidden Markov Model: an estimation model used to identify the frequency and magnitude of abrupt regime shifts in parameters assuming the observations depend on a latent or hidden underlying 'Markov' process

Leave-future-out cross-validation (LFO-CV): a method of selecting among Bayesian models with time-ordered data that evaluates out-of-sample predictive accuracy. In this method only data before the year being predicted are used to evaluate predictive accuracy

Limit Reference Point, LRP: The stock status below which serious harm is occurring to the stock. At this stock status level, there may also be resultant impacts to the ecosystem, associated species and a long-term loss of fishing opportunities, as described in DFO's Precautionary Approach Framework (DFO 2009)

Management Strategy Evaluation (MSE): the evaluation of management strategies using simulation, widely considered to be the most appropriate way to evaluate the trade-offs achieved by alternative management strategies and to assess the consequences of uncertainty for achieving management goals (Punt et al. 2016)

Productivity: the cumulate log(survival) from spawner to adult recruit in the absence of adult recruitment, parameterized as $\log_e(\alpha)$ in the Ricker spawner-recruitment model

Random Walk Model: an estimation model that includes parameters that change annually according to a probability distribution

Stationary (nonstationary): a stochastic process whose long-term average properties do not (do) change over time

WSP: Wild Salmon Policy (DFO 2005)

9. APPENDICES

APPENDIX A

Tables from a review of agency reports and the primary literature.

Table A1. Recommendations on estimating biomass-based reference points and target fishing mortality rates, F, and management strategies in general under environmentally driven changes in population parameters from various jurisdictions: Canada, US, Australia and ICES.

Jurisdiction, Legislation/ Policy/ Guidance Doc.	**Recommendation on biomass based reference points**	**Time frame for re-estimation**	**Approach**	**Recommendations on target *F***	**Timeframe for re-estimation**	**Approach**	**Recommendation on management strategies in general**
Canada							
Precautionary Approach Framework (DFO 2009)	"When developing reference points efforts should be made to take into consideration the range of factors which may affect the productivity of the stock including changes in ocean conditions, where information is available."		"In general, as long as a time series as possible should be used in establishing reference points for a stock"; "the only circumstances when reference points should be estimated using only information from a period of low productivity is when there is no expectation that the conditions consistent with higher productivity will ever recur naturally or be achievable through management"				
Wild Salmon Policy (DFO 2005)	Benchmarks should be estimated "given existing environmental conditions", recognizing that those values will vary through time.		Examples include SBC Chinook WSP assessment that included sensitivity analyses of benchmarks and status with lower (half) productivity, and Fraser Sockeye with sensitivity analyses of benchmarks				"Ecosystem considerations will be incorporated into salmon management. Indicators will be developed to assess the status of freshwater ecosystems. Information from ocean climate studies

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
			estimated with time-varying SR models.				of marine survival and of the biological condition of salmon will be integrated into the annual assessments of salmon abundance that guide salmon harvest planning"
Grant et al. 2020 The 2017 Fraser Sockeye Salmon (Oncorhynchus nerka) Integrated Biological Status Re-Assessments Under the Wild Salmon Policy Using Standardized Metrics and Expert Judgment		"Although there is no DFO guidance on how often CU biological statuses should be re-assessed, past WSP biological status assessments (Grant & Pestal 2012; G. Brown, DFO, pers. comm.; C. Parken, DFO, pers. comm.) have recommended that re-assessments should occur if one or more of the following apply: after one salmon generation (four years for Fraser Sockeye); when salmon productivity and/or abundance changes significantly; when new methods not previously peer reviewed are developed to assess WSP status."					

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
Holt et al. 2023 Guidelines for Defining Limit Reference Points for Pacific Salmon Stock Management Units		To derive CU-status LRPs, "Where available, we recommend applying CU assessments from recent peer-reviewed WSP status assessments, .." "As a general guideline, we suggest that 'recent' should mean within the most recent generation, though major perturbations such as landslide events may make even recent assessments unrepresentative of current status."					
DFO 2013 National Workshop on MSY reference points when productivity varies	Time-varying reference points associated with regime shifts should only be considered when the capacity of the environment to support the stock has changed with high certainty and the shift is considered to be irreversible in the short to medium term (longer of 10 years or one generation)			In most cases, changes in *F* reference points and management are recommended to respond to annual variability or regime changes in stock productivity, density independent survival, growth and fecundity.		.	
Fish Stocks provisions of	6.1(2) … the Minister shall set a limit						6.1 (1) In the management of

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
Fisheries Act (2019)	reference point and implement measures to maintain the fish stock above that point, taking into account the biology of the fish and the environmental conditions affecting the stock.						fisheries, the Minister shall implement measures to maintain major fish stocks at or above the level necessary to promote the sustainability of the stock, taking into account the biology of the fish and the environmental conditions affecting the stock.
DFO 2021b Science Advice for Precautionary Approach Harvest Strategies under the Fish Stocks Provisions	"any approach to identifying reference points and maintaining fish stocks at a specified level, or rebuilding depleted fish stocks, needs to consider alternative hypotheses to represent the effects of environmental variability where they can be identified".		"given the potential risks of adjusting reference points and management measures where mechanisms are not well understood, a means of evaluating the expected performance of management measures that account for environmental conditions should be introduced." (e.g., MSE)				"Reference points may or may not change as a result of accounting for environmental factors, but management measures can be adjusted in an attempt to improve the acceptability of management outcomes and eliminate those options that are likely to fail in practice" ; "given the potential risks of adjusting reference points and management measures where

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
							mechanisms are not well understood, a means of evaluating the expected performance of management measures that account for environmental conditions should be introduced.” (e.g., MSE)
DFO 2023 Science Advice on Guidance for Limit Reference Points under the Fish Stocks Provisions	“Currently the PA Policy recommends using “as long as a time series as possible” in estimating reference points and to avoid using low productivity periods alone unless there is no expectation of improved conditions in future”, but recognizes that “Management decisions based on static equilibrium reference points may not reflect stock dynamics in the future”	“Generally speaking, indicators and LRPs should be re-considered when a new advisory framework (e.g., a new assessment model) or management paradigm (e.g., initiation of a management strategy evaluation framework or closed-loop simulation) are adopted”	Dynamic B_0 is not recommended because of its assumption that “temporal changes in biological parameters (e.g., M, weight-at-age, maturity-at age, and recruitment anomalies) are independent of fishing (e.g., environmentally driven) and are not density-dependent”, which is unlikely. If truncating the time series used to estimate RPs, care must be taken in the choice of the reference period.	Recognizes that “F-based reference points … can be fine-tuned to account for changes in environmental drivers”			
US							

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
Magnuson-Stevens Act (MSA 2007)	Fisheries management plans must "assess and specify the present and probable future condition of, and the maximum sustainable yield and optimum yield from, the fishery", which requires identification of reference period to determine 'present and probably future' productivity for MSY calculations.		Example taken from Szuwalski et al. 2023, "groundfish stocks reviewed by the North Pacific Fisheries Management Council use recruitment time series from 1977 to the most recent year of reliably estimated recruitment to estimate MSY-proxy reference points. This decision is based on a perceived ecological regime shift in the late 1970s and consistent data availability after this time period"				
US National Standard Guidelines on Optimum Yield	recommend consideration of environmental factors in reference points and estimation of MSY and optimal yield, including re-estimation "as required by change in long-term environmental and ecological conditions, fishery technological characteristics, or new scientific information ", recognizing that it need	Re-estimation generally occurs on research track schedule of 5-10 years (as stated in ICES 2021, p.4)	Optimum yield should consider species interactions, "Species interactions that have not been explicitly taken into account when calculating MSY should be considered as relevant factors for setting OY below MSY"				

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
	not be estimated every year as MSY is a long-term average quantity						
Climate Science Strategy of the US National Marine Service (Busch et al. 2016)	"As stocks, protected species, habitats, aquaculture, and ecosystems are expected to respond to climate change, the reference points for these species, systems, and human uses will need to change to reflect those different conditions"..."stock assessments, biological reference points, and fisheries management plans based on these assessments [that ignore directional climate change]] may not adequately capture the future population dynamics in a changing ocean" "Avoiding misaligned management targets is more likely if these plans inform reference points with the best available climate-related science, including socio-economic analyses that show the consequences of neglecting climate						"identify management strategies that are robust to future change, various ecosystem, socio-economic, and LMR [living marine resources]] models can be coupled with scenarios of climate change to test the performance of current and alternate management decisions under future conditions" "Forward-looking management of LMRs depends on robust projections of future ocean conditions and the likely responses of ecosystems, LMRs, and human communities on appropriate temporal and spatial scales."

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
	change in biological reference points" "Misaligned reference points may result in foregone revenue or missed opportunities (e.g., best times to harvest stock for commercial or subsistence take, opportunities for ecotourism) due to climate-induced changes in production, distribution, or other dynamics of LMRs"						
Australia							
Australia's Commonwealth Fisheries guidelines (DAWR 2018)		"Long-term climate change could be managed with a series of updates to reference points every decade or so, depending on the species life span"	"if the overall productivity changes due to the environment, then this should be accounted for by ensuring that any assessment inputs and assumptions (such as M and SR parameters) are not temporally static, but reflect environmental conditions being experienced by the stock (reflecting a dynamic B0) over time"; "The effect of changing reference				recommend "assessment and management consider environmental variability, regime shifts and persistent trends, e.g., related to climate change, but these perceived changes should have high confidence with mechanistic understanding of impacts on stock. In addition, these should be considered when setting rebuilding

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
			points should be considered in MSEs used to test future harvest strategies, which could also test the frequency with which they should be updated.”;				targets and timeframes.” “Modifying harvest strategies on the basis of assumed but untested environmental explanations, rather than fishing-related causes for decline, should be avoided. …weight-of-evidence approach should be applied to use available scientific evidence to test a causal hypothesis”
ICES							
ICES 2017 ICES Guidelines on Category 1 and 2 Stocks	Assume static reference points estimated from the entire time series unless there is strong evidence of shift in recruitment success		“Unless strong evidence exists that a consistent change has occurred, the full time series of stock and recruitment should be used. Be careful not to mistake periodicity in recruitment success, induced by e.g. cyclic climate conditions, with prolonged shifts.” “Serial autocorrelation in recruitment (or recruitment				

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
			deviations from the model) may influence the results and should be included."				
ICES 2021 Workshop of Fisheries Management Reference Points in a Changing Environment	Where there are systematic changes in the environment identified during benchmark process associated with **density dependence**, then reference points may need to be revised. E.g., if the extent of recruitment habitat is halved, the SSB required to fill this habitat would only be half the previous B_{lim} (PA reference point). However, "the workshop considered that **more evidence should be required** to change precautionary biomass reference levels derived from stock recruitment relationships than to change FMSY."	iterative re-evaluation of reference points through periodic benchmarks (every **5-10 years**) or MSE exercises and the inter-benchmark process to account for urgent revisions where conditions require	Consider truncating data time series, modelling specific time-varying process (growth, maturity, cannibalism, mortality, inter-species interactions), time series or state-space models, compare across multiple stocks/data sources, likelihood ratio tests of alternative model structures. "Any estimation of reference points should include an evaluation of which processes are critical over the lifespan of the reference point" (i.e., which parameters are expected to change over the next 10 years) "care should be taken to ensure that reference points reflect changes that are likely to occur	They recommend adjusting the target F values based on environmental or ecological conditions where those relationships are understood, and within the bounds of precautionary fishing mortality levels as determined during benchmarks "In general, the ability to "tune" F_{target} within existing limit and potentially range reference points gives the flexibility to include some ecosystem variation into the quota advice without requiring re-estimation of the reference points"	Can occur an annual basis where relationships with env variables are understood		Suggest precautionary harvest strategy (e.g., double hockey stick) instead of adjusting references or F_{MSY} between benchmarks. "The process for estimating and updating reference points needs to be evaluated in the context of the harvest control rule and the advice that is based on it, in particular where F_{MSY} is used as the F_{target} in a HCR" *For projections, "care should be taken to include all relevant processes in the simulation with stochastic errors that match the observed patterns"

Jurisdiction, Legislation/ Policy/ Guidance Doc.	Recommendation on biomass based reference points	Time frame for re-estimation	Approach	Recommendations on target *F*	Timeframe for re-estimation	Approach	Recommendation on management strategies in general
			within a 10-year time period, conditioned on management decisions for interacting stocks”				

Table A2. Recommendations on non-stationarities in reference points (biomass-based and F-based), projections/rebuilding and harvest strategies and outstanding questions from the primary literature (non-exhaustive).

Authors	Biomass Reference Points	F-based Reference Points	Projections/rebuilding	Harvest Strategies	Outstanding questions
Berger 2019	Although caution is warranted when considering dynamic reference points, this paper shows these approaches are likely to be most useful when stock productivity shifts directionally				
Britten et al. 2017			When non-stationarity is present (in the form of auto-correlated residuals) recovery probabilities are diminished when evaluated over 10 year projections, suggesting that recovery timelines would be extended.		
Legault and Palmer 2016		When the empirical evidence is not strong, we recommend using a constant M. If strong empirical evidence exists, we recommend estimating F_{Target} for a range of stock–recruitment relationships and evaluating the trade-offs between risk of overfishing and forgone yield. Short-term gains in yield associated with high F_{Target} values should be considered in light of potential losses in future yield if the high total mortality rate			

Authors	Biomass Reference Points	F-based Reference Points	Projections/rebuilding	Harvest Strategies	Outstanding questions
		leads to a decrease in recruitment.			
Klaer et al. (2015)	Proposes a weight of evidence approach to determine regime shift with 4 criteria that incorporate qualitative and semi-quantitative ratings and assessments of available scientific evidence for or against productivity/regime shifts. Reference points and recommended catches are estimated from current regime, where the weight of evidence is strong.			(see column 2)	"In addition to scoring against the four suggested criteria, an important consideration is the evaluation of the risk of making an incorrect decision about a productivity shift. Such a risk evaluation can be made using management strategy evaluation"
Maunder and Thorson (2019)	"we recommend that biomass-based reference points be based on dynamic calculations that take the historical series of recruitment into consideration (e.g., Wang et al., 2009). However, care should be taken when using dynamic reference points in the presence of a strong stock-recruitment relationship. Limit biomass reference points might not be suitable for dynamic reference points because recruitment failure may be related to an absolute level of spawning biomass."	"Constant harvest rate strategies tend to be robust to recruitment variation and are recommended, but they still need good estimates of abundance if they are implemented using catch quotas" "Constant escapement strategies are optimal when recruitment is stationary and uncorrelated (Walters and Parma, 1996), while with cyclic recruitment, constant harvest rate strategies also inherently allow a buildup of spawning biomass during favorable periods (Parma, 1990). Therefore, constant harvest rate strategies	"Simulation shows that it is often necessary to estimate autocorrelated recruitment [and regime shifts] to generate reasonable population forecasts if recruitment is substantially autocorrelated"	"Due to the difficulty of estimating the stock-recruitment relationship …, we recommend basing management on concepts that are not sensitive to small changes in the assumed stock-recruitment relationship, or exploring the impact of changing assumptions using decision tables"	We "recommend more work regarding which of the alternative [recruitment] patterns is most robust to model mis-specification (i.e., is it better to incorrectly approximate a regime-shift as autocorrelation, or autocorrelation as a regime shift?)." We recommend use of "Regional meta-analysis regarding dominant patterns in recruitment", "information about cohort strength can be shared among stocks to improve recruitment estimates for data-poor species"

Authors	Biomass Reference Points	F-based Reference Points	Projections/rebuilding	Harvest Strategies	Outstanding questions
		may be preferable under strongly autocorrelated oceanographic forcing of recruitment (Walters and Parma, 1996)."			
Zhang et al. 2021b		See also column 4	"results suggest that caution should be taken when calculating [**projection-based**, F] MSY-based reference points in highly dynamic ecosystems, and correctly accounting for non-stationary population dynamics could, therefore, lead to more sustainable fisheries." F_{MSY} estimated from stochastic projections that ignored autocorrelation were higher than those that accounted for it		
Zhang et al. 2021a	"Reference points may be changed when there is "strong evidence" of ecosystem change, but the definition of "strong evidence" may vary among ecosystems and management jurisdictions. " (See column 5)		"we need to consider what are appropriate recovery targets and interim milestones for recovery of collapsed stocks. The consequences for not doing this and continuing the status quo are that we are more likely than not to produce advice mis-specified for the actual environmental conditions, and it will become more difficult to make appropriate management decisions." Projections are important to identifying if rebuilding targets are actually possible.	"management considerations are also important when deciding when to change reference points. There is a trade-off between management stability and performance. Frequently changing reference points may improve management performance, but the loss of management stability could impair the credibility of managers. In such cases, management may prefer to sacrifice a bit of performance to gain more stability. It is a common practice to consider a fixed frequency between	"Changing reference points is both a scientific and a political question, and for these reasons, it is important that scientists develop clear messaging around dynamic reference points", "we need to work across sectors to develop a set of collectively reviewed and agreed-upon guidelines, or guiding questions, that set the basis for reference point approaches and methods that could be applied under different circumstances or stocks." "recommendation was to test dynamic reference points in a MSE framework before applying them."

Authors	Biomass Reference Points	F-based Reference Points	Projections/rebuilding	Harvest Strategies	Outstanding questions
				changes of reference points."	
Sivar-Viladomiu et al. 2021	References point may change due to (i) continual improvement in data, estimation, and knowledge, (ii) growing inclusion of ecosystem concerns into management, (iii) time-varying conditions				"We recommend careful documentation of changes to assessment assumptions and data inputs (Punt et al., 2018), as well as the revision in estimation or selection of reference points and detection of shifts in productivity (Clausen et al., 2018). Communicating, explaining and justifying the changes is remarkably important to understand them and their relevance."
Szuwalski et al. 2023	MSY-based targets that are adjusted to reflect the productivity of current environmental conditions ('climate-adaptive strategy') may result in higher fishing pressure and associated conservation risks on populations relative to only small gains in harvest. Demonstrated for **biomass RPs** under simulated changes in capacity for 590+ (?) stocks.	Found similar results for Bering Sea Snow Crab when natural mortality increased or growth decreased (increasing F_{MSY}) in simulation	'status quo' approach "assumes that historical recruitment levels will be achievable. If declines are related to climate, this assumes that climate impacts can be mitigated to allow rebuilding to historical levels."	See columns 3 and 4	"There will likely be no one-size-fits-all solution for managing fisheries under a changing climate and, although status quo management may be a useful initial default, this does not mean improvements cannot be made", such as understanding the large-scale impacts of climate change
Bessell-Browne 2024	From MSE of 4 Australian pelagic fisheries. "This work highlights that the use of a dynamic B_0 HCR will, on average, maintain slightly higher catches than a static B_0 HCR, but the stock biomass (in magnitude) will be less than if a static B_0 HCR was adopted under declining productivity (here modelled as trends in			"The preference for dynamic B_0 or static B_0 HCRs then relates to the aims of the harvest strategy to be implemented. Some harvest strategies may be focused on preserving the relative stock status through time and the management objectives	"The variants of the dynamic B_0 HCRs tested here (dynamic B_0-target and dynamic B_0-slide) have attempted to take these considerations into account [need to maintain minimum abundances], by allowing movement of the target reference point and breakpoint to facilitate

Authors	Biomass Reference Points	F-based Reference Points	Projections/rebuilding	Harvest Strategies	Outstanding questions
	expected R_0 and M). Stock status then depends on the frame of reference – relative to static $B_{t=0}$ the status will be worse than relative to an estimate of annual unfished biomass (dynamic $B_{F=0}$). "			do not pertain to the absolute numbers of individuals in the population. In this circumstance, a dynamic B_0 HCR may meet the requirements of the harvest strategy. However, other strategies may require that a population does not drop below a pre-specified absolute size, as the species may provide prey for other species and processes that might lead to depensatory effects relate to absolute and not relative abundance. Additionally, maintaining absolute stock size above some minimum threshold may be equally important for ecosystem function. In this scenario a LRP relating to static B_0 would be more appropriate. "	improved yield while also preventing the LRP from dropping towards zero. Determining the range of permissible change in these parameters would need to be determined as part of harvest strategy development and would depend on the species and its role in the ecosystem in question, as well as policy goals "

APPENDIX B

Analytical tools to support guidance on time-varying parameters

samEst - R package to estimate spawner-recruitment relationship with stationary and time-varying parameters (productivity and capacity), where parameters are estimated using either random walk or hidden Markov models. https://github.com/Pacific-salmon-assess/samEst

samSim (branch timevar)– R package to simulate population dynamics of Pacific salmon, used to evaluated performance of assessment models and harvest control rules with either stationary or time-varying parameters. https://github.com/Pacific-salmon-assess/samSim/tree/sbccnk

APPENDIX C

Statistical reliability of stationary and time-varying estimation models

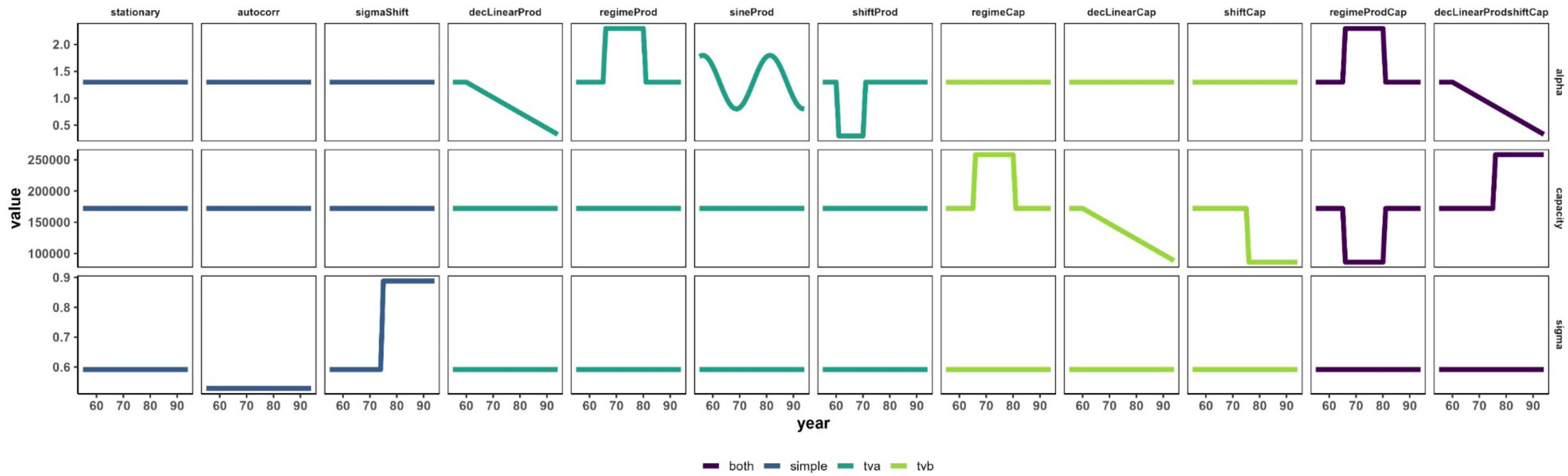

Figure C1. Illustration of the direction, magnitude and type of population processes explored in the simulation analyses. Colours represent scenarios where both productivity and capacity are stationary (blue, labelled 'simple'), productivity varies (turquoise, labelled 'tva'), capacity varies (light green, labelled 'tvb', or both productivity and capacity vary (purple, labelled 'both').

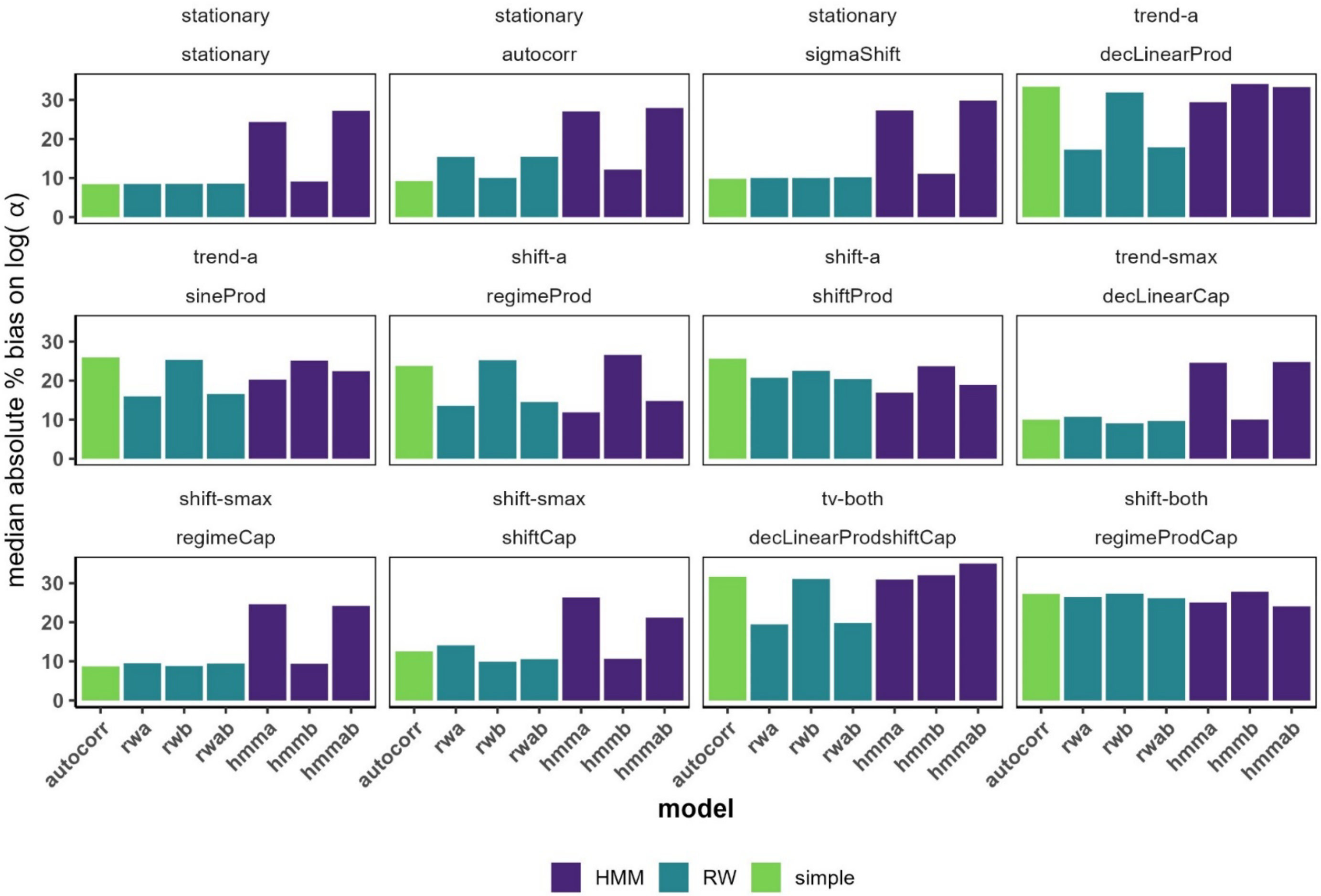

Figure C2. Median absolute bias in estimates of intrinsic productivity (log[α]) across 7 estimation models (x-axis), and 12 alternative scenarios (panels). Estimation models are sharded by if they assume stationarity (green, labeled 'simple'), a random walk in either productivity, capacity, or both (turquoise labeled 'rwa', 'rwb', 'rwab' respectively), or a regime shift in either productivity, capacity or both (purple, labelled 'hmma', 'hmmb', and 'hmmab' respectively). See Figure C1 for illustration of scenarios and Wor et al. (in prep. 'Recommendations for estimating and detecting time-varying spawner-recruit dynamics in fish populations') for more details on the simulation evaluation.

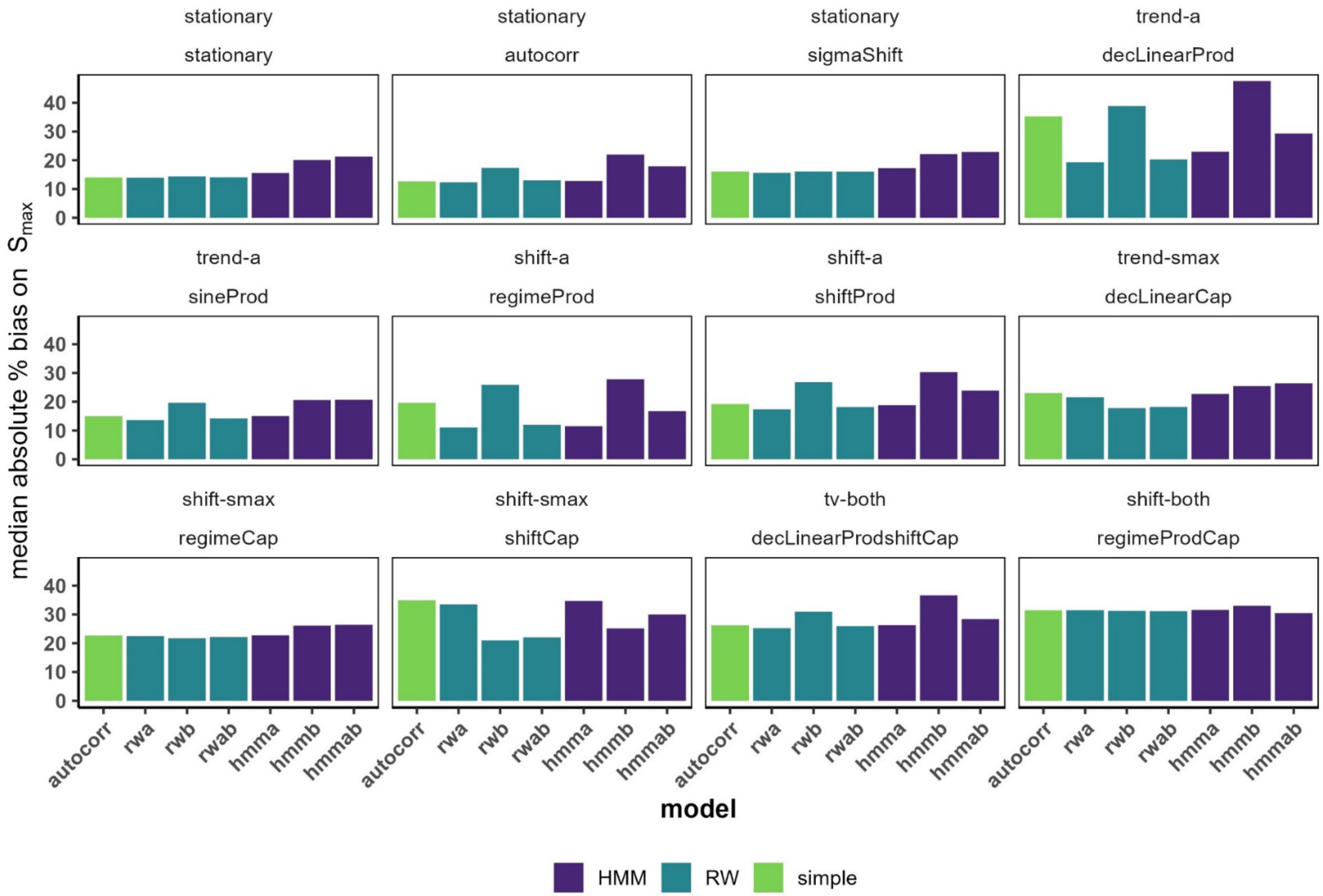

Figure C3. Median absolute bias in estimates of capacity (SMAX) across 7 estimation models (x-axis) and 12 alternative scenarios (panels). *See Figure C1 for illustration of scenarios, the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.*

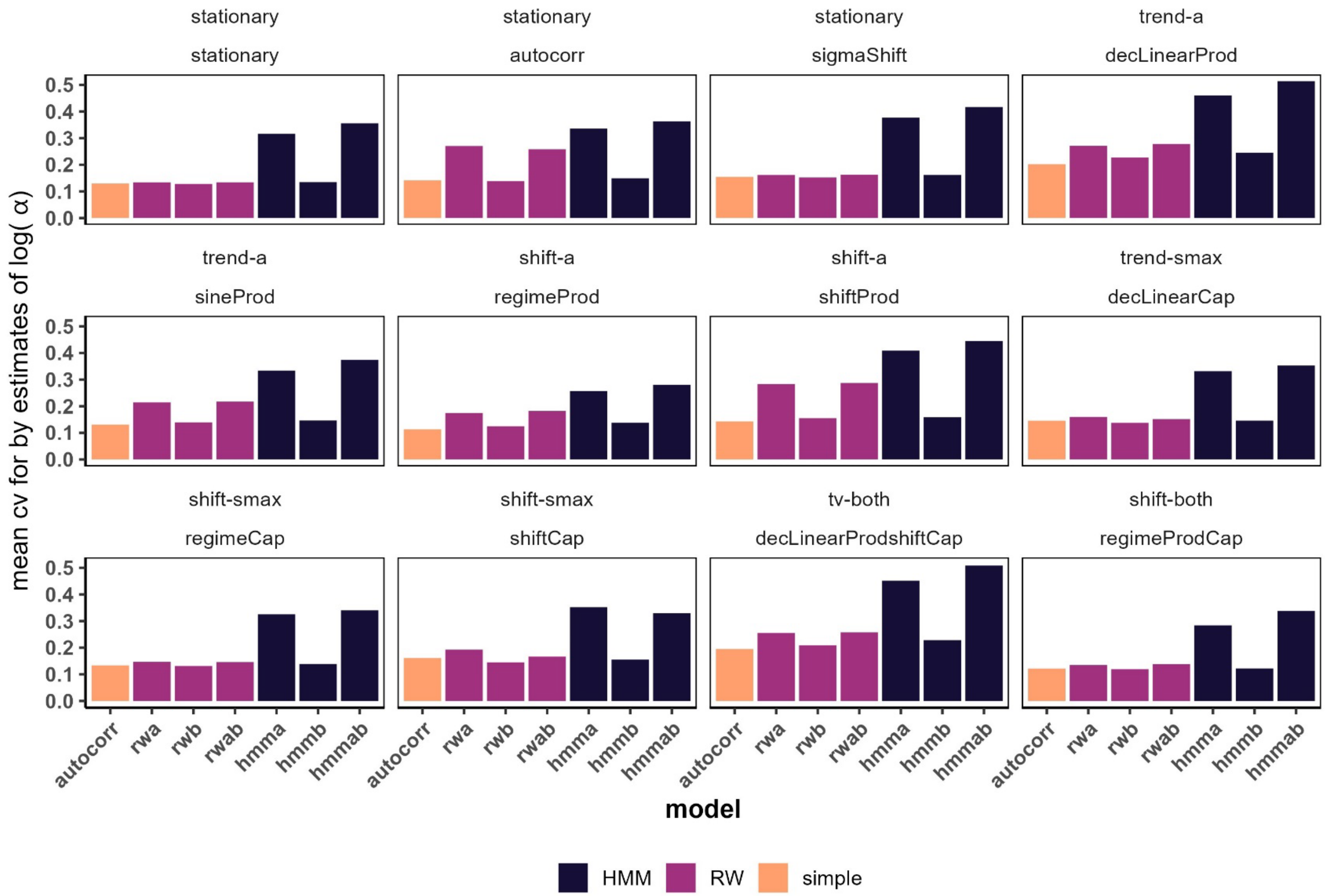

Figure C4. Precision (mean coefficient of variation [CV]) of estimates of intrinsic productivity (log[α]) across 7 estimation models (x-axis) and 12 alternative scenarios (panels). See Figure C1 for illustration of scenarios, the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.

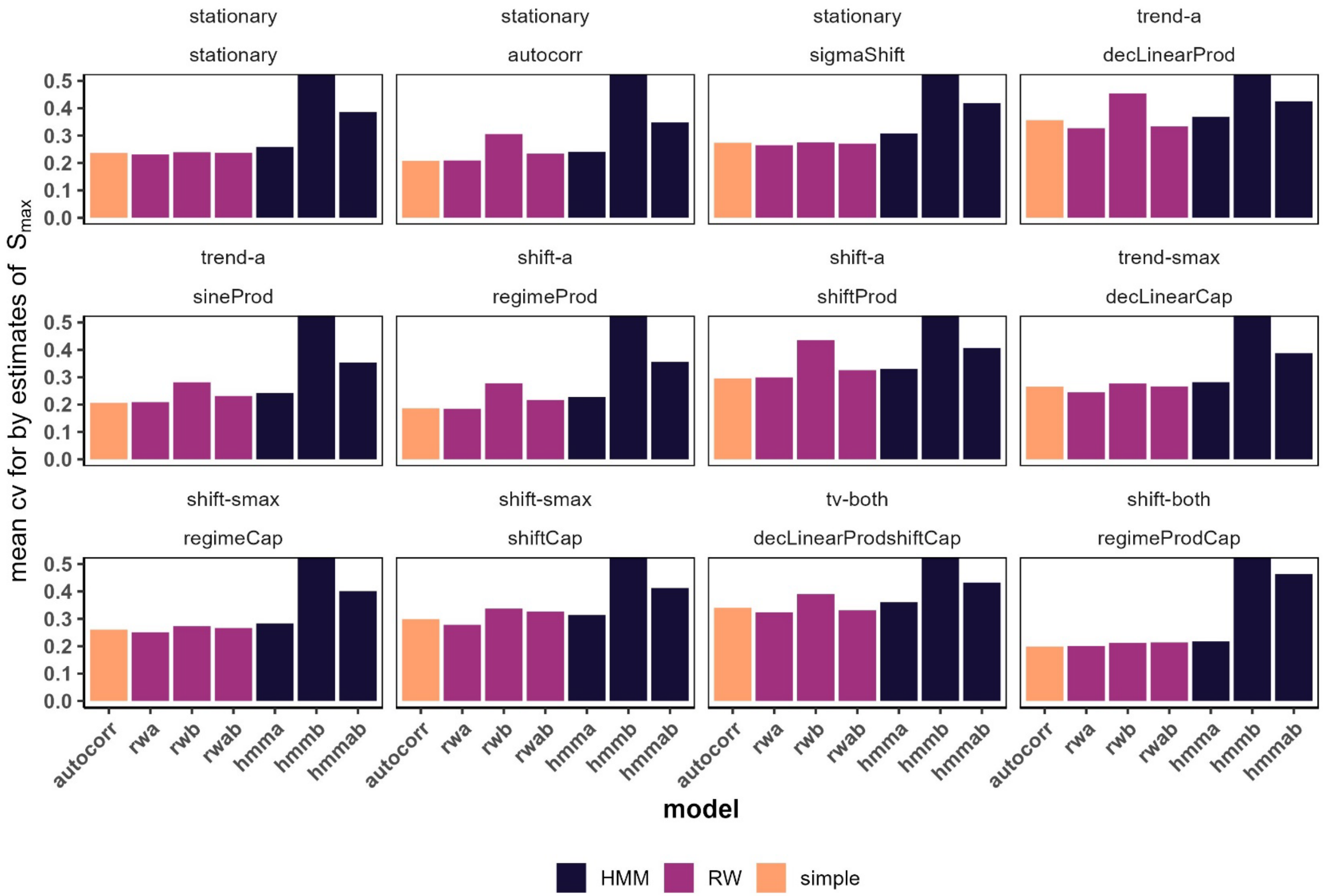

Figure C5. Precision (mean coefficient of variation [CV]) of estimates of capacity (S_{MAX}) across 7 estimation models (x-axis) and 12 alternative scenarios (panels). See Figure C1 for illustration of scenarios, the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.

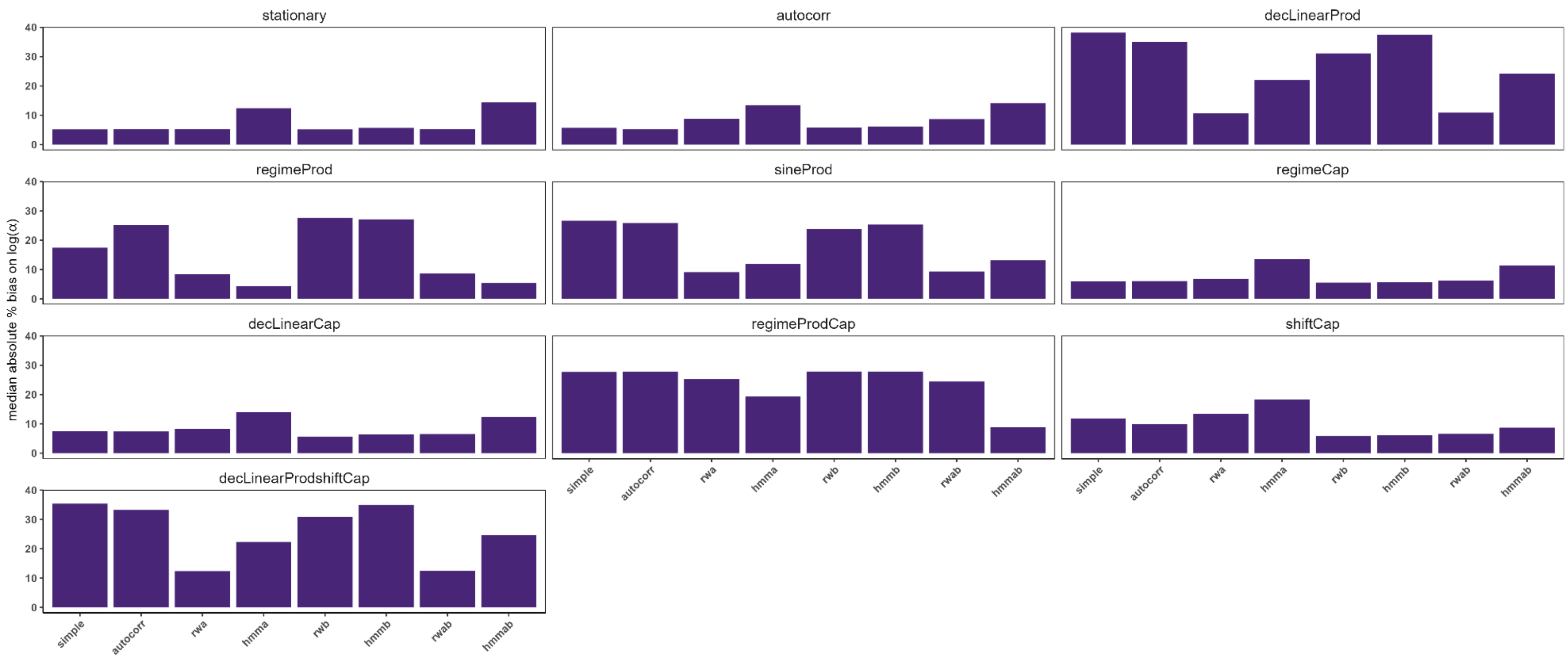

Figure C6. Median absolute bias in estimates of intrinsic productivity (log[α]) across 8 estimation models (x-axis) and 10 alternative scenarios (panels) for sensitivity analyses with recruitment residual variance of 0.3. See Figure C1 for illustration of scenarios, the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.

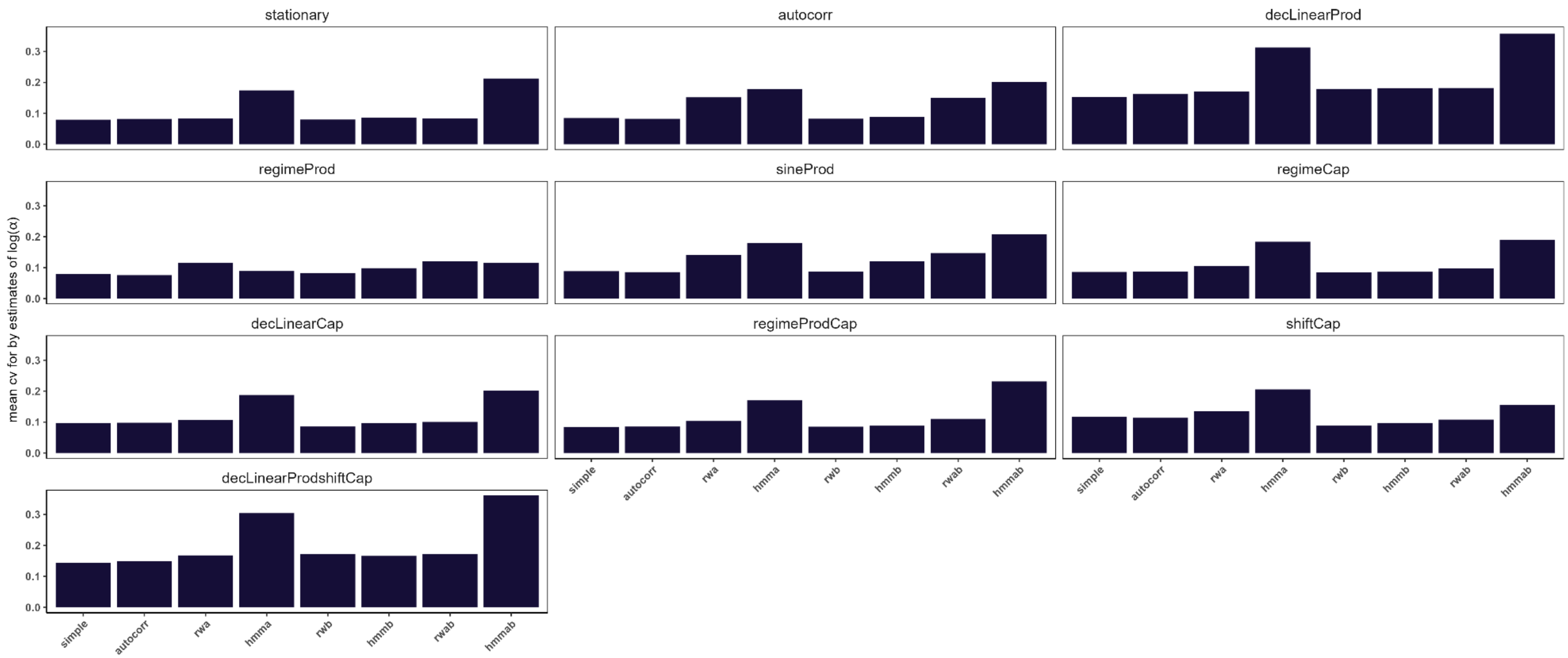

Figure C7. Precision (mean coefficient of variation [CV]) of estimates of capacity (SMAX) across 8 estimation models (x-axis) and 10 alternative scenarios (panels) for sensitivity analyses with recruitment residual variance of 0.3. See Figure C1 for illustration of scenarios, the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.

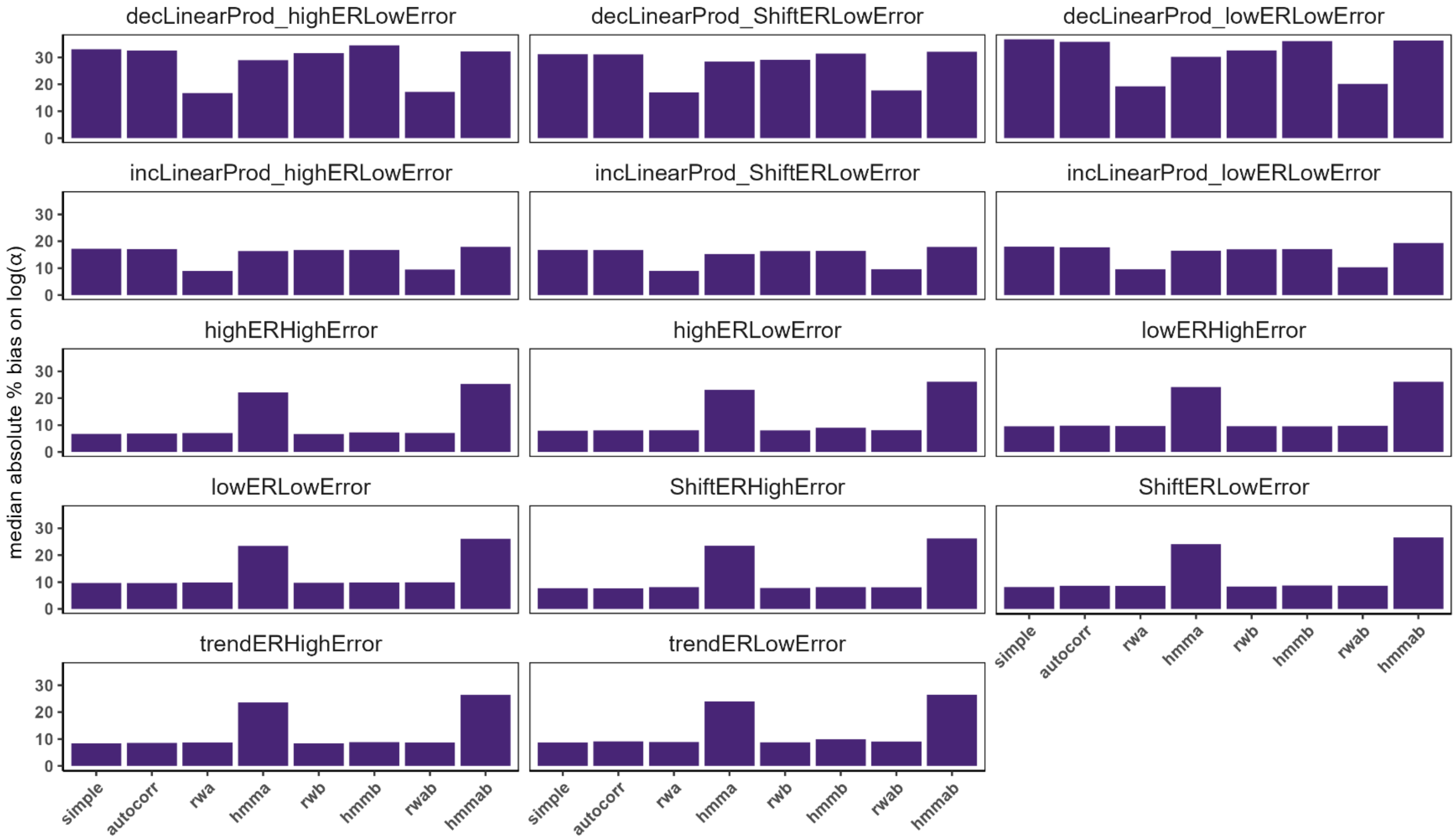

Figure C8. Median absolute bias in estimates of intrinsic productivity (log[α]) across 8 estimation models (x-axis) and alternative scenarios (panels) with high (60%) and low (20%) exploitation rates and a shift in exploitation rates from high to low (60%-20%), labeled 'highER', 'lowER', and 'shiftER'. The 'LowError' and 'HighError" scenarios are those with low and high interannual variability in exploitation rates (CV=0.225 and 0.445, respectively) . See the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.

Figure C9. Median absolute bias in estimates of intrinsic capacity (S_{MAX}) across 8 estimation models (x-axis), alternative scenarios (panels) described in the caption for Figure C8. See the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.

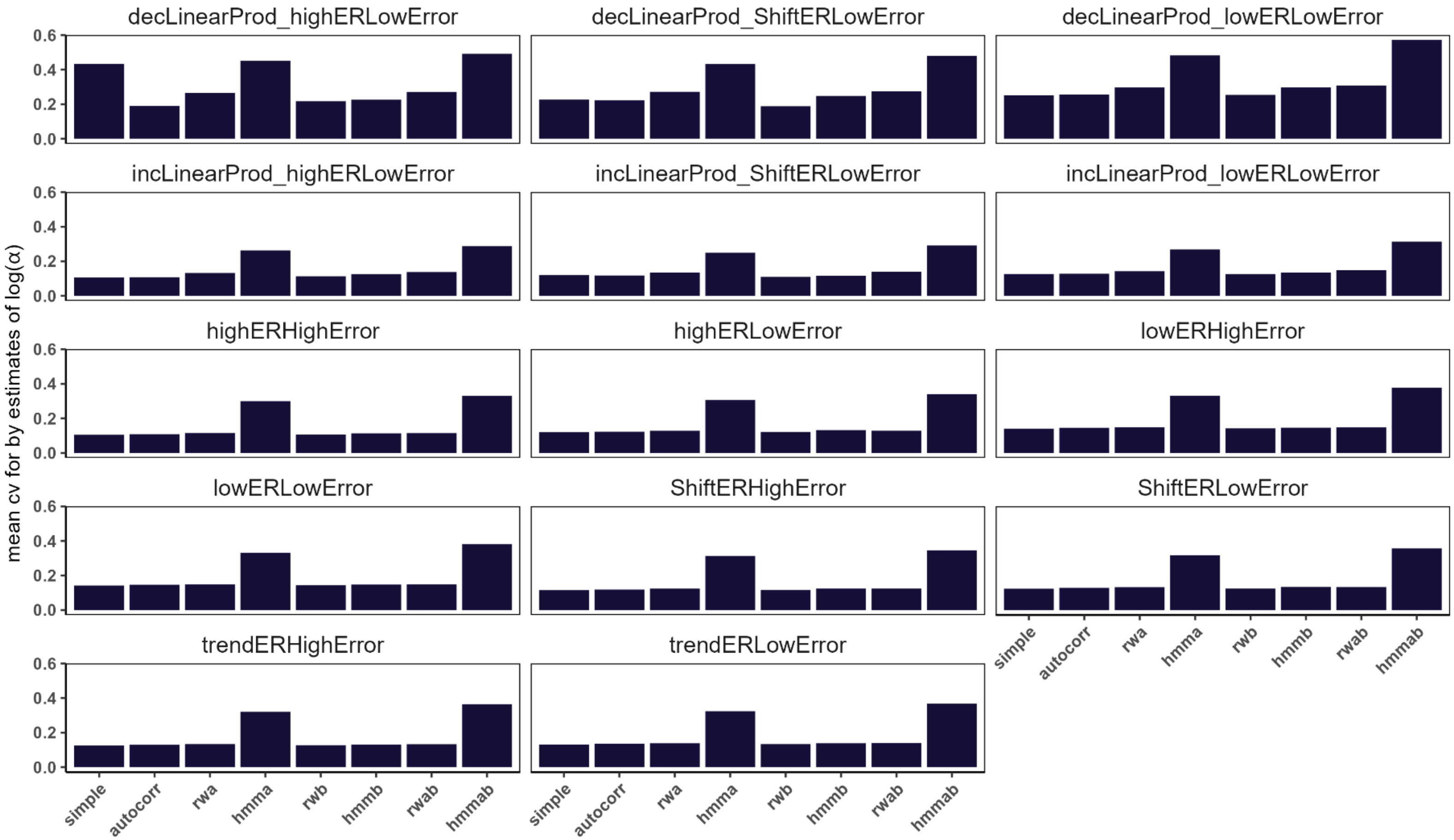

Figure C10. Precision (mean coefficient of variation [CV]) of estimates of intrinsic productivity (log[α]) across 8 estimation models (x-axis), alternative scenarios (panels) described in the caption for Figure C8. See the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation.

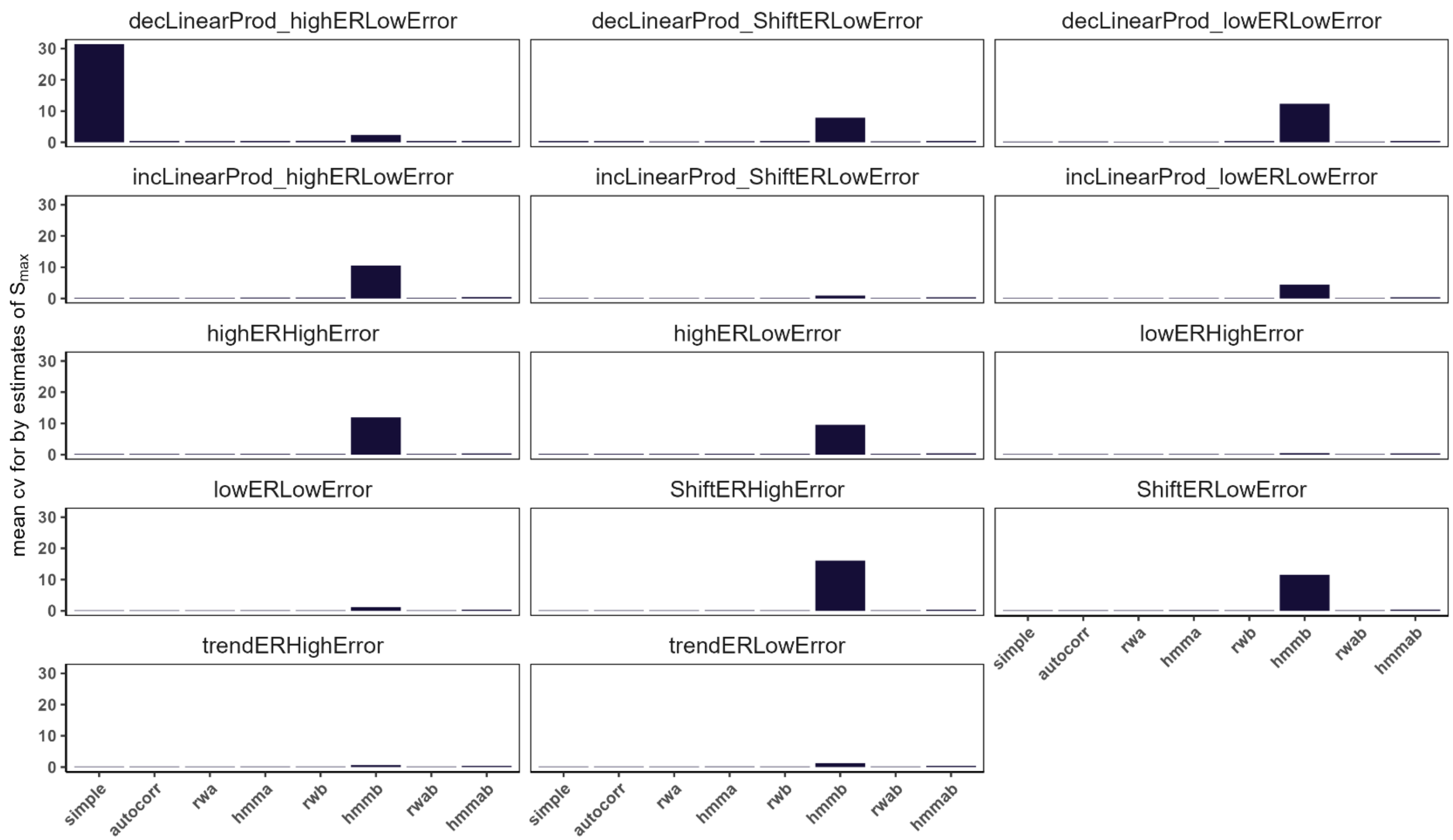

Figure C11. Precision (mean coefficient of variation [CV]) of estimates of intrinsic capacity (S_{MAX}) across 8 estimation models (x-axis), alternative scenarios (panels) described in the caption for Figure C8. See the caption for Figure C2 for a description of estimation models, and Wor et al. (in prep) for more details on the simulation evaluation. Note, the difference in y-axis scale for Figure C11 compared Figure C2.

APPENDIX D

Time series of benchmark estimates from the simulation to evaluate misclassificatoin rates, for the category of advice on assessments and benchmarks

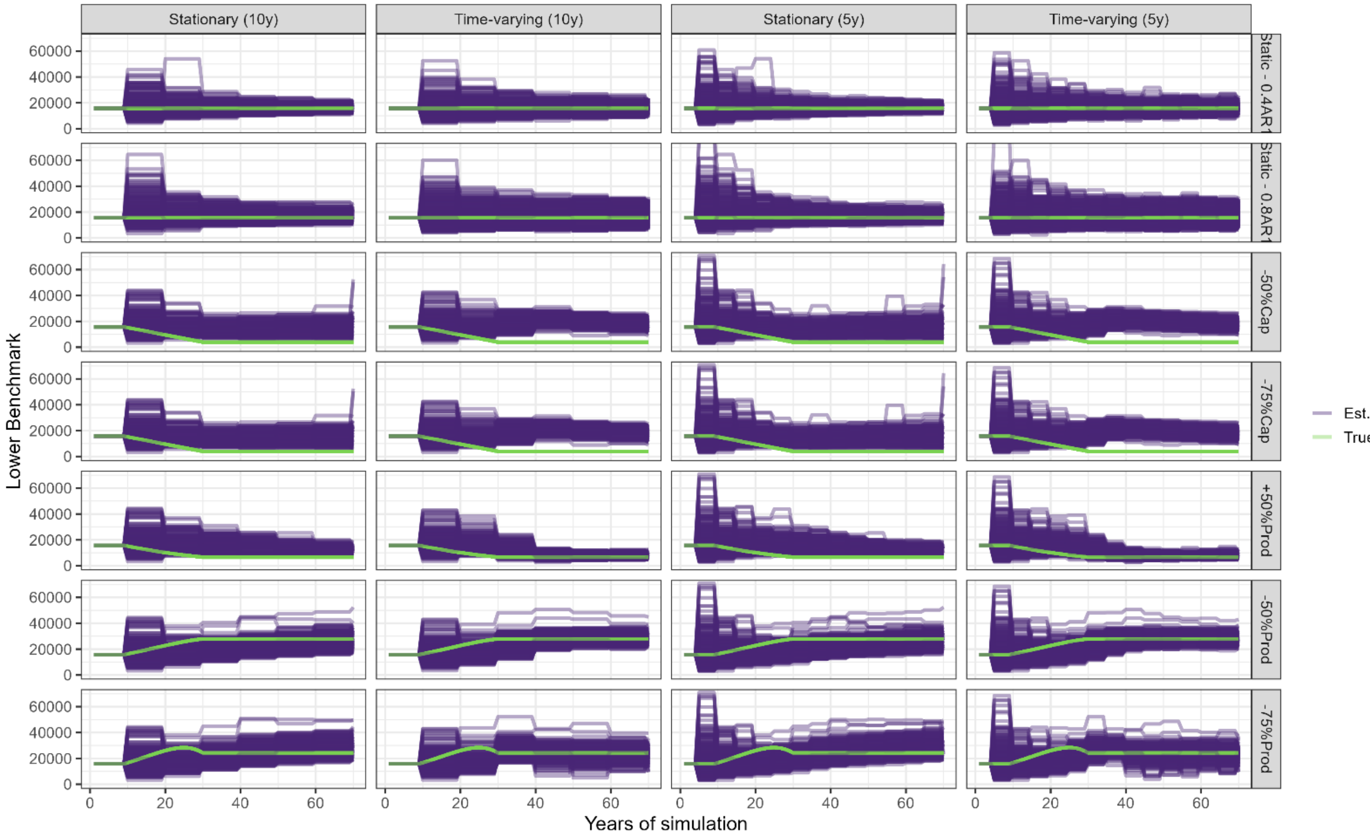

Figure D1. Illustration of how estimates of S_{GEN} ('Lower Benchmark') from stationary and time-varying estimation models (columns labelled 'Stationary' and 'Time-varying', respectively) change annually as productivity and capacity decline, and how the magnitude of decline influences them (purple lines, representing different MC trials) and 'true' annual estimates (green lines). In this simulation, both stationary and time-varying models are estimated every 5 or 10 years (last two columns, and first two columns, respectively) using only preceding data and are used to calculate benchmarks. Status is derived annually based on the most recent benchmark values. Rows represent scenarios. '-75%Cap' and '-50%Cap' represent linear declines in capacity to 25% and 50% of initial values over years 10 to 30. '-75%Prod', '-50%Prod', and '+50%Prod' represent linear declines or increases in log(recruits/spawner) over the same time period. 'Static - 0.8AR1' and ' Static – 0.4AR1' represent scenarios with stationary parameters and high and low levels of autocorrelation in annual recruitment deviations, respectively.

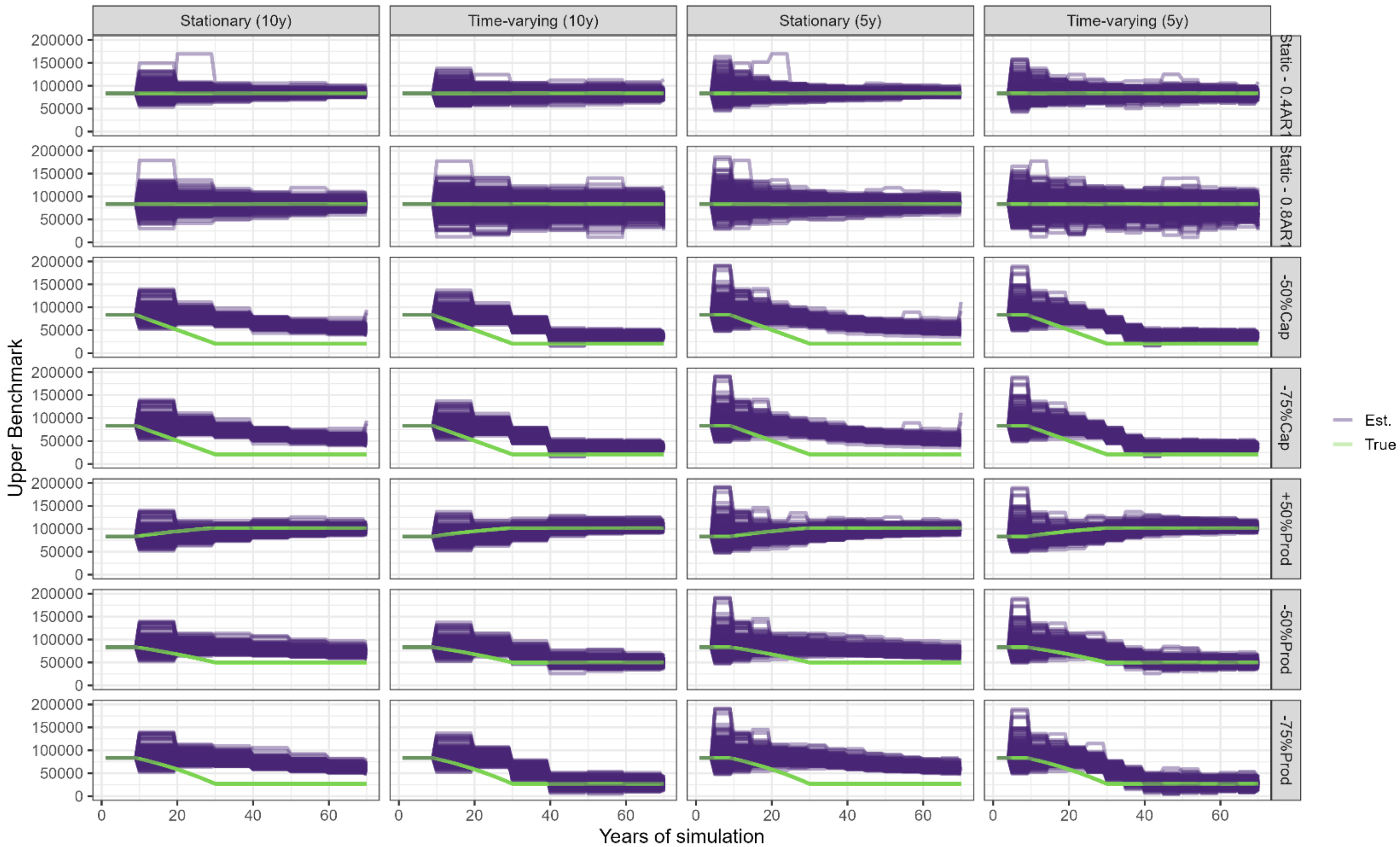

Figure D2. Illustration of how estimates of S_{MSY} ('Upper Benchmark') from stationary and time-varying estimation models (columns labelled 'Stationary' and 'Time-varying', respectively) change annually as productivity and capacity decline, and how the magnitude of decline influences them (purple lines, representing different MC trials) and 'true' annual estimates (green lines). In this simulation, both stationary and time-varying models are estimated every 5 or 10 years (last two columns, and first two columns, respectively) using only preceding data and are used to calculate benchmarks. Status is derived annually based on the most recent benchmark values. Rows represent scenarios. '-75%Cap' and '-50%Cap' represent linear declines in capacity to 25% and 50% of initial values over years 10 to 30. '-75%Prod', '-50%Prod', and '+50%Prod' represent linear declines or increases in log(recruits/spawner) over the same time period. 'Static - 0.8AR1' and ' Static – 0.4AR1' represent scenarios with stationary parameters and high and low levels of autocorrelation in annual recruitment deviations, respectively.

APPENDIX E

Results of simulation to evaluate impacts of HCRs with stationary or time-varying reference points

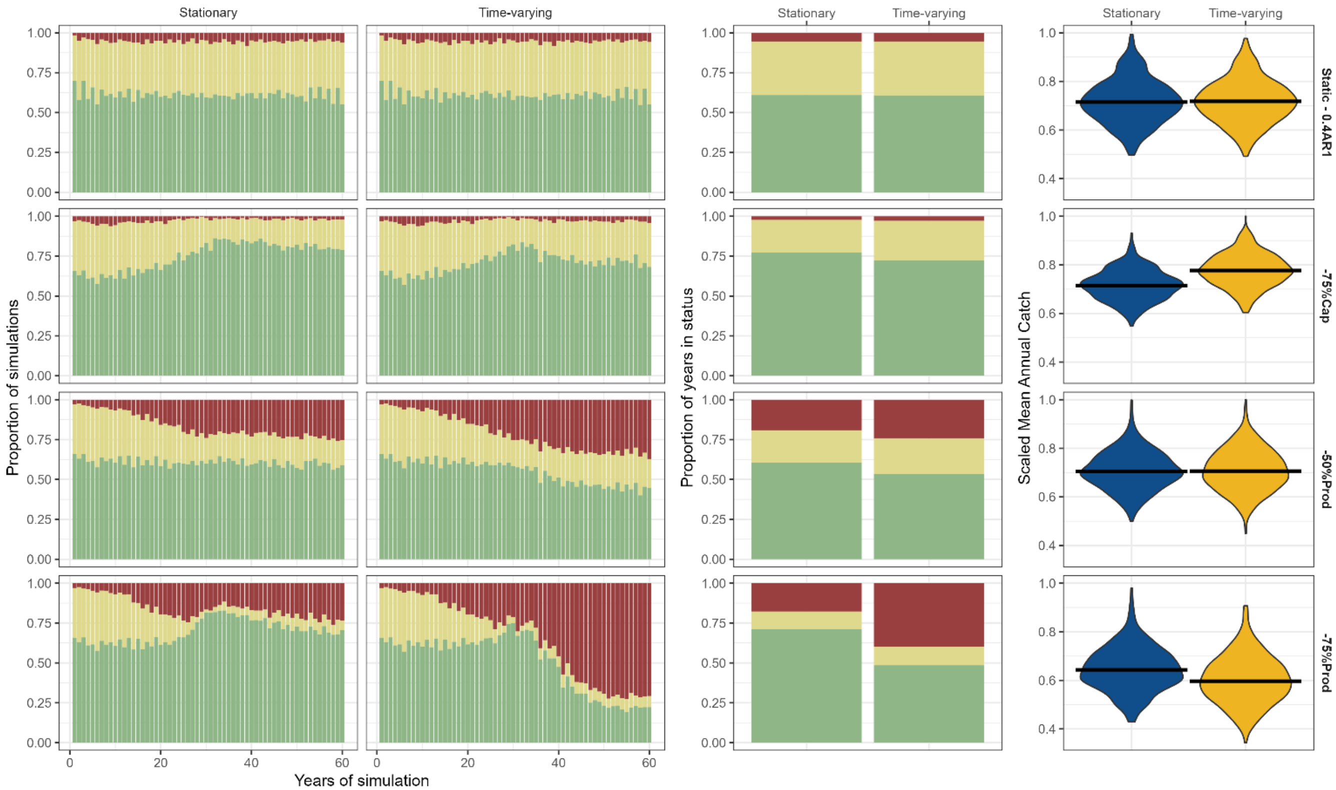

*Figure E1. Biological and fishery performance of harvest control rules with and without time-varying abundance-based reference points, where the harvest control rules includes a time-varying or stationary escapement goal at 80% of S_{MSY}, a fixed **target exploitation near U_{MSY} above the escapement goal at 75%, and fixed exploitation at 30% of the target below the escapement goal**. Left panels show the proportion of simulations where the population falls into true green, amber, or red status zones over time for harvest control rules with abundance based reference points that do ('time-varying') or do not ('stationary') vary over time based on either time-varying or stationary estimation models (columns) that are updated every 5 years under scenarios (rows) with either true declines in capacity, productivity, or transient "apparent" changes in productivity due to autocorrelation in recruitment ('static'). The middle panel summarizes the proportion of simulation years the population falls into each status zone and the right panel summarizes mean annual catch scaled to the maximum for that scenario over the 60 years of simulations.*

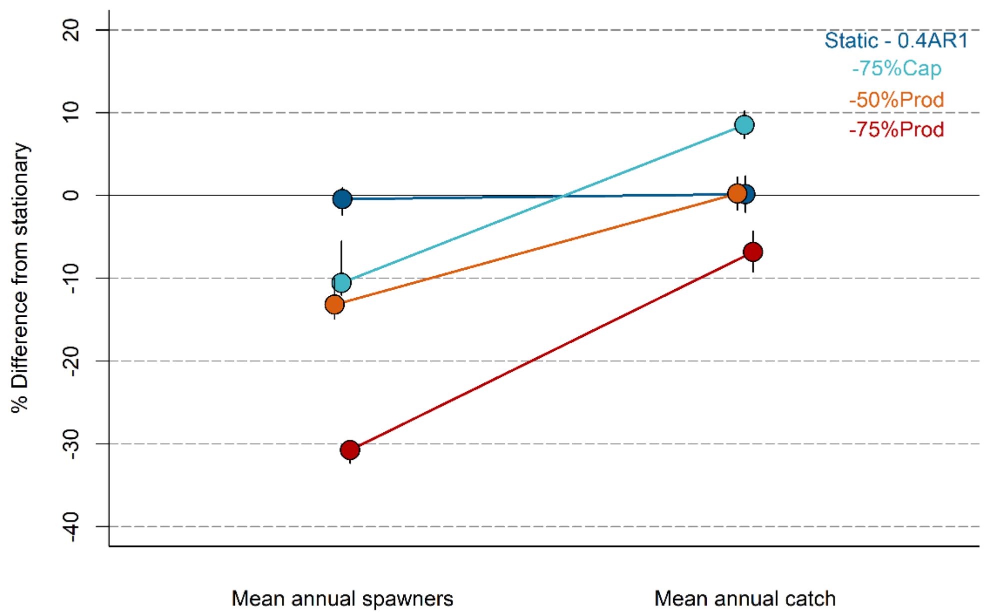

Figure E2. Biological and fishery performance of harvest control rules, HCRs, with time-varying abundance based reference points relative to a stationary harvest control rule, where the harvest control rules includes a time-varying or stationary escapement goal at 80% of S_{MSY}, a fixed ***target exploitation near U_{MSY} above the escapement goal at 75%, and fixed exploitation at 30% of the target below the escapement goal****. Each point is the percent difference in either mean annual spawner abundances or mean annual catch for a harvest control rule with time-varying abundance based reference point, under a given scenario (shading), relative to a harvest control rule based on a stationary abundance based reference point. Points below (above) the horizontal line at zero indicate worse (better) biological or fishery performance of the time-varying HCR. Error bars represent 95% confidence intervals.*

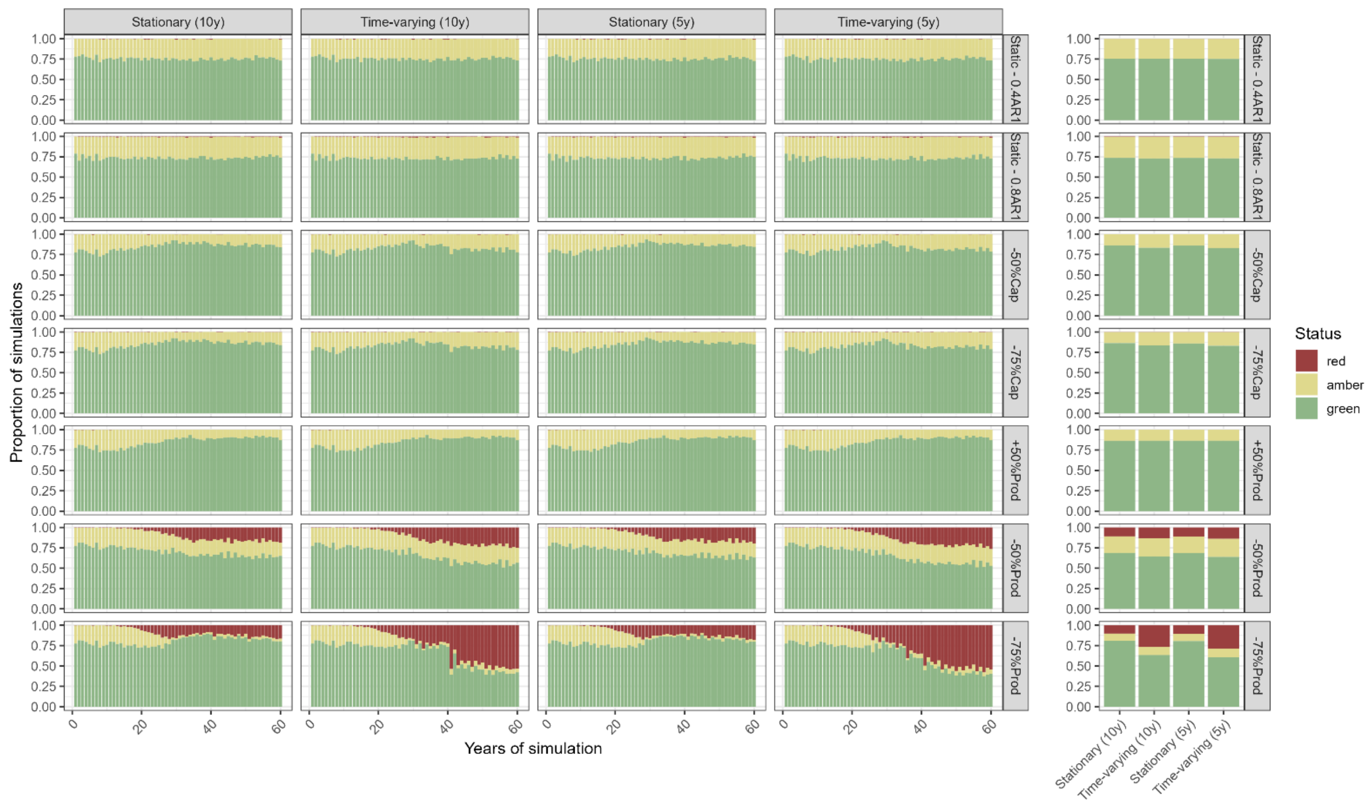

Figure E3. Biological performance of harvest control rules with time-varying abundance based reference points relative to stationary reference points, for base case harvest control rule with a time-varying or stationary escapement goal at 80% of S_{MSY}, a fixed target exploitation near U_{MSY} above the escapement goal at 65%, and fixed exploitation at 10% of the target below the escapement goal.Left panels show proportion of simulations where stock falls into true green, amber, or red status zones over time for harvest control rules with abundance based reference points that do not (stationary, first and third columns) and do (time-varying, second and fourth columns) under scenarios (rows) with either true declines or increases in capacity, productivity, or transient "apparent" changes in productivity due to autocorrelation in recruitment ('stationary'). Right panel summarizes the proportion of simulation years the stock falls into each status zone.

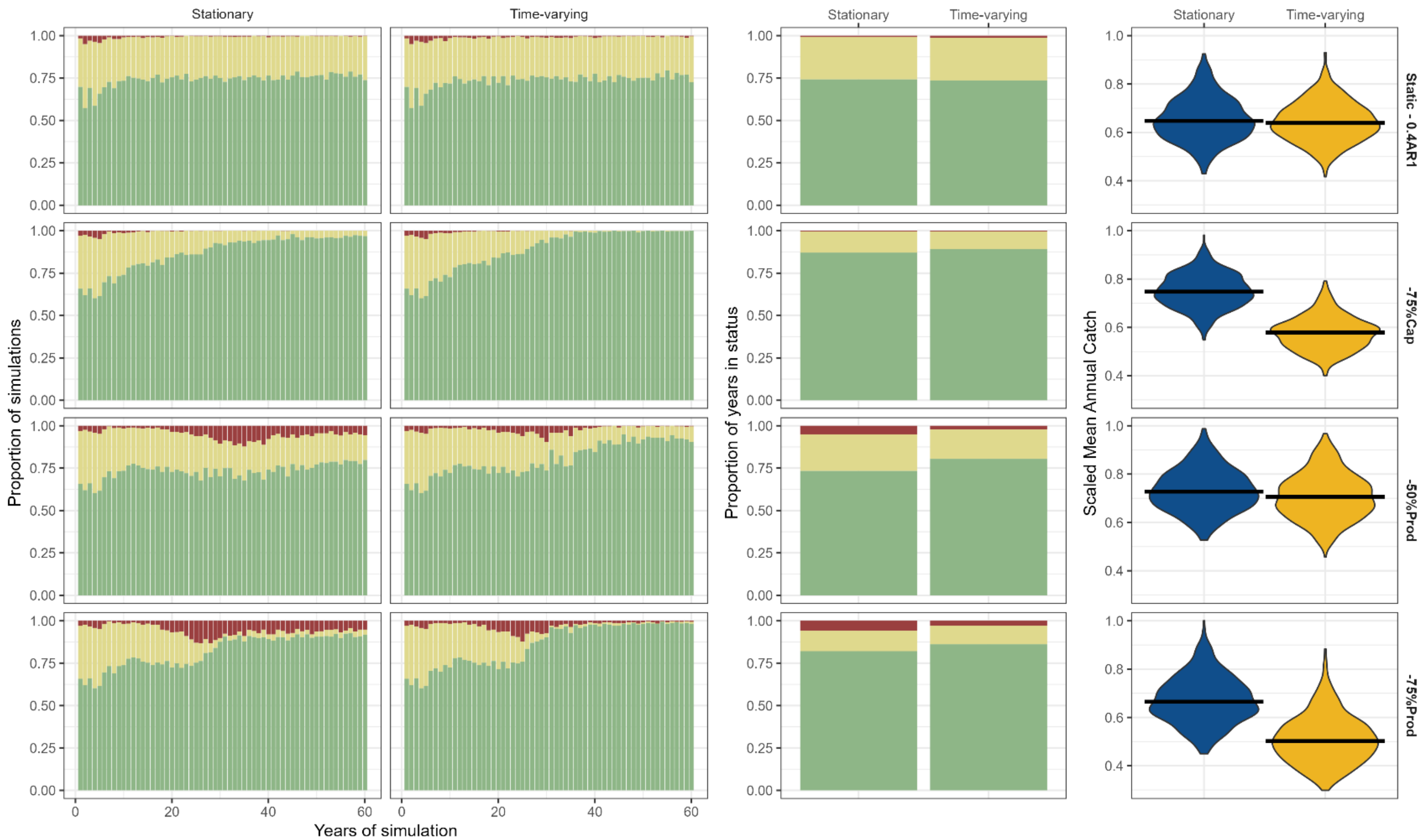

Figure E4. Biological and fishery performance of harvest control rules with and without time-varying F-based reference points, where the harvest control rule includes a fixed escapement goal, a time-varying or stationary target exploitation near UMSY (x0.9) above the goal, and time-varying or stationary exploitation rate of 30% of target below the escapement goal.Left panels show the proportion of simulations where the populations falls into true green, amber, or red status zones over time for harvest control rules with F-based reference point that do ('time-varying') or do not ('stationary') vary over time based on either time-varying or stationary estimation models (columns) that are updated every 5 years under scenarios (rows) with either true declines in capacity, productivity, or transient "apparent" changes in productivity due to autocorrelation in recruitment ('Static'). Middle panel summarizes the proportion of simulation years the population falls into each status zone and right panel summarizes mean annual catch scaled to the maximum for that scenario, both based on all 60 years of the simulation.

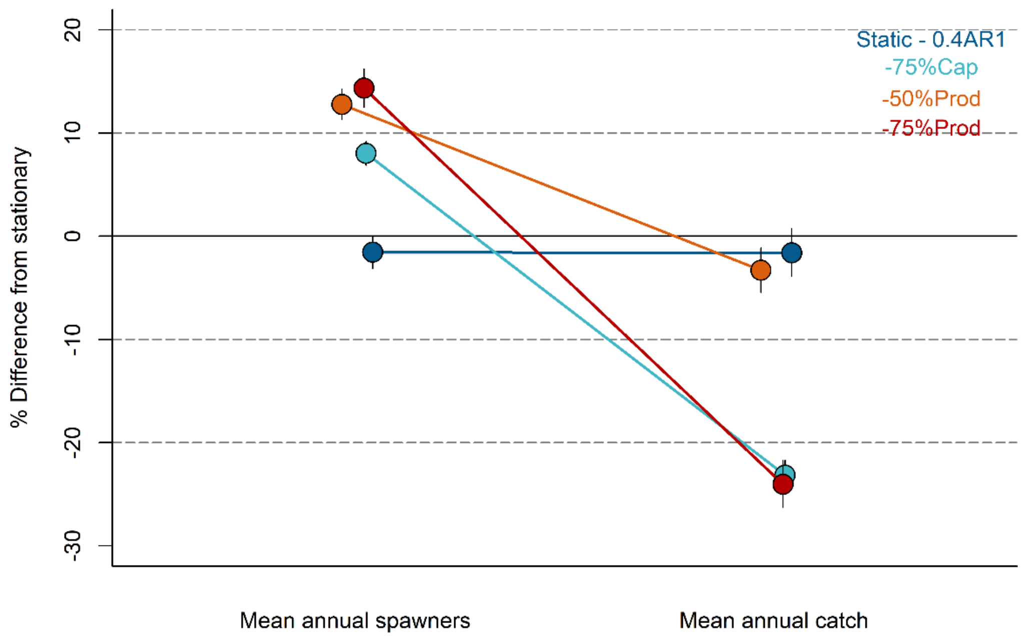

Figure E5. Biological and fishery performance of harvest control rules with time-varying F-based reference points relative to stationary harvest control rules, , where the harvest control rule includes a fixed escapement goal, a time-varying or stationary target exploitation near U_{MSY} (x0.9) above the goal, and time-varying or stationary ***exploitation rate of 30% of target below the escapement goal****. Each point is the percent difference in either mean annual spawner abundance or mean annual catch for a harvest control rule with time-varying F-based reference point, under a given scenario (shading), relative to a harvest control rule based on a stationary abundance based reference point. Points below (above) the horizontal line at zero indicate worse (better) biological or fishery performance of the harvest control rule with time-varying reference points. Error bars represent 95% confidence intervals.*

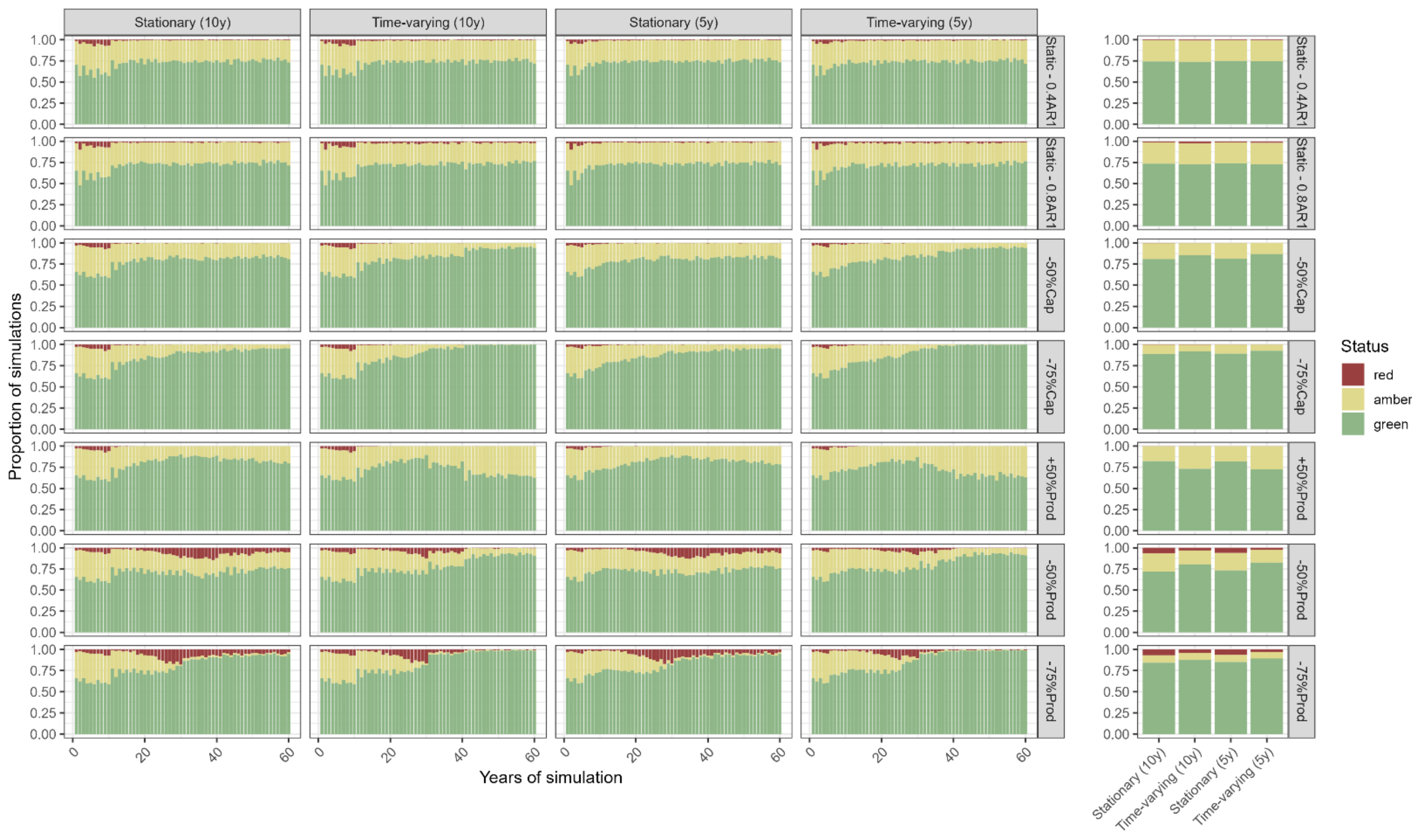

Figure E6. Biological performance of harvest control rules with time-varying F-based reference points relative to stationary reference points, for the base case harvest control rule that includes a fixed escapement goal, a time-varying or stationary target exploitation near UMSY (x0.9) above the goal, and a time-varying or stationary exploitation rate of 10% of target below the escapement goal. Left panels show the proportion of simulations where stock falls into true green, amber, or red status zones over time for harvest control rules with abundance based reference point that do not (stationary, first and second columns) or do (time-varying, third and fourth columns) vary over time based on either time-varying or stationary estimation models (columns) that are updated every 10 years (first and second columns) or 5 years (third and fourth columns) under scenarios (rows) with either true declines or increases in capacity, productivity, or transient "apparent" changes in productivity due to autocorrelation in recruitment ('stationary').Right panel summarizes the proportion of simulation years the stock falls into each status zone.