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Climate impacts on fished populations. Part 2: Effects of climate and environmental variability on fishery stock assessment accuracy

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EXECUTIVE SUMMARY

Neubauer, P.[1]**; A'mar, T.**[1]**; Dunn, M.**[2]**(2023). Climate impacts on fished populations. Part 2: Effects of climate and environmental variability on fishery stock assessment accuracy.**

***New Zealand Fisheries Assessment Report 2023/57*. 40 p.**

Fish stocks are influenced through direct physiological effects from changes in their marine habitat, such as temperature, dissolved oxygen, and acidity. At the same time, indirect bottom-up and top-down effects of these changing environmental factors, including impacts on food resources and predation, may also determine productivity changes. In combination, these direct and indirect influences may result in productivity changes in local fish stocks, particularly if the latter are unable to shift spatially to avoid environmental changes. In turn, these changes in productivity interact with fisheries, which also affect stock productivity through plastic, density-dependent effects, including increased growth of fish at reduced densities.

This study used a model of individual eco-physiological response to environmental and climate factors to derive population level outcomes of fish stocks. It was also used to investigate how fisheries stock assessments are influenced by climate and bottom-up variability in production parameters.

The outcome from this investigation showed that, on average, the assessments provided unbiased estimates of stock status even though there were annual and decadal fluctuations in all production-related parameters. Nevertheless, a considerable spread in assessed stock status was not readily explained by production changes or the mis-specification of production parameters. We hypothesise that this unexplained variation in assessment error is predominantly related to information content of stock-specific data as opposed to environmentally-determined parameter variability *per se*.

Beyond this basic variability, there were persistent and predictable biases introduced by directional (e.g., climate change related) changes in temperature and bottom-up constraints. Nevertheless, the assessment error in the presence of interannual and decadal variability only (i.e., without directional trends) in production was considerably greater than variability induced by climate scenarios considered here. On the basis of these scenarios, it is suggested that assessments focus on structural and model uncertainties such as the exploration and evaluation of time-varying parameters to obtain more realistic estimates of model uncertainty, and more relevant management quantities. These improvements in assessment methodologies and practice could inform and facilitate more responsive management in variable environments, and mitigate risks from over-confidence in model estimates, yet provide opportunity by closely tracking environmental variability.

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1. INTRODUCTION

Since Hjort's 1914 seminal work on recruitment in fish populations, climate variability and change have traditionally been regarded as strong influences on fish populations (Aksnes & Browman 2014). Despite this enduring focus on environmental influences on fish stocks, it has been difficult to establish the precise relationships by which the environment influences fisheries production (Gilbert 1997, Myers 1998, Payne et al. 2017, Stock et al. 2017).

In the context of climate change, changes in production have been observed in a number of stocks (Britten et al. 2016, Free et al. 2019). Although many of these analyses remain open to alternative explanations (Szuwalski 2016, Szuwalski 2019), changes and regime-like patterns in productivity (i.e., switching between low- and high-production regimes) are frequently standard rather than the exception for fish stocks (Vert-Pre et al. 2013, Szuwalski et al. 2015, Szuwalski & Hollowed 2016).

Although there is a general understanding that fish stock dynamics are largely determined by the environment, fisheries stock assessments tend to assume stationary production parameters, with only recruitment varying temporally around a stationary mean process. This assumption implicitly implies that production changes are solely determined by fishing-induced density-dependent release (compensation) or recruitment overfishing. Although the latter aspect can be considered prudent for maintaining precautionary catch limits (i.e., reducing catch at low abundance, consistent with the assumption that fishing caused the decline; Hilborn 1997), environmental changes in production have the potential to obscure true stock status by violating assessment model assumptions of stationarity and, thereby, lead to unreliable stock assessments (Szuwalski & Hollowed 2016).

Biases in stock assessments often manifest as retrospective patterns caused by changes in production parameters (Hurtado-Ferro et al. 2015). Nevertheless, the direction and magnitude of retrospective patterns appear largely unrelated to the direction and magnitude of bias (Hurtado-Ferro et al. 2015). In addition, retrospective biases can often be addressed by letting parameters vary over time within stock assessments; however, identifying which parameters truly change over time may be difficult (Szuwalski & Hollowed 2016). In addition, letting the wrong production parameters vary (e.g., growth when mortality is the true varying parameter) may introduce additional bias in assessed stock status.

In the context of variable ecosystems and climate change, it is likely that not only one parameter but all production parameters (recruitment, mortality, and growth) vary over time (Andersen et al. 2009, Thorson et al. 2015b, Szuwalski & Hollowed 2016, Neubauer et al. 2023). In addition, fishing alone will lead to stronger links between stock and environmental factors caused by the differential survival of smaller, fast-growing, and early-maturing fish (Planque et al. 2010, Shelton & Mangel 2011, Audzijonyte et al. 2016). For this reason, environmental factors are likely to interact with stock status and exploitation history to determine the magnitude of change in production parameters.

In view of the difficulties of distinguishing fishing and environmental influences on production, and the likelihood that most parameters are likely time-(and co-)varying on some scale, it is unclear whether current assessment approaches can reliably determine the status of stocks undergoing regime-like or directional changes in production parameters. Within this context, the current study tried to address this uncertainty by using the outputs from a coupled eco-physiological model to evaluate the magnitude of bias introduced in stock assessments by the (co-)variation of production parameters (see companion study, Neubauer et al. 2023). The eco-physiological model simulated changes in production parameters under temperature and bottom-up forcing. It was used here for stock assessments that were performed as "standard" assessments, in that they were largely naive to underlying environmentally-determined changes in production.

In addition, the current study explored the value of commonly-collected data (i.e., annual length-at-age data) to improve stock status estimates. The approach used here differed from several recent investigations of assessments and management in the context of time-varying production parameters, which use assessment models themselves as operating models (Deroba & Schueller 2013, Hurtado-Ferro et al. 2015, Johnson et al. 2015, Thorson et al. 2015b, Szuwalski et al. 2018, Stawitz et al. 2019). In contrast to these previous studies, the operational model, an eco-physiological model simulating linked stochastic changes in demographic parameters driven by temperature and changes in per-capita food supply, differed fundamentally from the age-structured catch-at-age model used to assess the simulated populations.

2. METHODS

To test the effects of environmental variability and climate on assessment accuracy and bias, the present study used the trait-based eco-physiological simulations from Neubauer et al. (2023) as a basis to construct fishery-like data. The overall approach can be described as follows:

1. consistent fisheries were simulated over a period of 50 years on populations with scenarios including annual to decadal fluctuations and long-term trends in productivity for two trait scenarios; these simulations used constant catch simulations from Neubauer et al. (2023), because they led to a wide range of outcomes (Figure 1);
2. identically-parameterised stock assessments were then applied in three configurations for each replicate simulation; and,
3. a series of regression models was applied to the present baseline assessment outcomes to assess the how much production characteristics in our simulations, and mis-specification or poor estimation in the assessments, led to biased assessments. This process also assessed if there were obvious indicators of assessment bias in assessment diagnostics.

The eco-physiological framework simulated individual bioenergetics based on a previous study by Neubauer & Andersen (2019), with temperature and environmental influences on a quarterly time step (see detailed description of the framework by Neubauer et al. 2023). Importantly, the framework led to simulations with fluctuating stock productivity determined by concurrent changes in all production-related parameters. These parameters included natural mortality (M), growth rate (K) and asymptotic size (L_∞), and recruitment, determined by temperature and bottom-up changes in ecosystem production (also referred to as habitat suitability). Generally, the simulated populations had slight declines in production for all climate scenarios.

2.1 Environmental scenarios

Environmental scenarios were designed to reflect environmental variability at different scales. To reflect small-scale variability in environmental condition at the population level and within a time step, variability within the population was assumed in vital rates; it was expressed as 100 realisations of a random variable at each time step, for metabolic requirements (k), resource availability (Θ), and natural mortality (M). The latter two random draws were linked, assuming that higher resource availability means higher mortality (i.e., it is accompanied by higher predator presence). This approach had the practical effect that stark fitness advantages (i.e., high resource availability and low M) in parts of the population were avoided. The coefficient of variation (CV) for k was set to 0.1, and for Θ and M to 0.4, drawing parameter distributions from a log-normal distribution.

The second level of variability was simulated as interannual and decadal environmental and temperature variability at the level of simulation replicates. For each replicate, auto-correlated deviations were simulated from a mean for the magnitude and productivity of available resources (i.e., the intercept K_r and r_{max} of the resource size spectrum); maximum recruitment R_{max} was allowed to follow these same trends. Temperature was simulated seasonally, with seasonal variation applied to the mean, and autocorrelated deviations from seasonal means were applied to the resulting time series as a correlated deviation related to the environment by a correlation term.

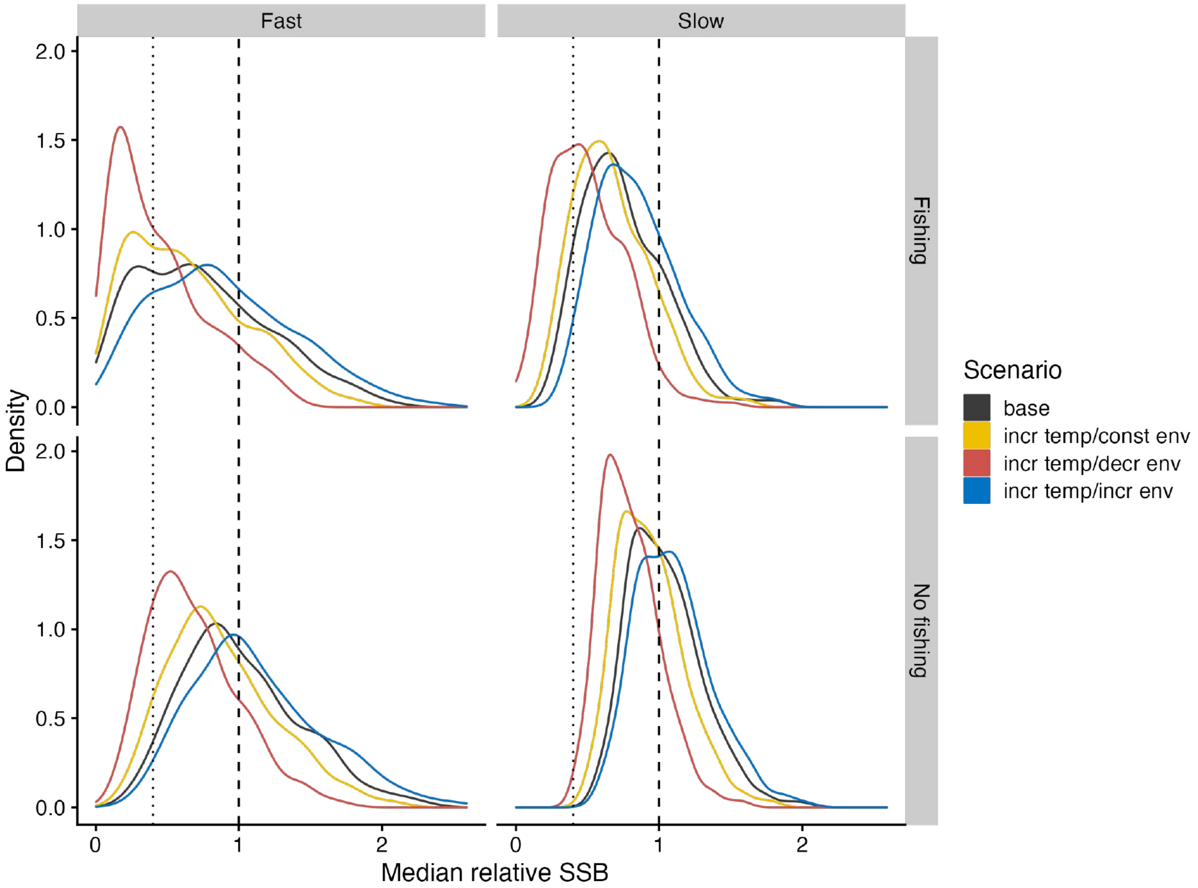


Figure 1: Simulation outcomes for stock status (relative spawning stock biomass, *SSB*) for the final simulation year for fish stocks with fast (left column) and slow (right column) life histories. Fishing mortality was assumed to be constant. Simulations were with and without fishing for four different climate scenarios: base, no temperature or environmental change; incr temp/const env, increasing temperature, no environmental change; incr temp/decr env, increasing temperature, declining environment; incr temp/incr env, increasing temperature, increasing environmental suitability. All simulation replicates started from the same random seed. Dotted line indicates $0.4 \cdot SSB_0$, and the dashed line indicates SSB_0, the unfished equilibrium spawning stock biomass at year 50 (i.e., before fishing commenced for fished scenarios).

A total of 384 replicates were run for a range of four climate scenarios —the last level of variation—each with or without fishing (Figure 2). Each replicate used the same random seed across climate and fishing scenarios, resulting in a set of eight simulation runs per replicate (random seed) across each of the two species traits (slow and fast life histories).

Climate scenarios were defined as the baseline (base) with no temperature or environmental change, a scenario with increasing temperature only (incr temp/const env), a scenario with increasing temperature and environmental decline (incr temp/decr env), and a scenario with increasing temperature and increasing environmental suitability (incr temp/incr env) (see parameter values for environmental trends in Neubauer et al. 2023). Environmental or habitat suitability here was considered synonymous for bottom-up-determined declines or increases in food availability (e.g., changes in zooplankton composition or availability). Changes in top-down controls were not explored.

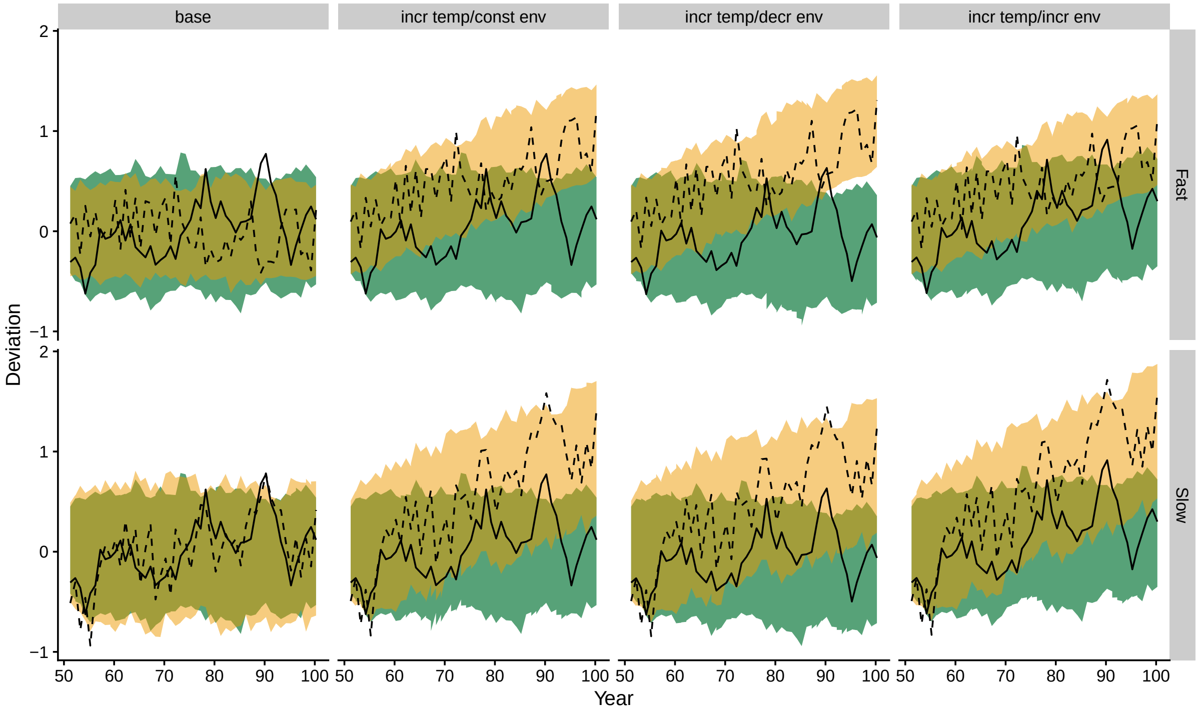


Figure 2: Simulations of different climate scenarios for fish stocks with fast (top panels) and slow (bottom panels) life-history traits. Relative environmental suitability (green) and temperature (yellow) across all simulations and for a single replicate (dashed line, temperature; solid line, environmental suitability). Climate scenarios were: base, no temperature or environmental change; incr temp/const env, increasing temperature, no environmental change; incr temp/decr env, increasing temperature, declining environment; incr temp/incr env, increasing temperature, increasing environmental suitability.

2.2 Trait scenarios

To ensure a level of generality beyond existing species-specific eco-physiological models, the consequences of climate, ecosystem, and fishing effects were explored in a trait-based context (Barnett et al. 2019). Specifically, species were distinguished along a gradient of life history; at one end, production was maximised (energy acquisition, referred to as "fast strategy") at the cost of increased metabolism and mortality; at the opposing end, mortality and metabolic costs were minimised at the expense of production ("slow strategy"). This axis led to an approximately constant ratio of production to mortality, and corresponded to a line of equal size in the life-history space proposed by Charnov et al. (2013). Specifically, this axis distinguished species of similar size with defensive and slow versus active life histories (the most relevant simulation results for the constant catch scenarios are shown in Appendix A, Figures A-1 to A-13).

2.3 Simulating fisheries data

Fishery data were simulated as catch with corresponding catch length frequencies, and survey indices with corresponding age frequency information. Total catch was constant for all years (and seasons) for a given population replicate, with catch for each replicate drawn from a normal distribution (truncated at 0) around a mean catch with a CV of 20%.

To generate data for stock assessments, a lognormal error was applied, with bias correction, to simulated catches C_y for year y:

$$\widehat{C}_y = C_y \exp[\varepsilon_y^{fishery} - \frac{\sigma_{fishery}^2}{2}], \quad (1)$$

where

$$\varepsilon_y^{fishery} \sim N(0, \sigma_{fishery}^2). \quad (2)$$

Survey index observations were generated from the same observation model, with errors of 2% applied to catch and 10% applied to the index. Survey age composition and fishery length composition data were simulated by multinomial sampling from the true age/length composition, drawing 100 samples per year for fishery age composition data, 1000 samples per year for survey age composition data, 1000 samples for survey length-at-age data, and 10 000 samples for fishery and survey length composition data. Although the errors may appear small (especially for surveys) compared with the realised errors in actual surveys (and potential temporal biases in indices), the focus here was on assessment performance. For this reason, it was important to maintain sufficient signal in the simulated data.

2.4 Assessment set-up and processing

The stock assessment software package CASAL (Bull et al. 2005) version 2.30 was used as the estimation model. CASAL has a set of transition processes that occur in a default order:

1. ageing;
2. recruitment;
3. maturation (if maturity is a characteristic of the partition);
4. migration (in a multi-area model);
5. growth (in a size-based model); and
6. mortality (natural and fishing).

The CASAL model was set up as an age-based, single-area, four-season model with no sex or maturity partition. Fishing occurred in season 1 with a maximum harvest rate of 0.95. The survey occurred in season 2. Maturity was assumed to be knife-edged, starting at a stock-specific minimum reproductive age. Ageing, recruitment, maturation, and spawning occurred in season 1. The Beverton-Holt stock-recruitment relationship had steepness (h) fixed at 0.8 and σ_R fixed at 0.5. The age-length growth relationship was the von Bertalanffy function with CV set to 0.05 or species-specific values. The parameters for the length-weight relationship ($W = \alpha L^{\beta}$) were fixed at the values used in the simulations.

Observation data included:

- fishery annual catch;
- fishery annual length frequency;
- biennial survey biomass index, starting 20 years after the start of the fishery;
- biennial survey age frequency (note that one of the modelling scenarios used a single age frequency and length-at-age observation); and
- biennial length-at-age from survey age observations.

Estimated parameters included:

- SSB_0;
- recruitment year-class strength (YCS);
- parameters for ascending logistic fishery selectivity-at-length;
- parameters for ascending logistic survey selectivity-at-length;
- survey catchability (q); and
- natural mortality (M), estimated with informed priors from samples (initial trials with fixed M led to similar results, but more persistent biases, corresponding with results from simulation modelling by Johnson et al. (2015), which found that estimating M when M is time-varying is the most robust approach).

Priors for SSB_0 and catchability were uniform-log, with uniform priors on selectivity parameters. Only natural mortality had an informed prior applied based on the Chapman-Robson estimator for total mortality, calculated from mean survey age $\bar{a}$ over n samples as $\hat{Z} = \log(\frac{1+\bar{a}+1/n}{a})$. Mortality was set at $\hat{M} = \hat{Z}/2$, assuming $F = M$ *a priori*. The CV was set at twice the estimated CV of the estimator.

Assessments were run in three modes:

1. Baseline assessments assumed a single ageing study and survey age composition observation, with most of the data weight on index observations. This configuration, with a single ageing study, contained information about growth at one point in time, but otherwise assumed stationary mean productivity.
2. The same model as above was run with biennial survey length-at-age data and age composition observations which provided information about changes in growth.
3. A third model configuration used annual survey age composition and length-at-age observations, with increased weight on the survey observations, up-weighting changes in composition over the survey index.

These scenarios gave progressively more weight to potential indicators of changing productivity that are currently available to a range of stock assessments. Models with time-varying growth information were expected to produce estimates of management quantities closer to simulated ones compared with the simple model with a single growth assumption.

2.5 Assessment error and bias

To understand the origins of assessment errors and bias, relative assessment error for stock status estimates (RE = $\frac{SSB_T^{assess} - SSB_T^{sim}}{SSB_T^{sim}}$) was explored at three levels:

1. RE was related to production parameter trends and characteristics (e.g., standard deviation) in the simulations, addressing the question “what levels of change lead to bias?”.
2. Testing of certain mis-specifications or estimation errors for their influence on the RE in assessments, exploring which mis-specifications are most important in determining assessment bias.
3. Assessing whether assessment biases would be readily detected as characteristic trends in residuals or recruitment year-class strength values in assessments.

Based on the assessment set-up with hierarchical levels of environmental variability, the current approach investigated assessment error in stock status in relation to levels of environmental variation: within climate scenarios, it was possible to assess the importance of short-term fluctuations in production (annual to decadal) on assessment accuracy. After accounting for variability among replicates in assessment outcomes, it was also possible to compare assessment outcomes among climate scenarios within replicate simulation runs. For this reason, two regression models were run for each of the three analyses listed above (see Table 1 for regression model parameters). The first model was run within the base climate scenario without long-term climate trends, using only replicates within this scenario to investigate the importance of short-term variability. The analysis was then repeated with all scenarios, using a random effect for replicates within scenarios, which ensures that parameter estimates measure between-scenario differences.

Because assessment performance is often linked to differences in relative abundance time series and, therefore, to stocks being fished down and rebuilding, this term was included in the regression models as an “offset”; it also included interaction terms with production parameters.

Table 1: Variables included in the regression models. For formulas, SD is the standard deviation, *SSB* is the spawning stock biomass, *YCS* is year-class strength, LM is a linear regression model with slope β, t is time in year up to terminal year T, *est* specifies assessment model estimates, *spec* refers to values fitted/specified outside of the assessment (fixed parameters), *obs* are true simulated values. LFs are length frequencies, with their residuals averaged by year.

Description	Name in the model	Formula
Simulation determinants of stock status error		
Maximum depletion	b_max_depl	$\min(SSB_1^{\text{obs}}...SSB_T^{\text{obs}})$
Variability (SD) in M	b_sim_sd_M	$\text{SD}(M_1^{\text{obs}}...M_T^{\text{obs}})$
Trend (slope) in M	b_sim_trend_M	$\text{LM}(M^{\text{obs}} \sim t)$
Trend (slope) in K	b_sim_trend_K	$\text{LM}(K^{\text{obs}} \sim t)$
Trend (slope) in L_∞	b_sim_trend_Linf	$\text{LM}(L_\infty^{\text{obs}} \sim t)$
Trend (slope) in year classes	b_sim_trend_YCS	$\text{LM}(YCS^{\text{obs}} \sim t)$
Mis-specifications as determinants of stock status error		
Maximum depletion	b_max_depl	$\min(SSB_1...SSB_T)$
Bias in M	b_end_bias_M	$1/5 \sum_{t=T-5}^{T} M^{\text{est}} - M_t^{\text{obs}}$
Bias in K	b_end_bias_K	$1/5 \sum_{t=T-5}^{T} K^{\text{spec}} - K_t^{\text{obs}}$
Bias in L_∞	b_end_bias_Linf	$1/5 \sum_{t=T-5}^{T} L_\infty^{\text{spec}} - L_{\infty,t}^{\text{obs}}$
Bias in year-class trends	b_trend_bias_YCS	$\beta_{YCS}^{\text{est}} - \beta_{YCS}^{\text{obs}}$
Indicators of stock status error		
Trend (slope) in year classes	b_YCS_trend	$\text{LM}(YCS^{\text{est}} \sim t)$
Variability (SD) in year classes	b_YCS_sd	$\text{SD}(YCS^{\text{est}})$
Autocorrelation (AC) in year classes	b_YCS_ac	$\text{AC}(YCS^{\text{est}})$
Trend (slope) in index residuals	b_index_resids_tr	$\text{LM}((I^{\text{obs}} - I^{\text{est}}) \sim t)$
Variability (SD) in index residuals	b_index_resids_sd	$\text{SD}(I^{\text{obs}} - I^{\text{est}})$
Trend (slope) in LF residuals	b_lf_resids_tr	$\text{LM}(\overline{(LF^{\text{obs}} - LF^{\text{est}})} \sim t)$
Variability (SD) in LF residuals	b_lf_resids_sd	$\text{SD}(\overline{LF^{\text{obs}} - LF^{\text{est}}})$

3. RESULTS

3.1 Assessment outcomes

The assessment results were, on average, nearly unbiased, even for models that were uninformed about changes in productivity throughout the course of the simulated population dynamics (Figure 3). Nevertheless, there were some differences between environmental scenarios: for both slow and fast life histories, assessments were more biased towards overestimating stock status for scenarios where temperature increased and the environmental suitability declined (red line in Figure 3). The latter decline was particularly evident for fast life-history species that were influenced by the environment: for these stocks, an increase in temperature alone led to more of the replicate assessments being positively biased. For both life histories, scenarios of increasing environmental suitability had the most conservative estimates (i.e., slight bias towards under-estimating stock status).

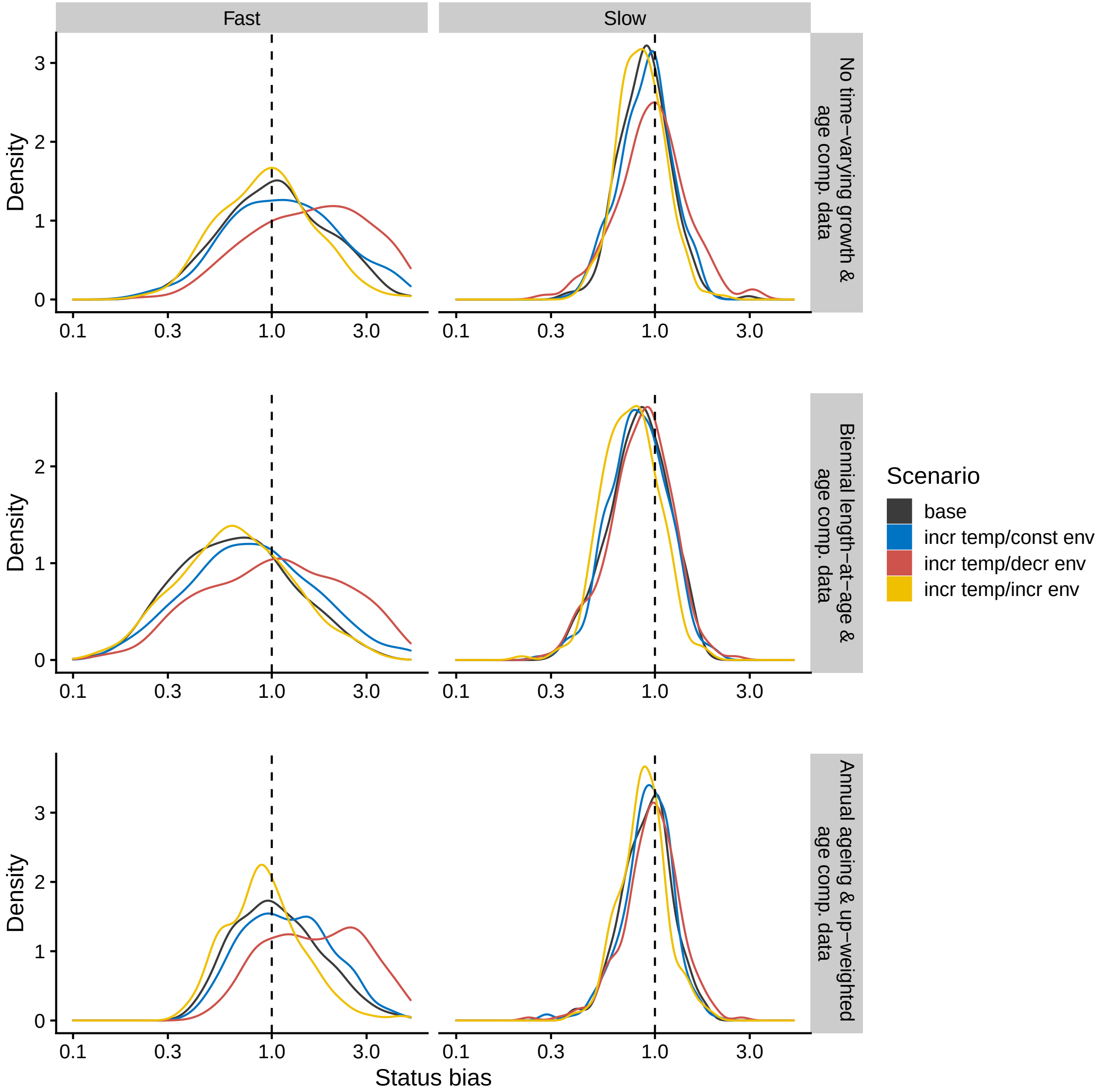


Figure 3: Relative stock status (assessed spawning stock biomass relative to simulated spawning stock) for the last simulation year for fish stocks with fast (left column) and slow (right column) life histories in three different assessment approaches. Assessments were with no time-varying growth and age composition data (top row), with biennial length-at-age and age composition data (middle row), and with annual ageing and up-weighted age composition data (bottom row). Simulations were for four different climate scenarios: base, no temperature or environmental change; incr temp/const env, increasing temperature, no environmental change; incr temp/decr env, increasing temperature, declining environment; incr temp/incr env, increasing temperature, increasing environmental suitability.

Adding regular age and growth information to the model led to a shift towards more conservative estimates, but the spread in the RE about its mode remained similar (Figures 3 and **??**). In particular, most assessments with declining environmental suitability were unbiased in this scenario (red line in

Figures 3). Nevertheless, up-weighting the age information led to a similar level of bias as the initial simulations (Figure 3). This finding suggested that the age composition data do not alleviate bias even in “ideal” situations, such as when the age composition data are fully representative of the catch and underlying population.

3.2 Simulation characteristics as predictors of relative error in stock status

Relating RE to simulation characteristics revealed that relatively little of the variability in RE within a given environmental scenario could be explained by characteristics of the simulations themselves (Figure 4; and see Appendix B, Figure B-1 for the model fit). For fast life-history species, the only predictor showing a strong effect on performance was the maximum depletion level. For slow life-history species, changes in all of the production-related quantities (*M*, *K*, L_∞, recruitment) affected RE, although they explained only a small proportion of variance in assessment bias within environmental scenarios.

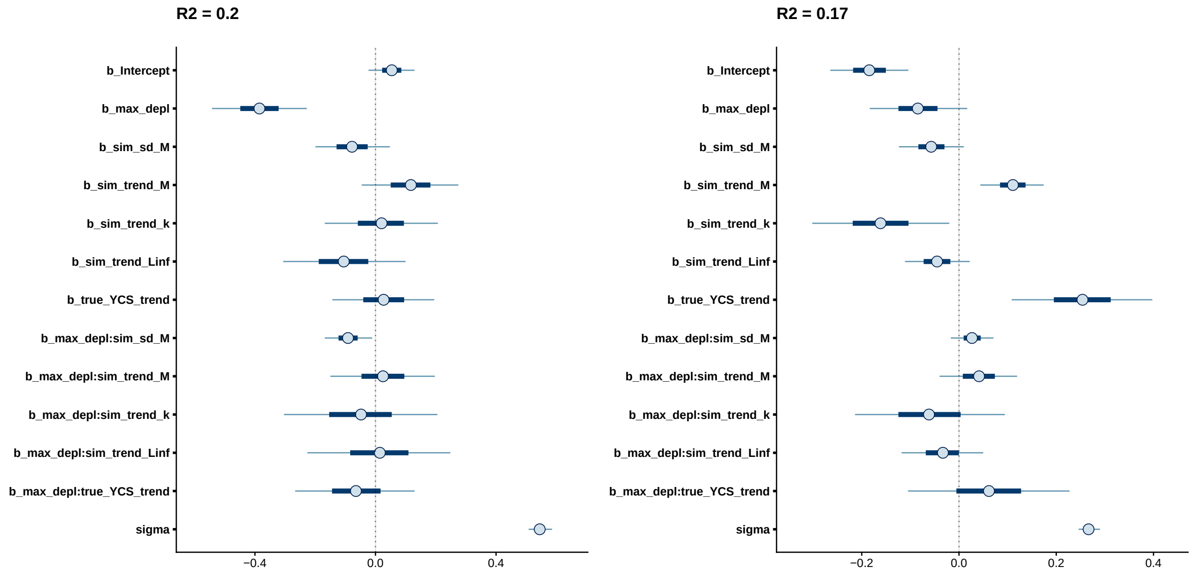
Among scenarios, most of the variability was explained by consistent bias for individual replicates (random seeds) which were replicated across scenarios (see sd-rep-idx–intercept parameter in Figure 4c&d). The remaining variation was mainly explained by differences in maximum depletion levels and natural mortality trends (and their interaction) for fast life-history stocks, whereas trends in *M* and year-class strength in assessments were associated with bias in assessments of slow life-history stocks (Appendix B, Figures B-2 to B-4).

3.3 Assessment mis-specifications relating to bias

When examining differences in specification and estimated quantities between assessments and simulated dynamics within regression models, relatively little variability in RE was explained within environmental scenarios (i.e., within the base scenario; Figures 5a&b; Appendix B, Figure B-5). Although all production-related parameters affected RE, the proportion of explained variance was only 0.32 for fast life-history stocks, and 0.29 for slow life-history stocks. Among climate scenarios, within replicates, however, a relatively large proportion of the variance was accounted for by production parameters (Figures 5c&d), especially by changes in *M* and ensuing mis-specification in assessments among scenarios of increasing or decreasing environmental suitability relative to the base simulation (Figures B-6 to B-9).

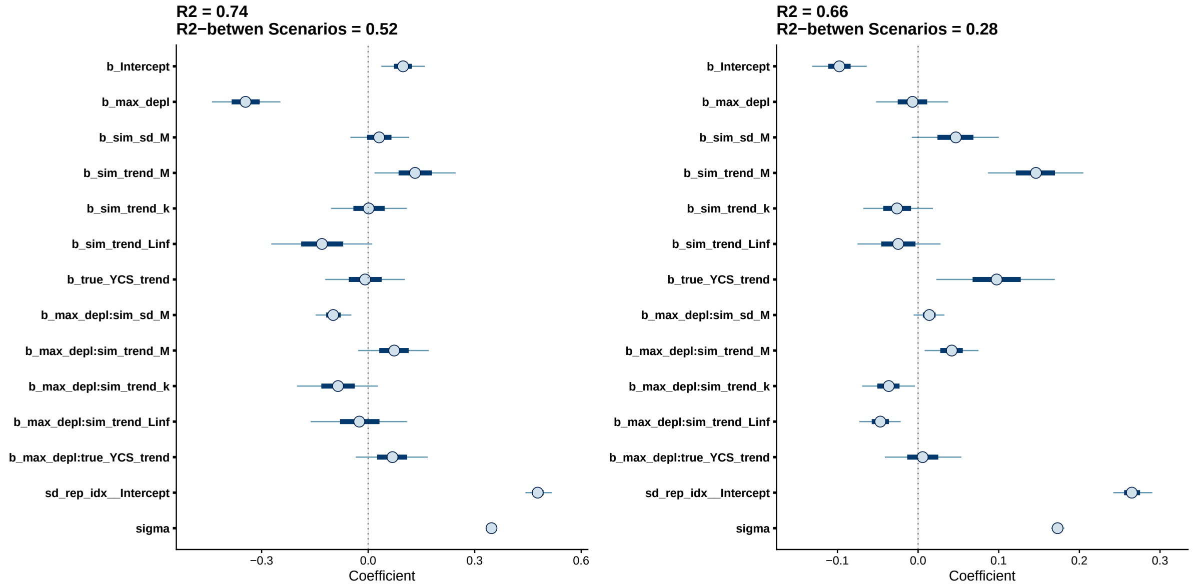
3.4 Assessment outcomes as indicators of bias

No residual indicators showed a particularly strong or consistent relationship with RE within scenarios (Figures 6a&b, B-10). Among scenarios, indicators were more consistent, except for year-class strength trends, which showed opposing relationships with bias for slow compared with fast life-histories. Trends in residuals were the most consistent indicators of bias among scenarios (Figures 6c&d, B-11 to B-13).



(a) Base - fast life history

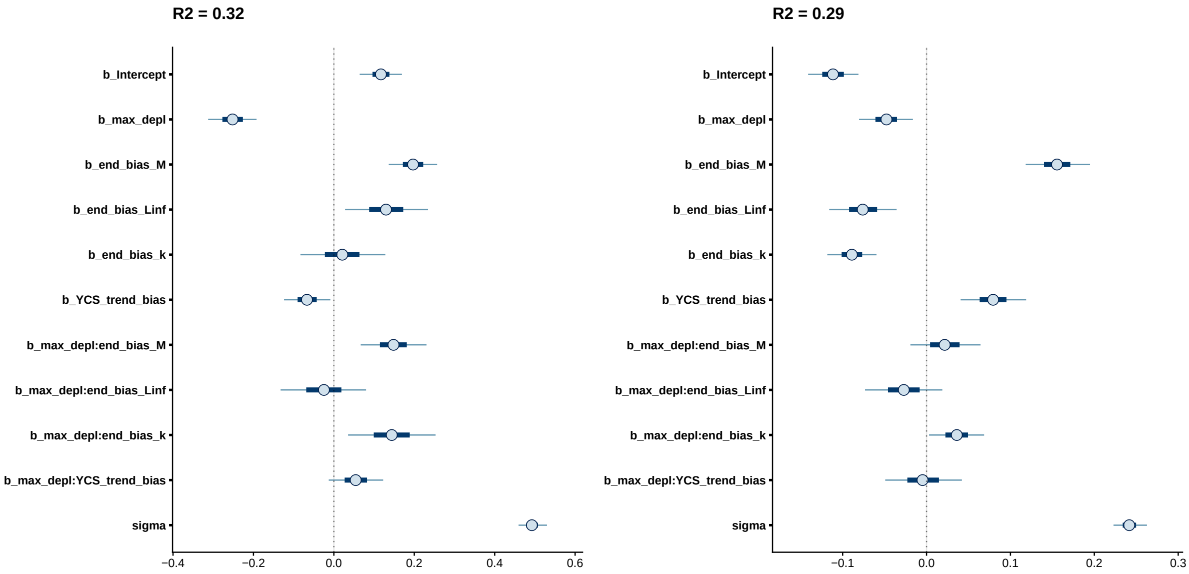
(b) Base - slow life history



(c) Climate scenarios - fast life history

(d) Climate scenarios - slow life history

Figure 4: Marginal effects of characteristics in simulated populations on assessment bias within the base scenario (top row) and among climate scenarios within replicates (bottom row) for fast (left column) and slow (right column) life histories.



(a) Base - fast life history

(b) Base - slow life history

(c) Climate scenarios - fast life history

(d) Climate scenarios - slow life history

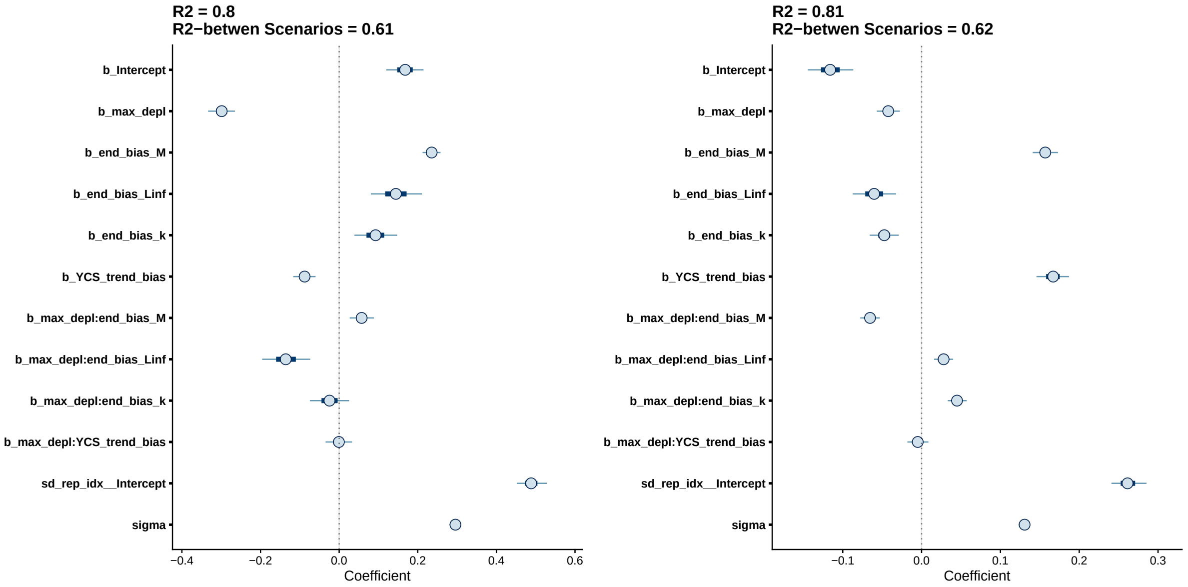
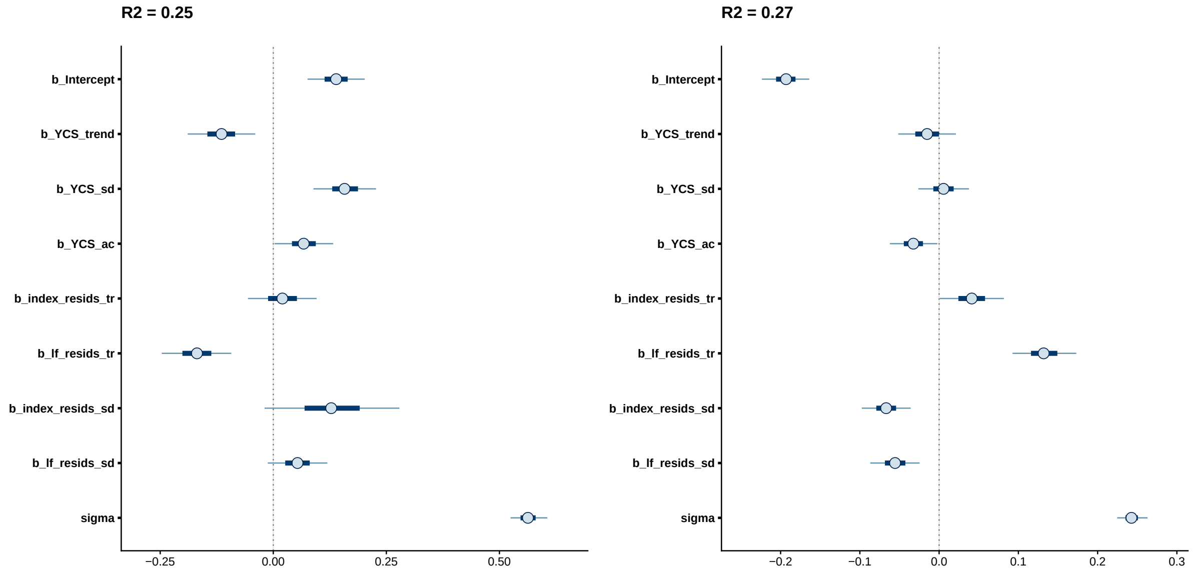
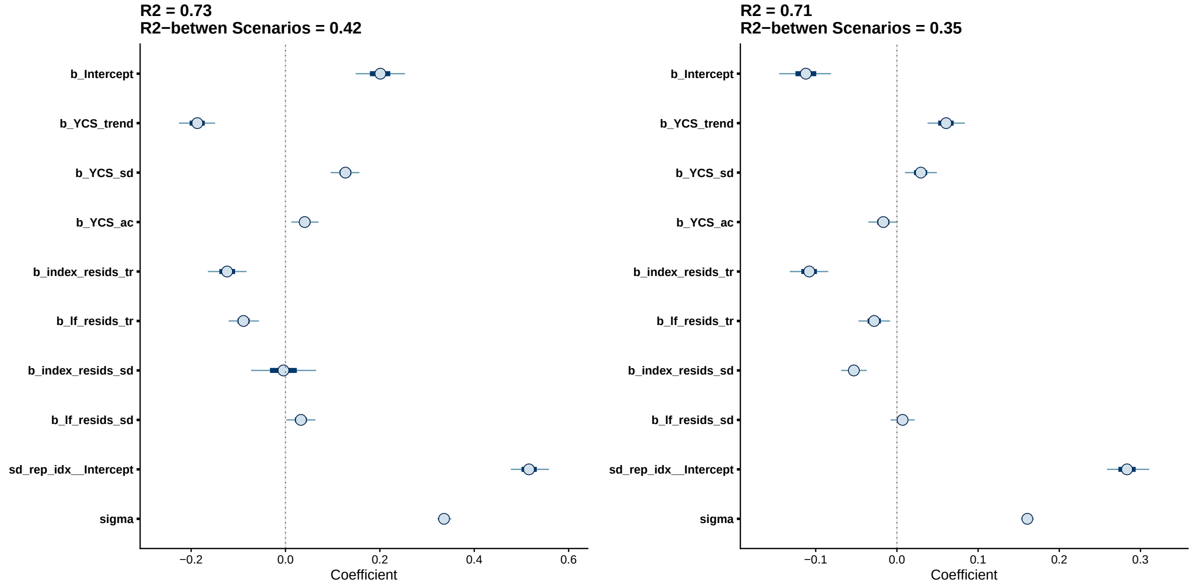


Figure 5: Marginal effects of mis-specifications on relative error in stock status within the base scenario (top row) and among climate scenarios within replicates (bottom row) for fast (left column) and slow (right column) life histories.



(a) Base - fast life history

(b) Base - slow life history



(c) Climate scenarios - fast life history

(d) Climate scenarios - slow life history

Figure 6: Marginal relationship of potential indicators and relative error in stock status within the base scenario (top row) and among climate scenarios within replicates (bottom row) for fast (left column) and slow (right column) life histories.

4. DISCUSSION

The current study attempted to examine the robustness of commonly-used age-based statistical stock assessment methods. The latter methods are often considered the “gold-standard” for assessing wild populations, in view of fluctuating and changing productivity. Assessments for both stocks with fluctuating, but stable long-term average productivity and for stocks with declining or increasing productivity were nearly unbiased on average; however, results for individual assessments were not necessarily accurate. Instead, estimates commonly indicated twice or half the true stock status, particularly for fast life-history stocks.

Relatively little of this variation was explained by differences in trends of production parameters in the simulations themselves. Nevertheless, considerable variation among climate scenarios (i.e., within replicates with the same random seed) was explained by changes in production parameters, particularly natural mortality *M*, and the corresponding mis-specification in assessments. Mis-specification and changes in *M* are expected to lead to bias in assessments, because this parameter is difficult to estimate or specify correctly (Johnson et al. 2015, Punt et al. 2021). At the same time, *M* has disproportionate significance for other management quantities, such as spawning biomass and catch targets (Thorson et al. 2015b).

Productivity changes for climate scenarios were largely negative in previous simulations (Neubauer et al. 2023). The changes led to baseline assessments (i.e., without information on changing growth) that were more positively biased when bottom-up production changes co-occurred with rising temperatures, particularly for fast life-history simulated stocks. For slow life-history simulations, assessments were still mostly unbiased, but showed wider tails, indicating more cases where stock status was markedly overestimated. Although these biases were attenuated when adding time-varying growth and age composition information to assessment models, the inclusion of the growth data also led to a slight conservative bias (stock status underestimated on average) for other climate scenarios. The latter may be due to the growth rate increasing in all climate scenarios, suggesting increasing productivity when true aggregate productivity was declining or stable due to concomitant increases in natural mortality. From a management perspective, these simulations, therefore, suggest that adding information about time-varying growth could lead to overall more precautionary management decisions in a changing climate for stocks affected by varying production and directional changes in productivity.

Because production itself is determined by a combination of recruitment, growth, and mortality, adding information about changes in growth in the form of time-resolved length-at-age data does not necessarily improve the accuracy of stock assessments (unless growth is the only time-varying production factor; Stawitz et al. 2019); for simulated stocks here, however, improvements in assessment accuracy were expected from the combination of time-varying growth and added age composition data (Lee et al. 2011, Maunder & Wong 2011). Representative or accurate age composition data are necessary, but not sufficient, to obtain relatively reliable estimates of *M* (Lee et al. 2011), which in turn, lead to more accurate estimates of stock status (Ono et al. 2015). Nevertheless, the spread of assessment error in the simulations here did not change with additional composition data, nor did it change markedly when age composition data were allowed to dominate the assessment (i.e., see assessment approach 3). This lack of improvement may be due to age composition data being available to the baseline assessment, so that additional age composition data do not necessarily provide improved estimates of *M*. Across climate and assessment scenarios, changes in assessment errors from inclusion and weighting of age data were more pronounced for the fast life-history species, corresponding with expectations from other studies (Ono et al. 2015).

Overall, the assessment error resulting from interannual and decadal variability (i.e., the current base scenario) in production was considerably greater than variability induced by climate scenarios considered here. The current simulation-estimation approach also showed that long-term declines in productivity may lead to bias in assessments and potential overestimation of stock status. Including time-varying information, such as length-at-age data and parameters (e.g., time-varying *M*), in assessments can alleviate these biases (Johnson et al. 2015, Stawitz et al. 2019); however, including this information is challenging due to the potential introduction of biases if the wrong parameters are set to be time-varying. In addition, parameters such as *M* are confounded by catchability, selectivity, and recruitment estimates (Jacobsen et al. 2019), which themselves may vary in time. This is the reason why some stock assessment scientists advocate against estimating *M* in assessment models.

For many major stocks, biological and ecological knowledge may inform *a priori* expectations about climate and regime-like environmental impacts, which may be used to derive reasonable assumptions in stock assessments. For example, the most recent snapper (*Chrysophrys auratus*, SNA) stock assessment in fisheries management area SNA 8 in New Zealand used growth epochs to model apparent variation in growth rates over time (Langley 2021). Nevertheless, similar data are not usually available for other time-varying parameters and, even for major stocks, it will be difficult to reconstruct mortality patterns over time.

For these reasons, a key recommendation from this study is for analysts to be open to exploring alternative model formulations with various time-varying parameters (e.g., time-varying *M*, catchability). This exploration of alternative formulations is recommended even if there are no robust data sources to provide evidence for trends or variability in parameters such as *M* (or catchability; Wilberg et al. 2009). Random effects formulations can provide some constraint on time-varying parameters (Thorson et al. 2015a), but are not generally available in all stock assessment packages. With careful implementation, however, time-varying parameters can still be estimated (Thorson et al. 2015a, Jacobsen et al. 2019, Stawitz et al. 2019), even if it often leads to lower precision in assessment quantities. Given the prevalence of time-varying life-history and fishing-related quantities, however, time-varying formulations may be used to bound the space of plausible stock status estimates and provide bounds on management quantities that account for uncertainty introduced by time-varying production (Legault 2020).

Accounting for the influences of climate change and environmental variability is at odds with the assumptions of most stock assessment models, but the present results highlight the value of exploring alternative model formulations even when assessments appear to fit the data well. Here, exploring assessment error in relation to residual patterns showed no strong or consistent indicators for assessment error among replicates. This result suggests that beyond variability and non-stationarity in productivity, the ability of assessment models to accurately estimate stock status and related management quantities depends on a complex interplay between stock trajectories, life history, and data quality (i.e., information content; see also Ono et al. 2015). Although trends in index and length frequency residuals over time were indicative of bias introduced by climate scenarios, they provided little information to discern among assessments for simulation replicates with high and low RE, and provided contradictory signals between life-history simulations.

The inability to detect bias in stock status estimates of otherwise well-fitting models highlights the need for a strong focus on structural uncertainties, including time-varying parameters and biological assumptions. This focus is required to provide realistic estimates of total uncertainty beyond parameter uncertainty. In addition to mitigating risk from under-estimation of overall assessment uncertainty, these types of exploration could lead to the adoption of more appropriate management quantities that acknowledge non-stationarity of production, and which, in turn, could provide more responsive management in increasingly variable environments. The appropriateness and risk from adopting these measures need to be explored to ensure that sustainability risks from tracking environmental production trends are sufficiently mitigated (e.g., that trends resulting from fishing are not confounded with environmental factors, thereby risking effective controls on fishing (Hilborn 1997)).

5. ACKNOWLEDGEMENTS

The authors thank Mary Livingston, Pamela Mace and members of the Biodiversity Research Advisory Group and Statistics, Assessments and Methods Working Group for comments and suggestions over the course of this project. The project was funded under Fisheries New Zealand project ZBD2018-03.

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APPENDIX A: RESULTS FOR CONSTANT CATCH SIMULATIONS

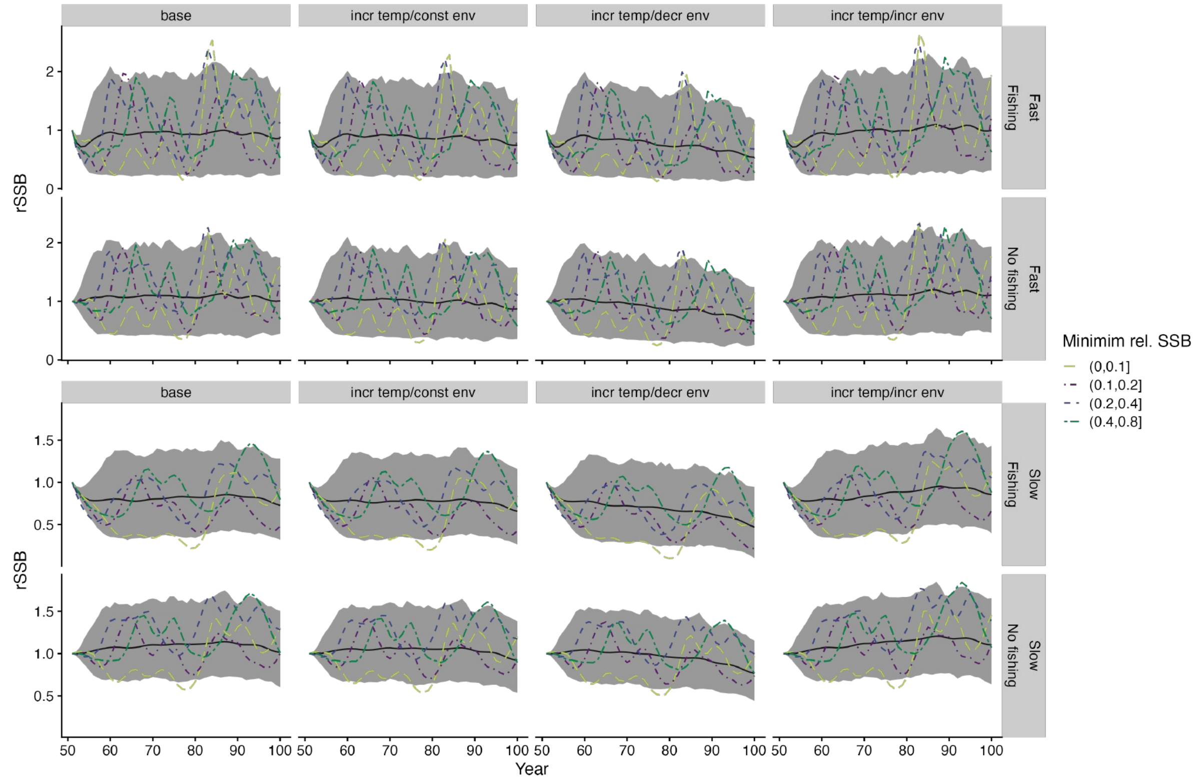


Figure A-1: Trajectories of simulated relative spawning stock biomass (*rSSB*) for randomly selected simulation replicates (coloured lines), with *rSSB* across all simulations (black line, median by year; grey-shaded area, 95% confidence interval), with catch constant. Simulations were for fish stocks with fast (top two rows) and slow (bottom two rows) life histories, for four different climate scenarios: base, no temperature or environmental change; incr temp/const env, increasing temperature, no environmental change; incr temp/decr env, increasing temperature, declining environment; incr temp/incr env, increasing temperature, increasing environmental suitability.

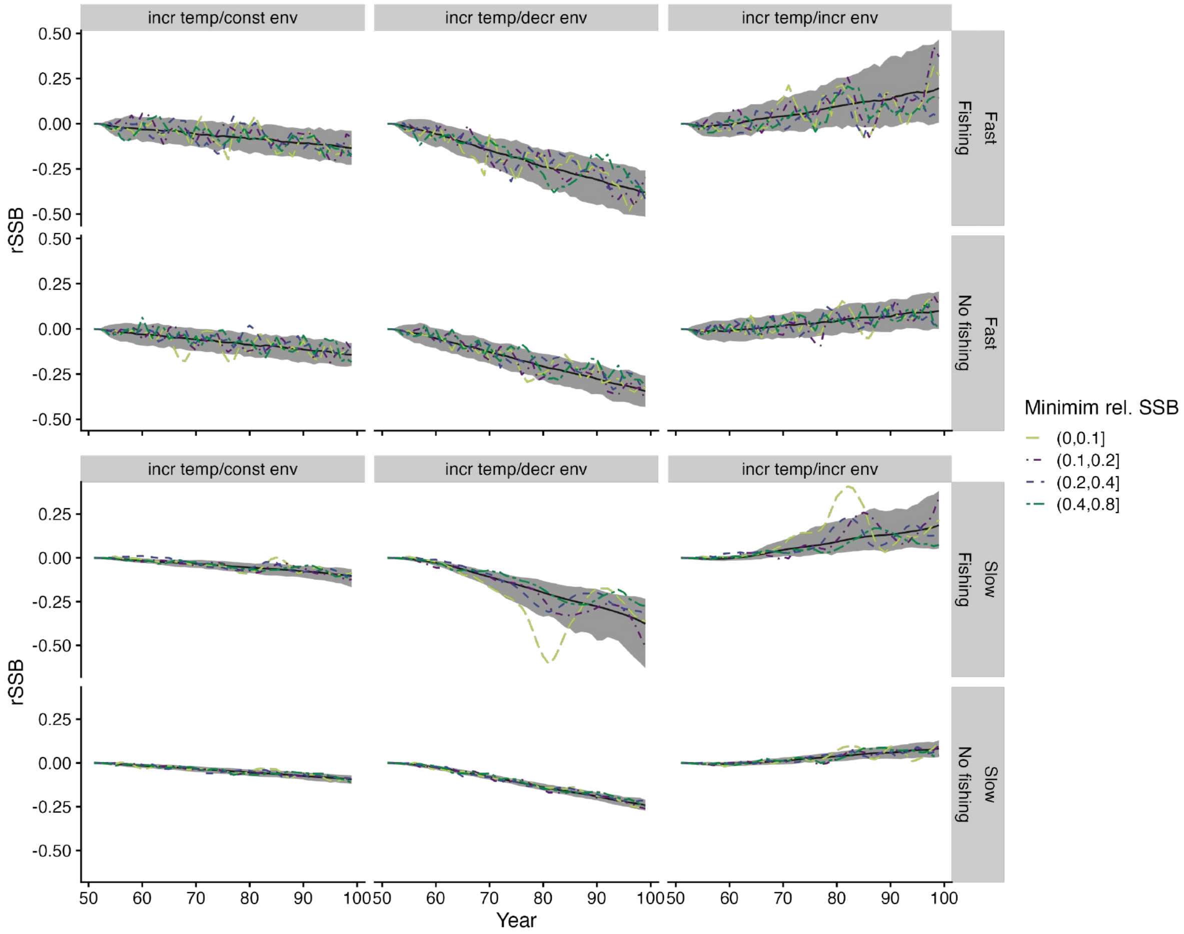


Figure A-2: Simulated relative spawning stock biomass (*rSSB*) trajectories relative to base replicates for randomly selected simulation replicates (coloured lines), with *rSSB* across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 3 scenarios of mean environmental and temperature trends relative to the base scenario: constant (const) temperature (temp), constant environment (env). Rows are fast life history (top); and slow life history (bottom), with simulations with and without fishing shown for each life history.

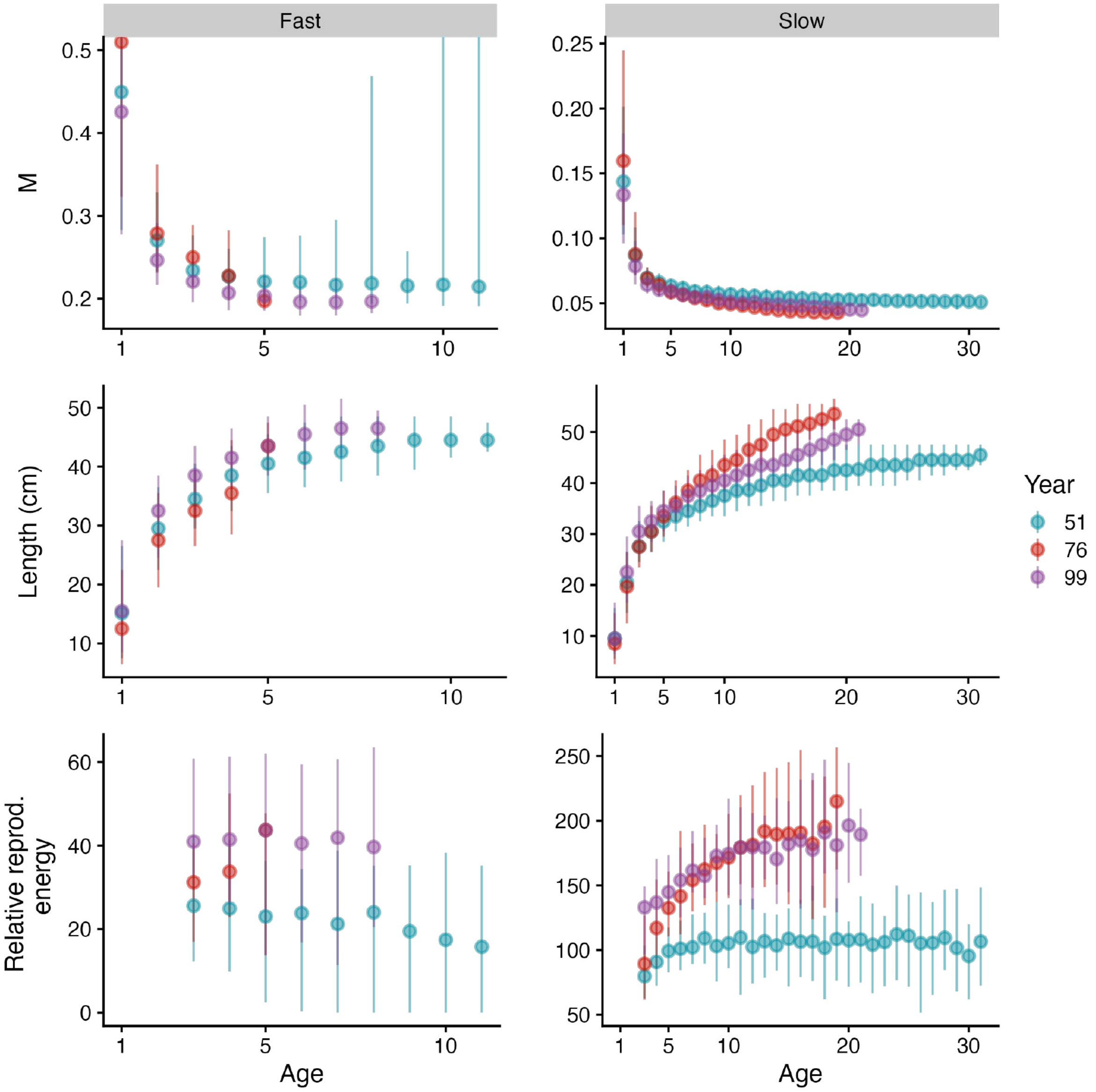


Figure A-3: Simulated values for productivity parameters for a single replicate for the base environmental scenario—all parameters shown as abundance-at-size weighted means-at-age for fast (right column) and slow (left column) life histories at the beginning of fishing (year 51), half-way through fishing history (year 76) and for the penultimate fishing year (year 99). M, natural mortality. The simulation applied constant catch.

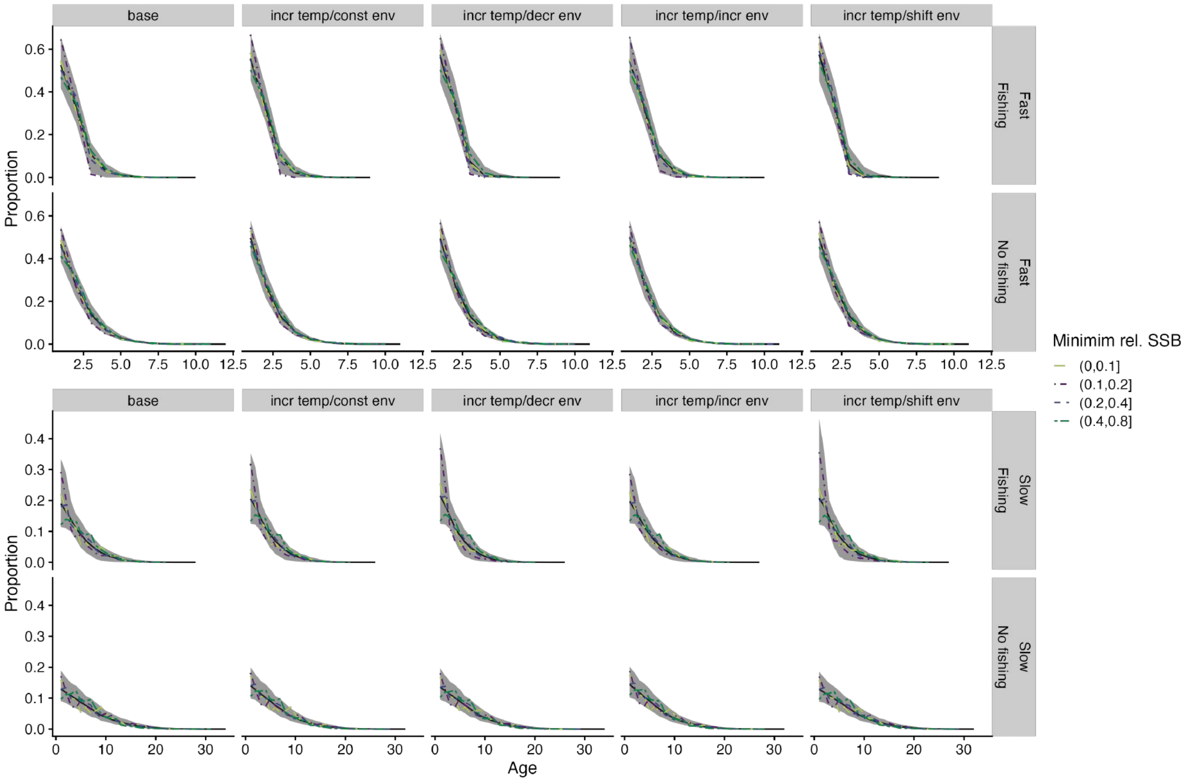


Figure A-4: Simulation proportions-at-age in the final fishing year for randomly selected simulation replicates (coloured lines), with proportions-at-age across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 4 scenarios of mean environmental and temperature trends (Base: constant (const) temperature (temp), constant environment (env)). Rows are fast life history (top); and slow life history (bottom), with simulations with and without fishing shown for each life history.

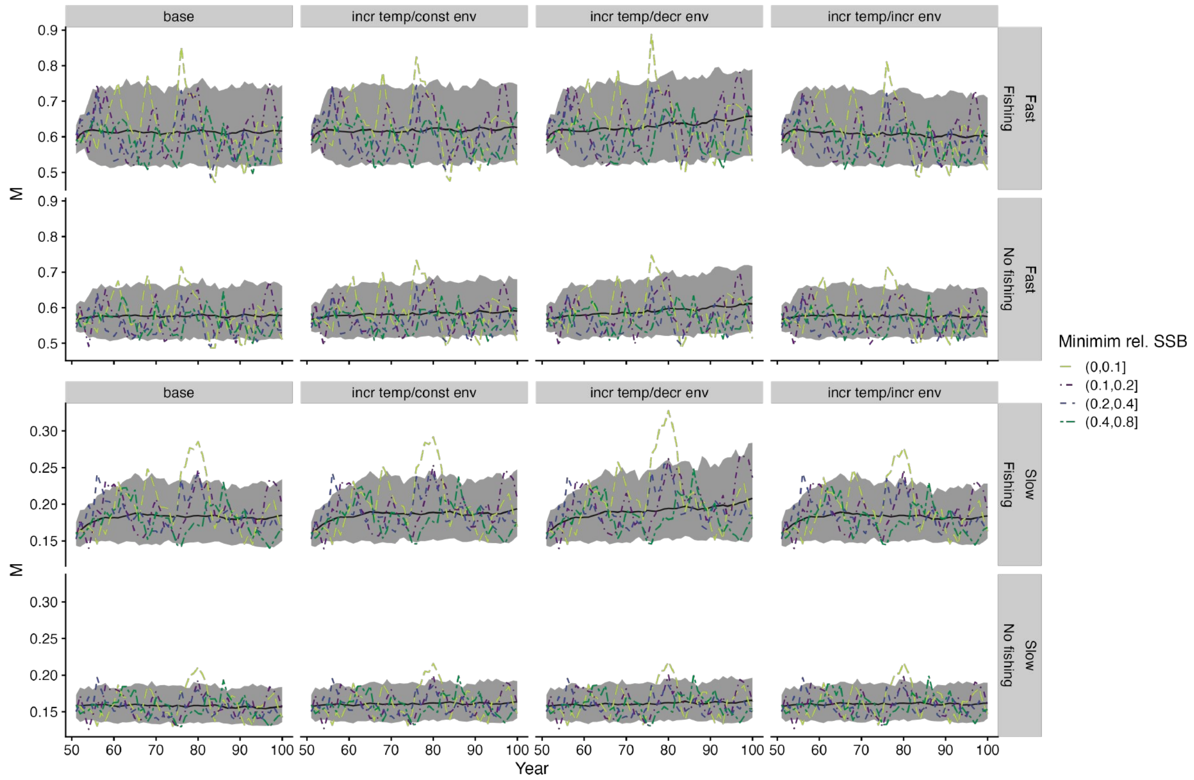


Figure A-5: Simulated natural mortality (*M* - abundance-weighted mean natural mortality) trajectories for randomly selected simulation replicates (coloured lines), with *M* across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 4 scenarios of mean environmental and temperature trends (Base: constant (const) temperature (temp), constant environment (env)). Rows are fast life history (top); and slow life history (bottom), with simulations with and without fishing shown for each life history.

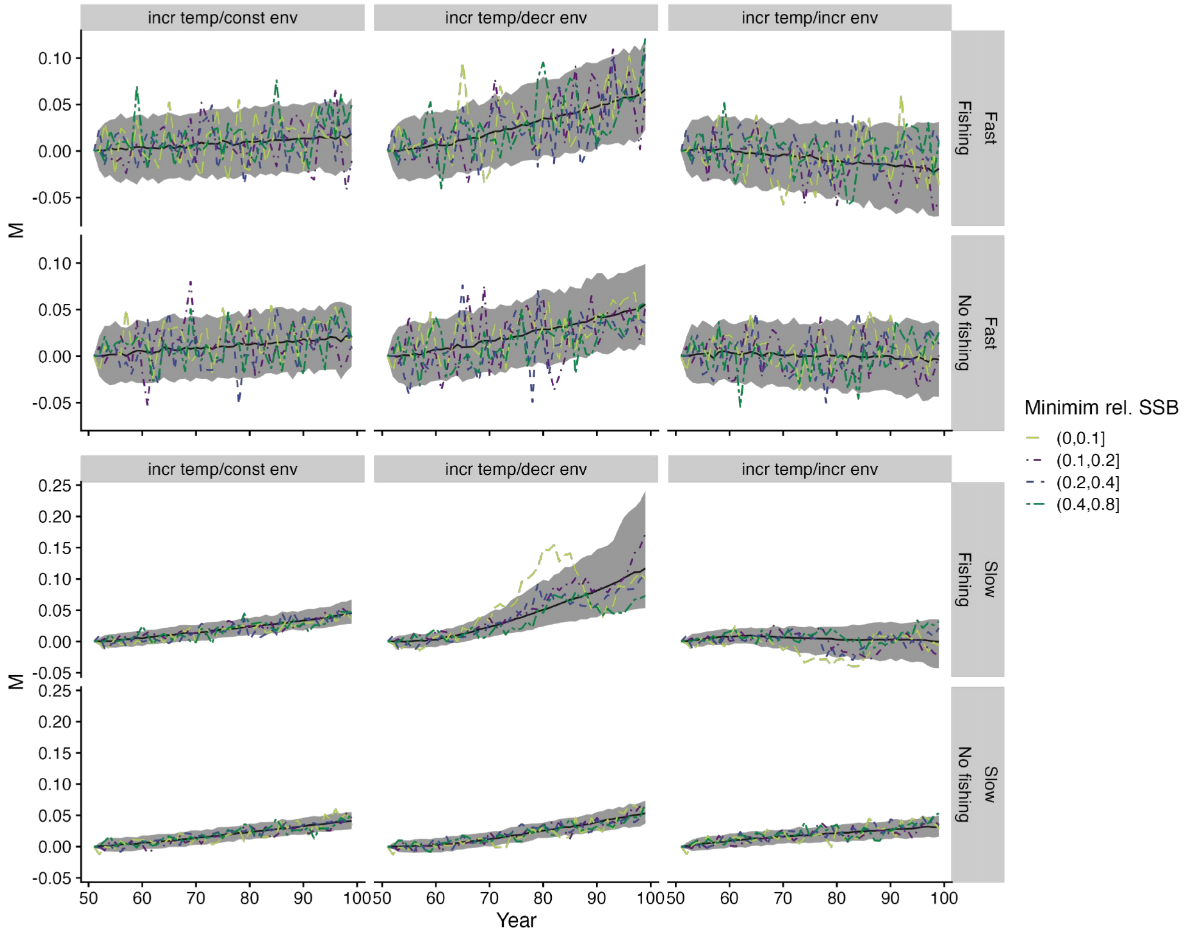


Figure A-6: Relative natural mortality (*M* - abundance-weighted mean natural mortality) trajectories for randomly selected simulation replicates (coloured lines), with *M* across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 3 scenarios of mean environmental and temperature trends relative to the base scenario: constant (const) temperature (temp), constant environment (env). Rows are fast life history (top); and slow life history (bottom), with simulations with and without fishing shown for each life history.

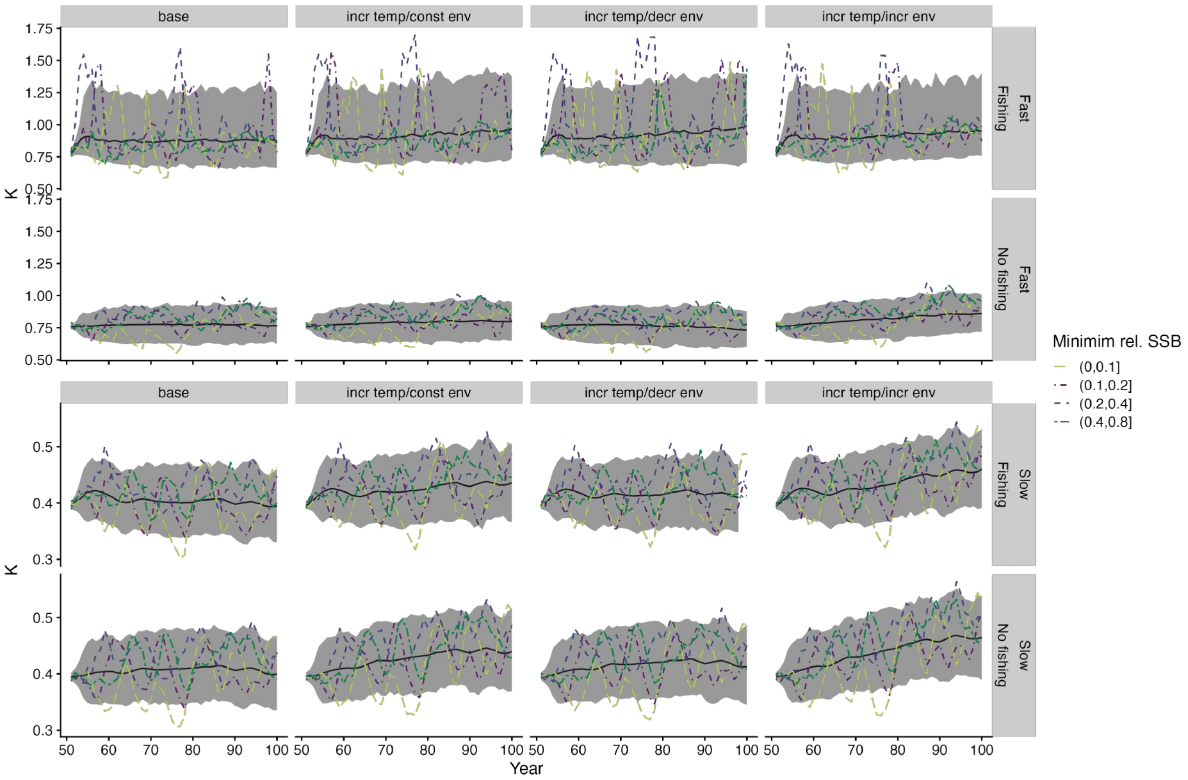


Figure A-7: Simulated von Bertalanffy growth rate trajectories (K - estimated from length-at-age for each year) for randomly selected simulation replicates (coloured lines), with K across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 4 scenarios of mean environmental and temperature trends (Base: constant (const) temperature (temp), constant environment (env)). Rows are fast life history (top two rows); and slow life history (bottom two columns), with simulations with and without fishing shown for each life history.

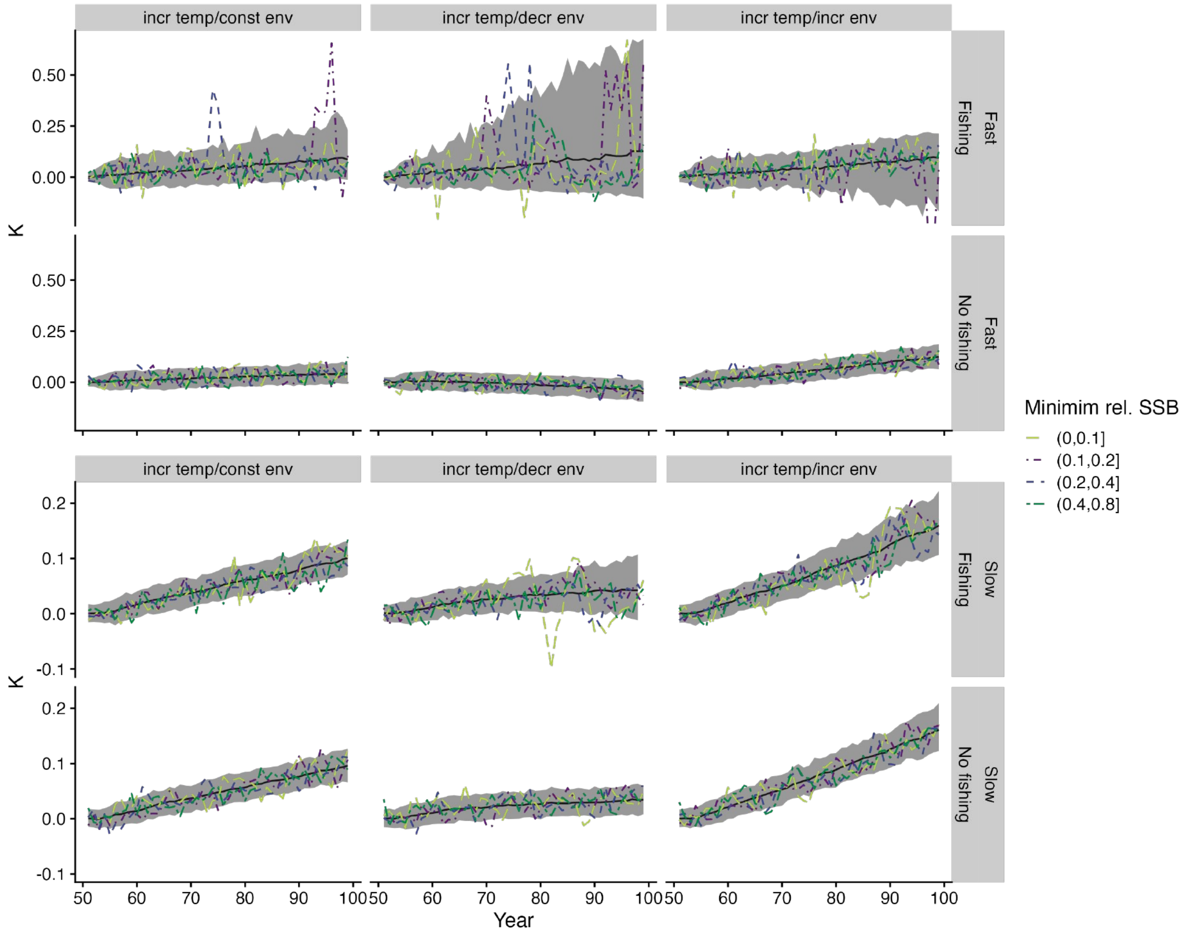


Figure A-8: Relative von Bertalanffy growth rate trajectories (K - estimated from length-at-age for each year) for randomly selected simulation replicates (coloured lines), with K across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 3 scenarios of mean environmental and temperature trends relative to the base scenario: constant (const) temperature (temp), constant environment (env). Rows are fast life history (top two rows); and slow life history (bottom two columns), with simulations with and without fishing shown for each life history.

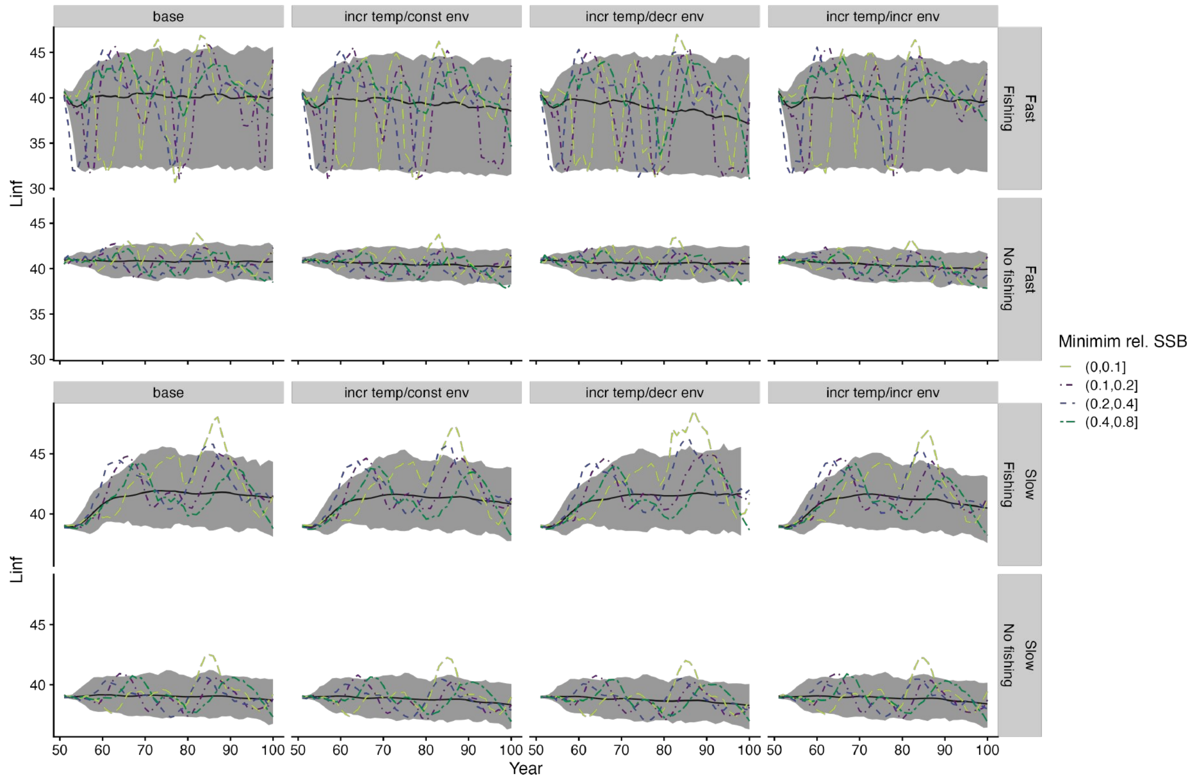


Figure A-9: Simulated asymptotic fish size (L_∞ - estimated by fitting von Bertalanffy growth curves from length-at-age for each year) trajectories for randomly selected simulation replicates (coloured lines), with L_∞ across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 4 scenarios of mean environmental and temperature trends (Base: constant (const) temperature (temp), constant environment (env)). Rows are fast life history (top two rows); and slow life history (bottom two columns), with simulations with and without fishing shown for each life history.

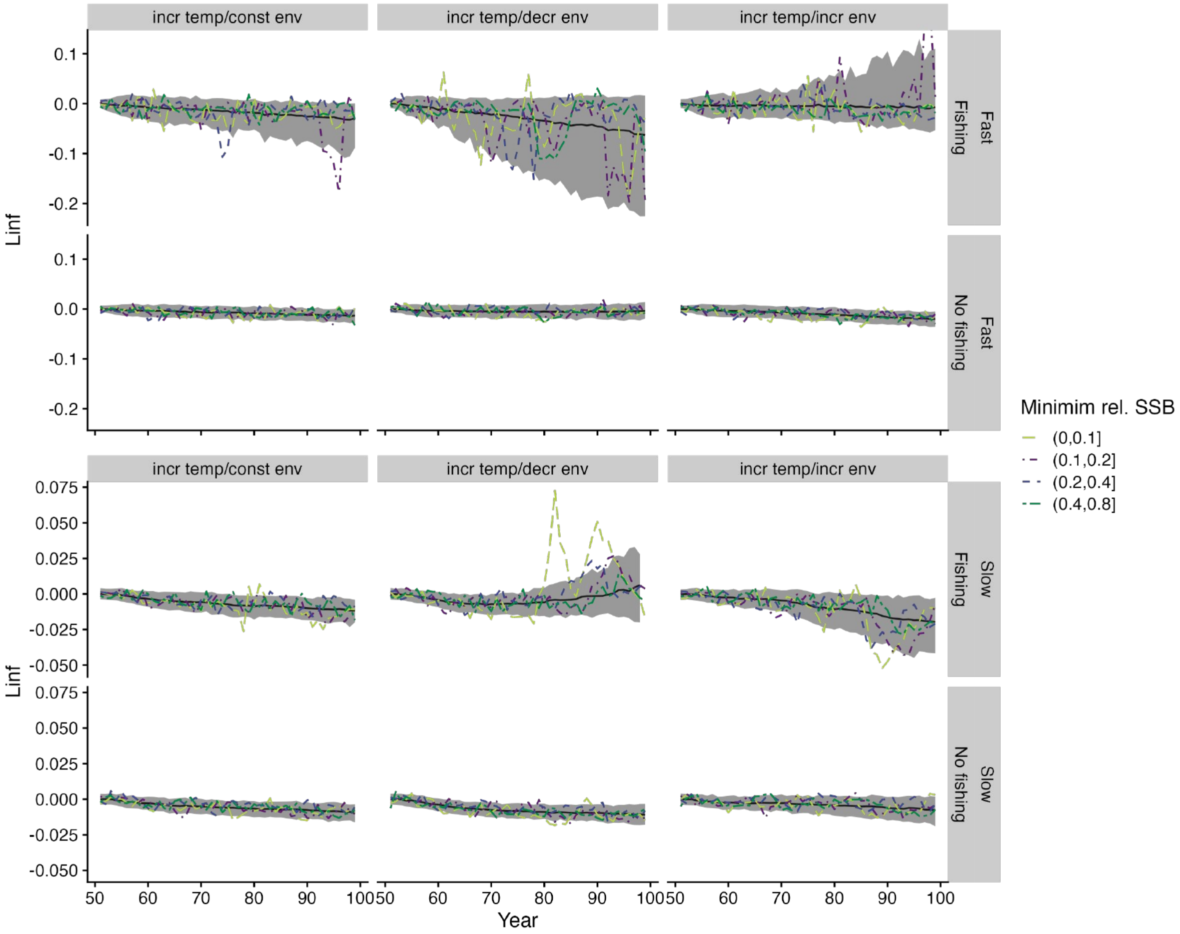


Figure A-10: Relative asymptotic fish size (L_∞ - estimated by fitting von Bertalanffy growth curves from length-at-age for each year) trajectories for randomly selected simulation replicates (coloured lines), with L_∞ across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 3 scenarios of mean environmental and temperature trends relative to the base scenario: constant (const) temperature (temp), constant environment (env). Rows are fast life history (top two rows); and slow life history (bottom two columns), with simulations with and without fishing shown for each life history.

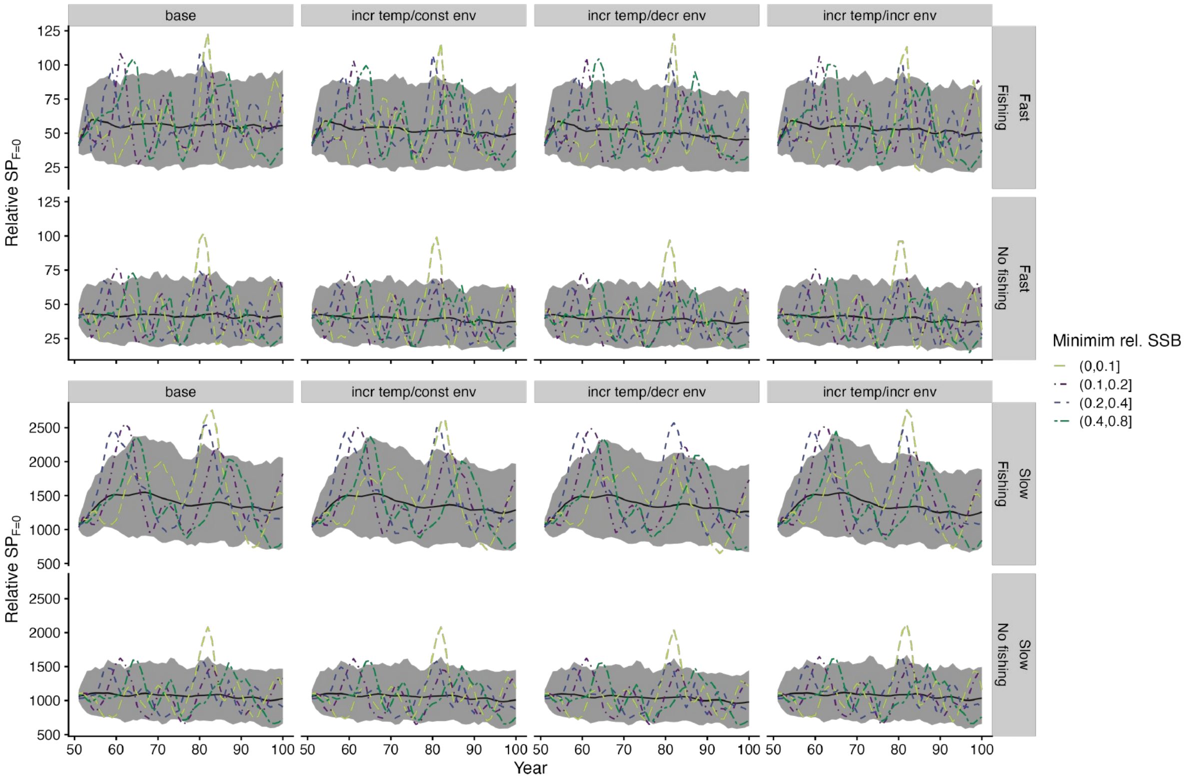


Figure A-11: Simulated instantaneous spawning potential in the absence of fishing (SP_{noF} - calculated taking annually realised production parameter values across age classes present in that year) for randomly selected simulation replicates (coloured lines), with SPnoF across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 4 scenarios of mean environmental and temperature trends (Base: constant (const) temperature (temp), constant environment (env)). Rows are fast life history (top two rows); and slow life history (bottom two columns), with simulations with and without fishing shown for each life history.

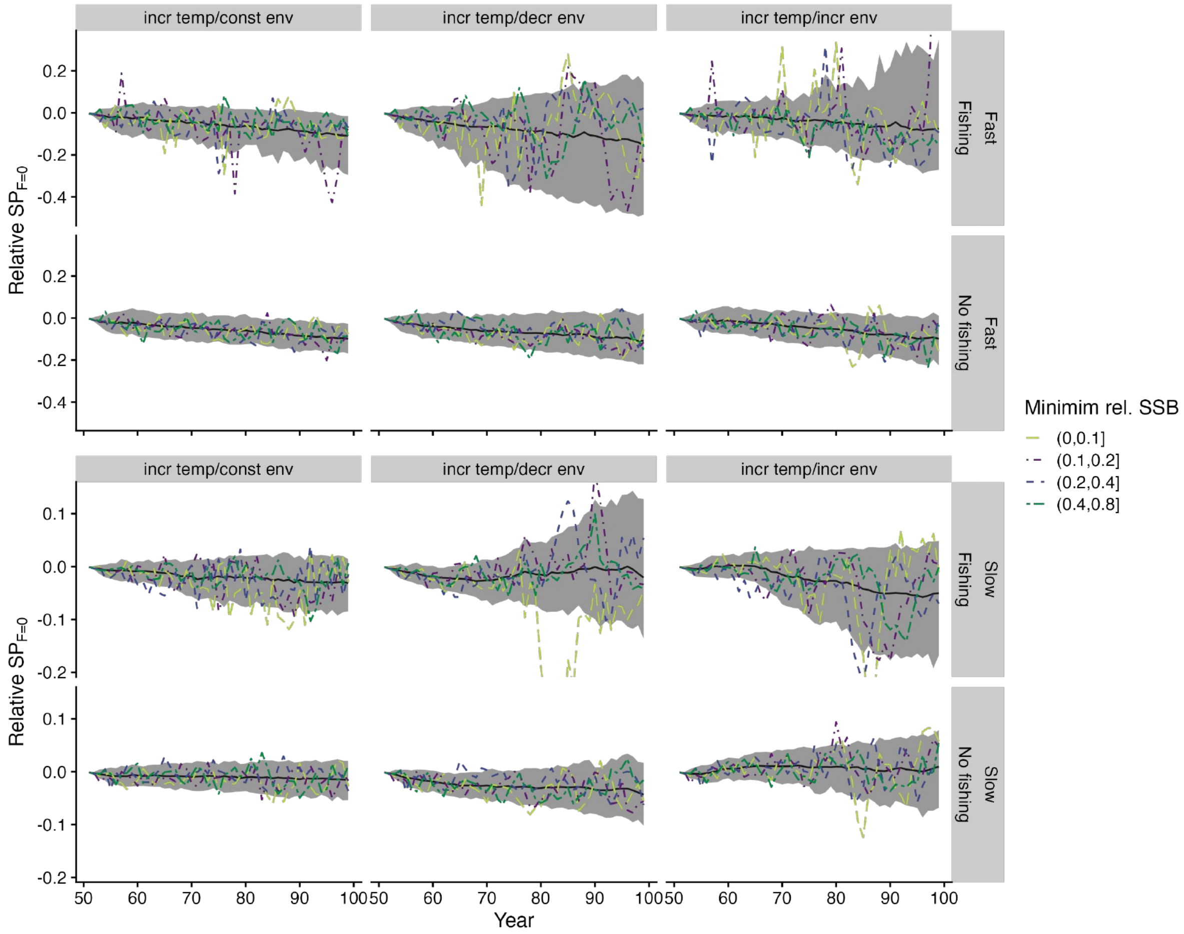


Figure A-12: Relative instantaneous spawning potential in the absence of fishing (SP_{noF} - calculated taking annually realised production parameter values across age classes present in that year) for randomly selected simulation replicates (coloured lines), with SP_{noF} across all simulations (median by year; black line and 95% confidence interval; grey shaded area) for simulations with constant catch, across 3 scenarios of mean environmental and temperature trends relative to the base scenario: constant (const) temperature (temp), constant environment (env). Rows are fast life history (top two rows); and slow life history (bottom two columns), with simulations with and without fishing shown for each life history.

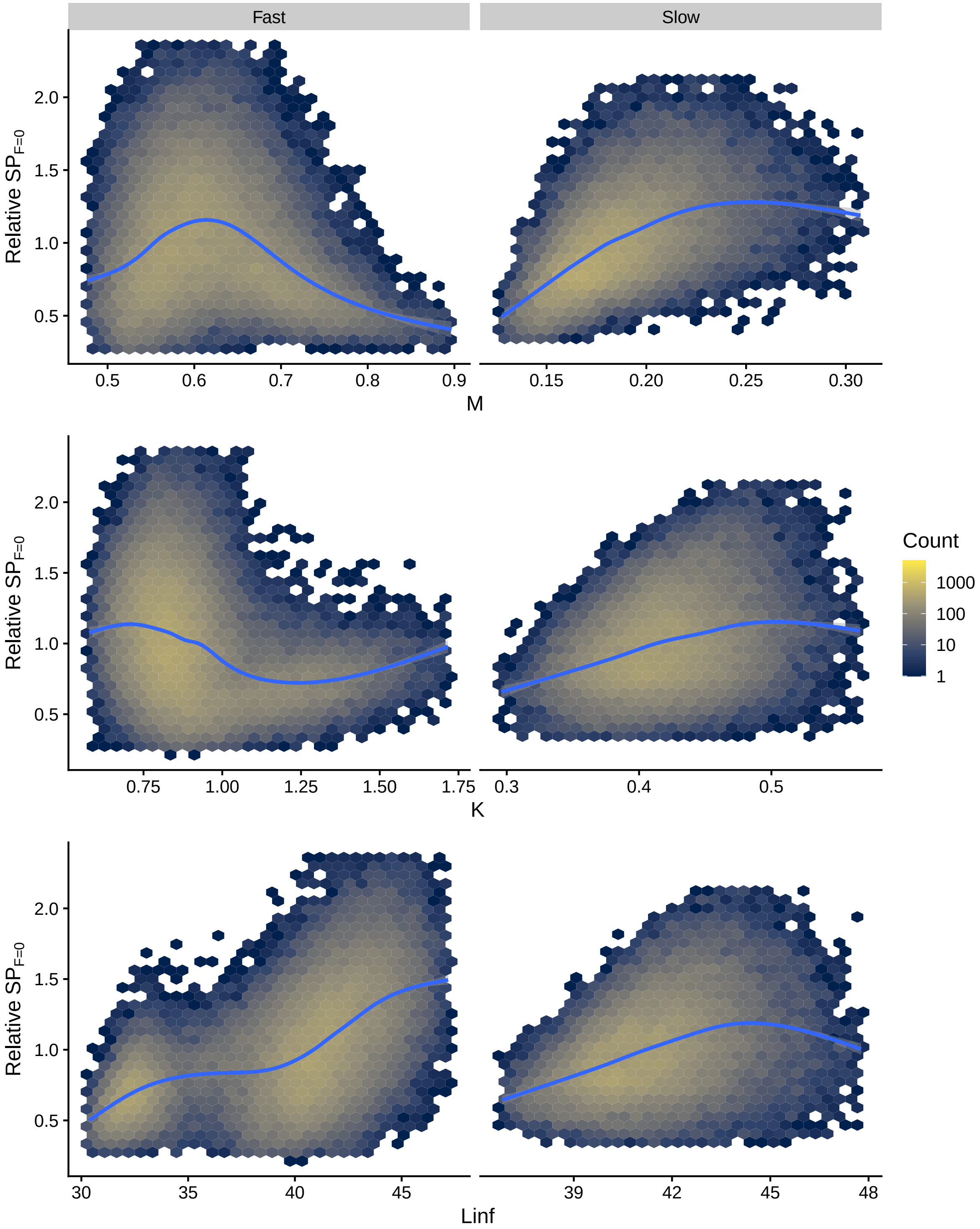
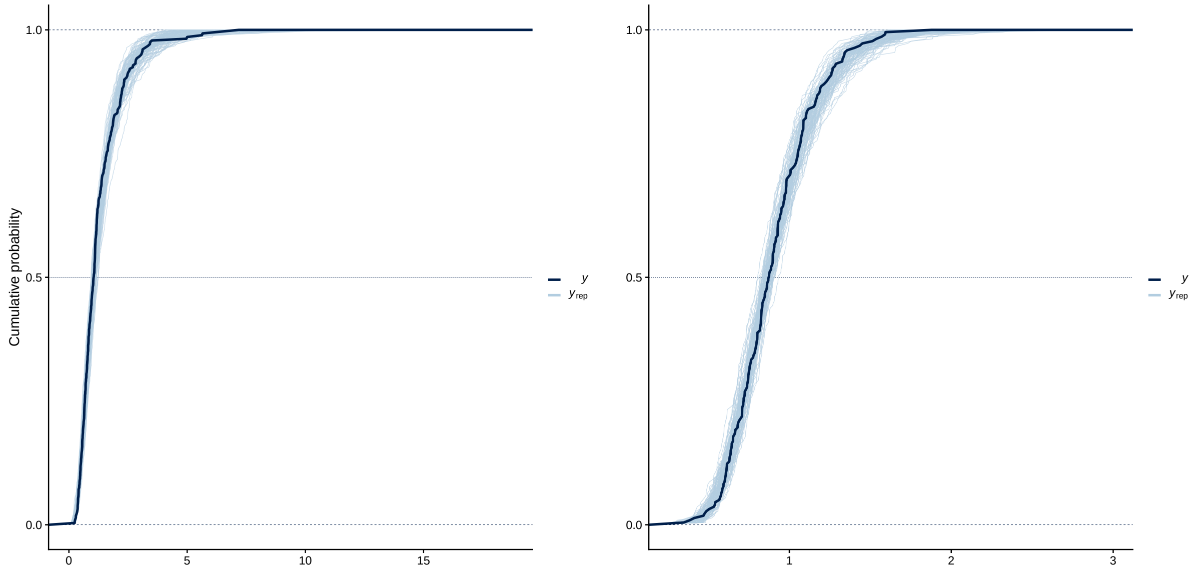


Figure A-13: Correlation between spawning potential in the absence of fishing (*SP_{noF}* - calculated taking annually realised production parameter values across age classes present in that year) and individual production parameters in the assessment model for simulations with constant catch.

APPENDIX B: ADDITIONAL ASSESSMENT OUTPUTS

B.1 Simulation characteristics as predictors of bias

(a) Climate scenarios - fast life history **(b) Climate scenarios - slow life history**



(c) Base - fast life history **(d) Base - slow life history**

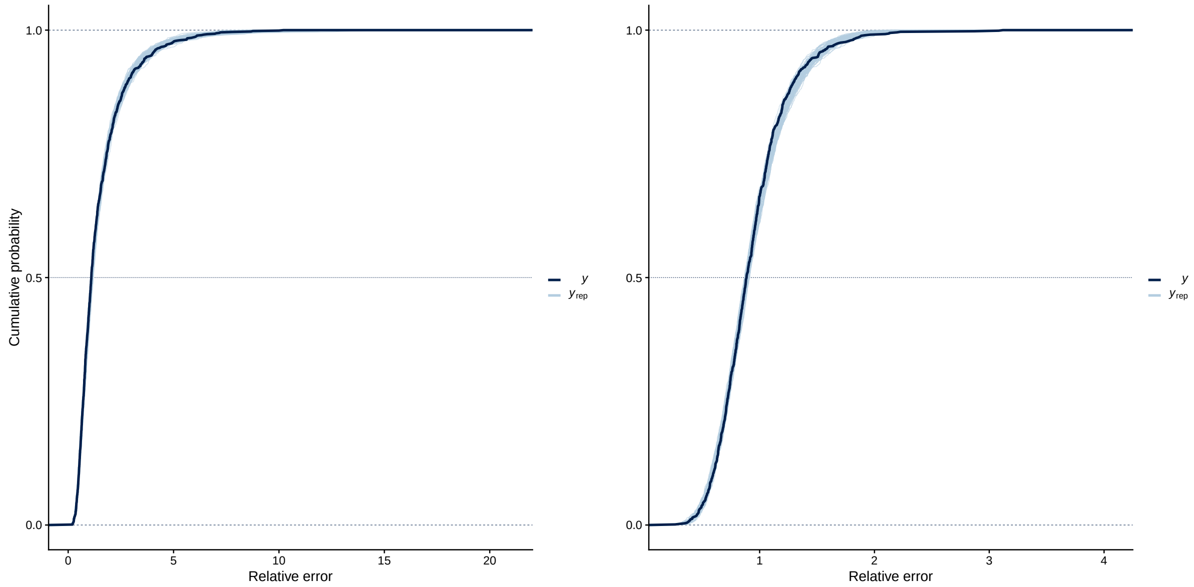


Figure B-1: Model fit for model relating characteristics in simulated populations to assessment bias, assessed by posterior predictive draws from the model (blue lines) against the empirical distribution of data (assessment bias).

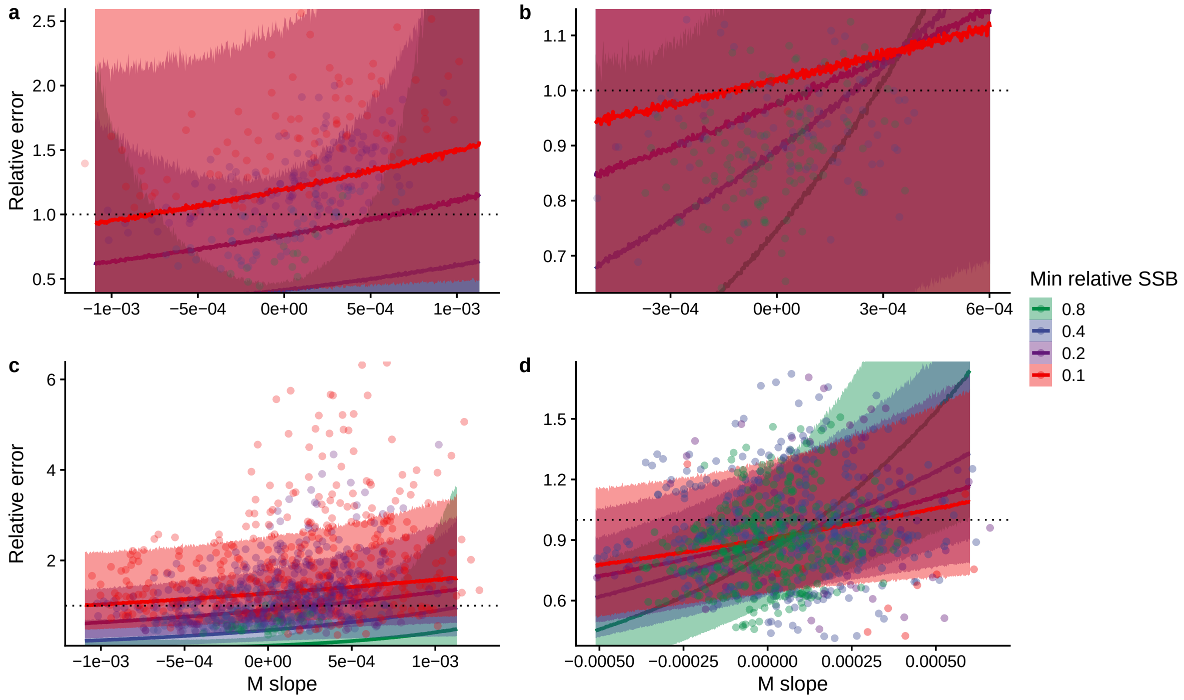


Figure B-2: Marginal effects for trends in M in simulated population dynamics on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

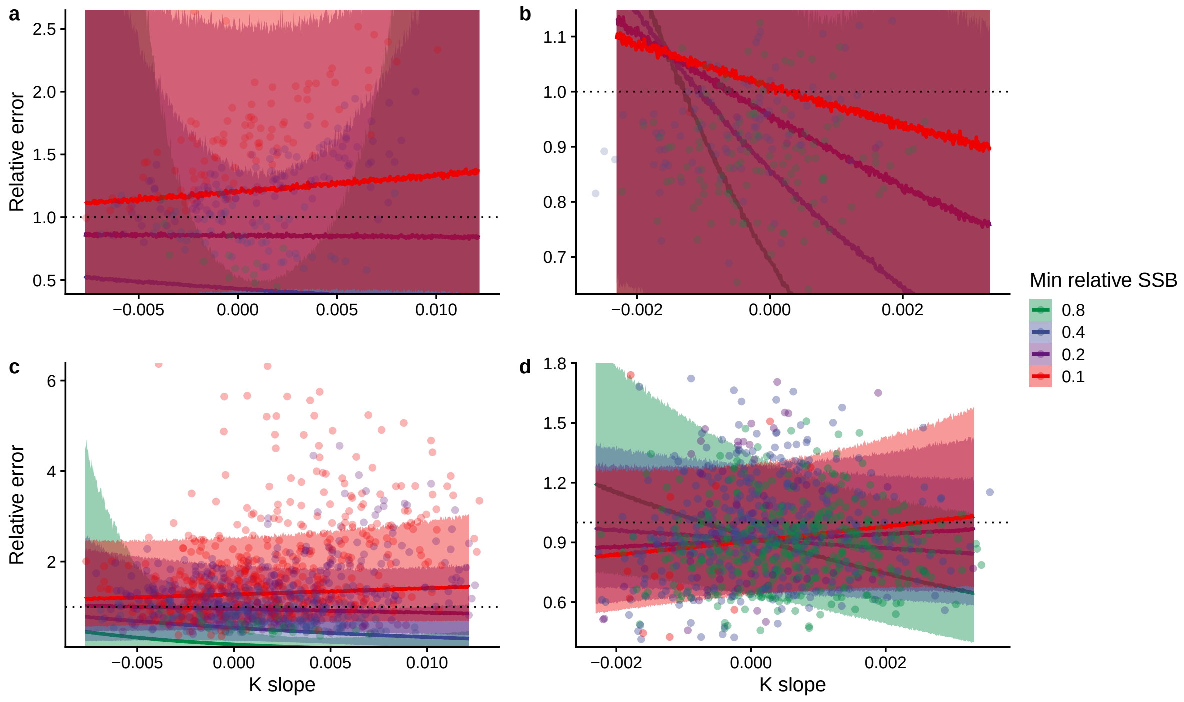


Figure B-3: Marginal effects for trends in K in simulated population dynamics on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

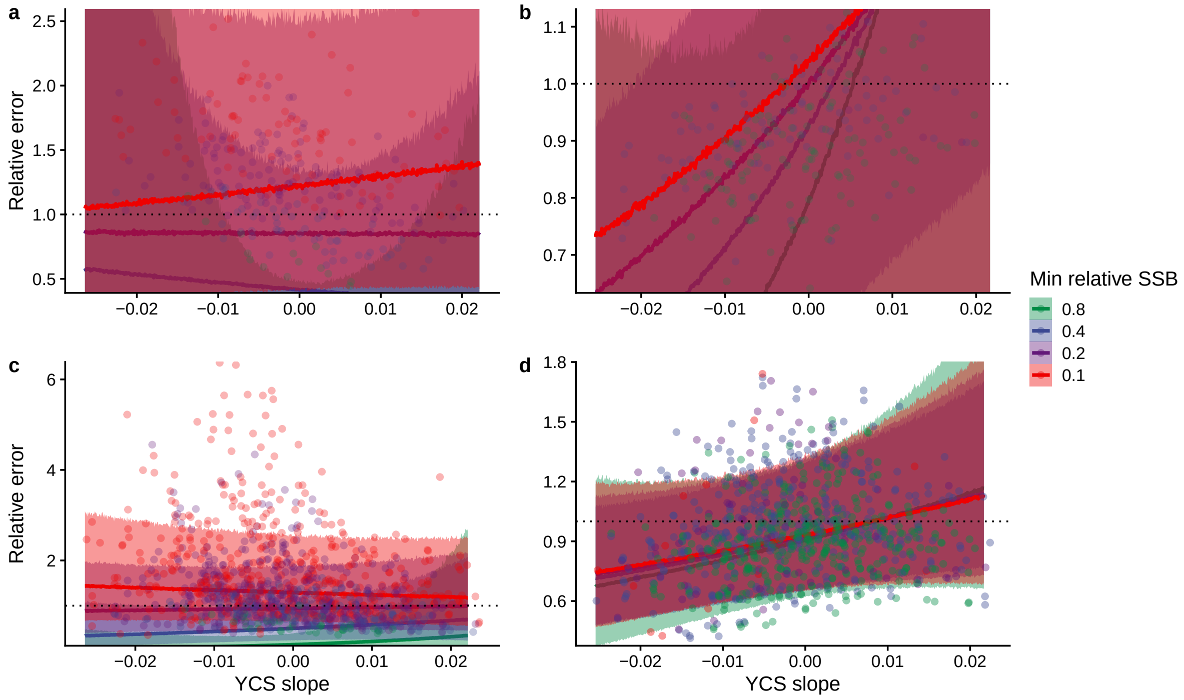
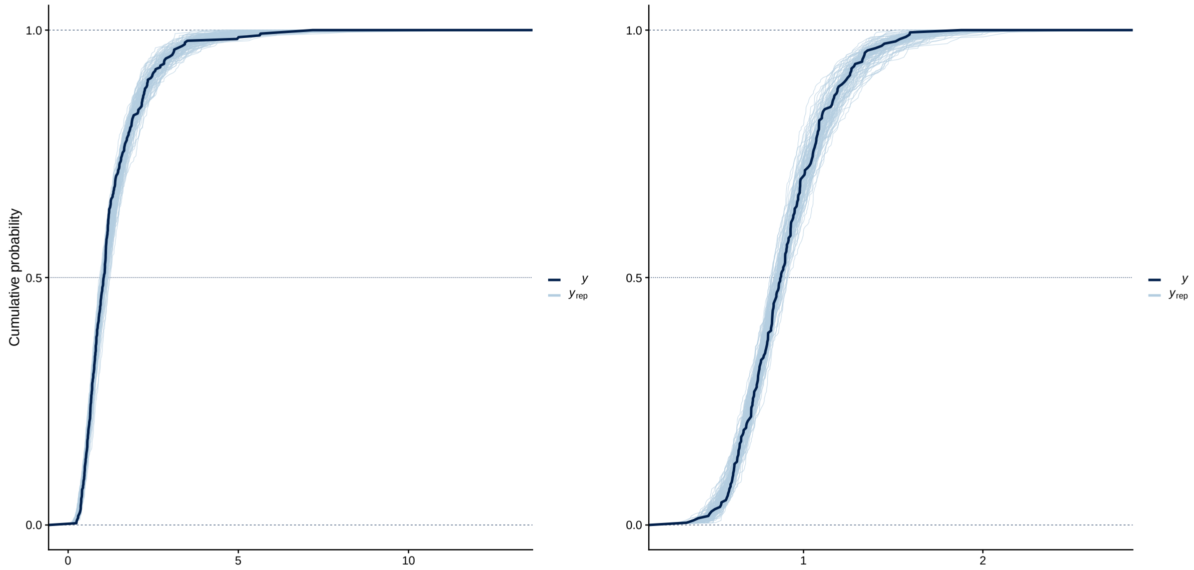


Figure B-4: Marginal effects trends in year-class strength in simulated population dynamics on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

B.2 Assessment mis-specifications relating to bias

(a) Climate scenarios - fast life history **(b) Climate scenarios - slow life history**



(c) Base - fast life history **(d) Base - slow life history**

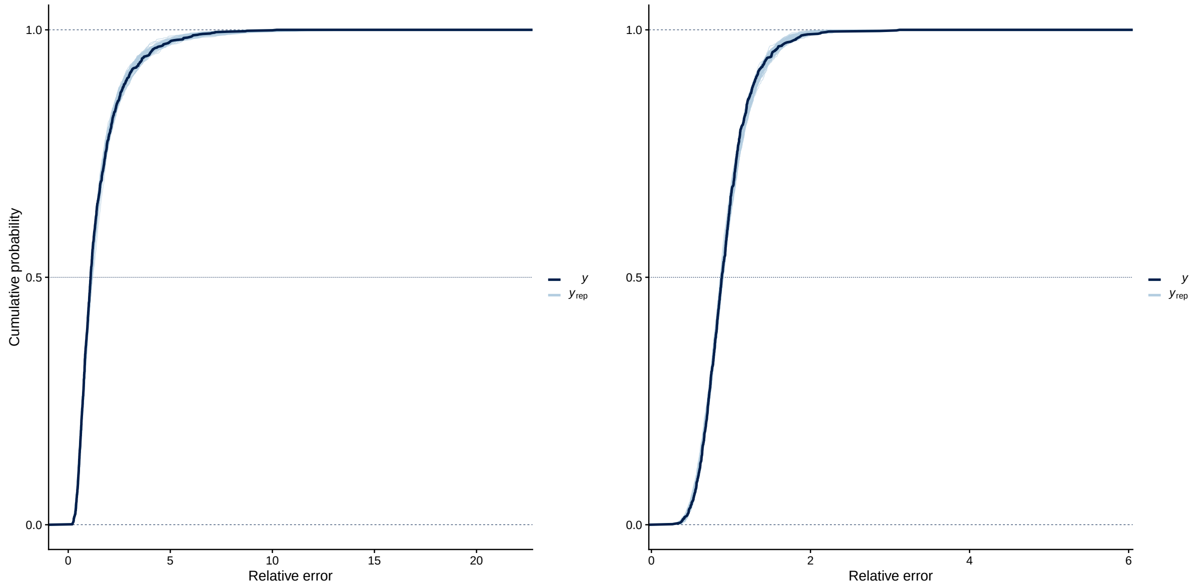


Figure B-5: Model fit for model relating model mis-specifications to assessment bias, assessed by posterior predictive draws from the model (blue lines) against the empirical distribution of data (assessment bias).

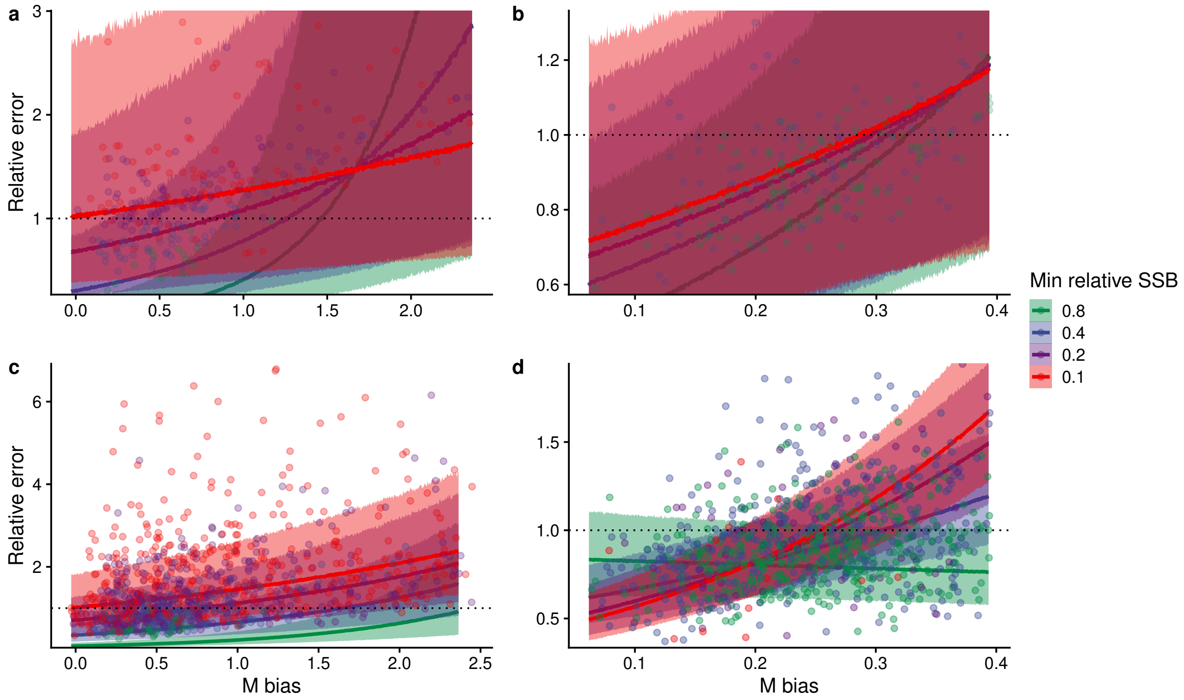


Figure B-6: Marginal effects of estimated M on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

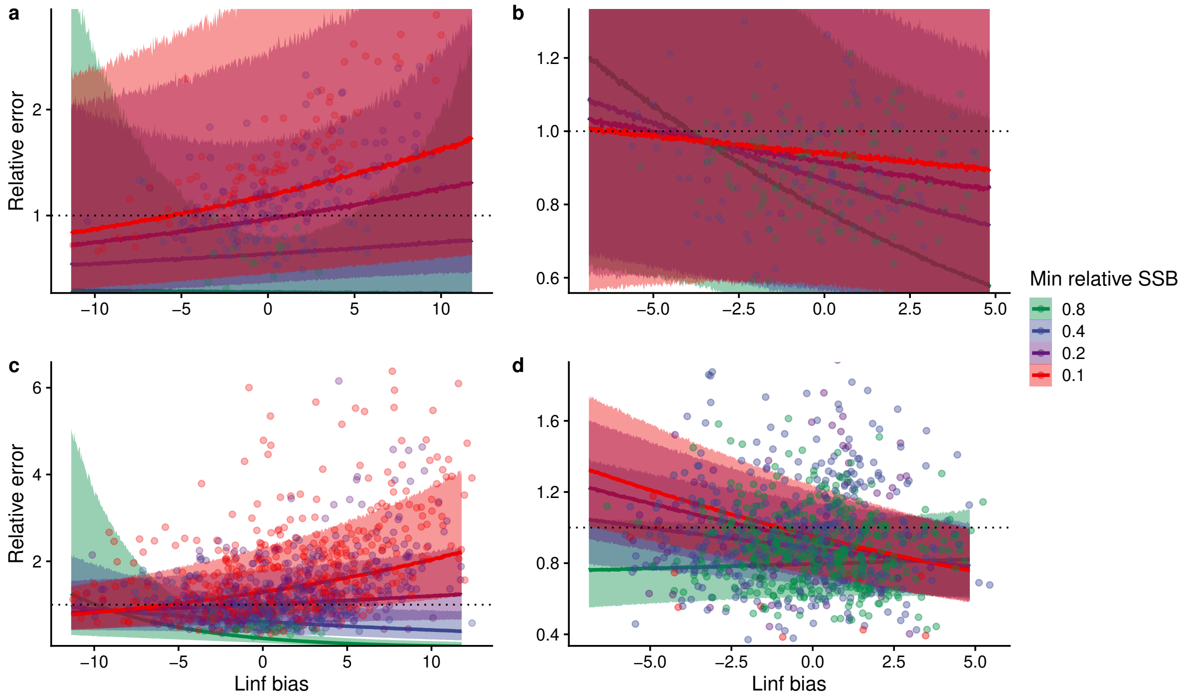


Figure B-7: Marginal effects of mis-specification of L_∞ on assessment bias within the base scenario (a&b) and among climate scenarios within replicates (c&d) for fast (left column) and slow (right column) life histories.

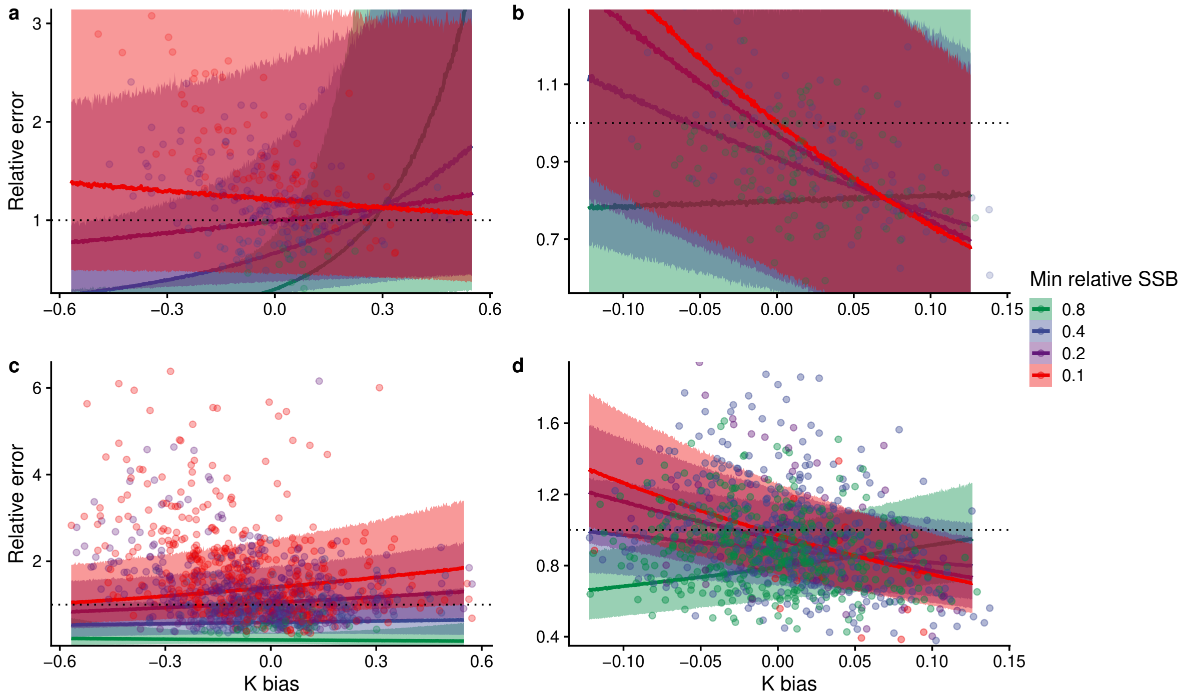


Figure B-8: Marginal effects of mis-specification of K on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

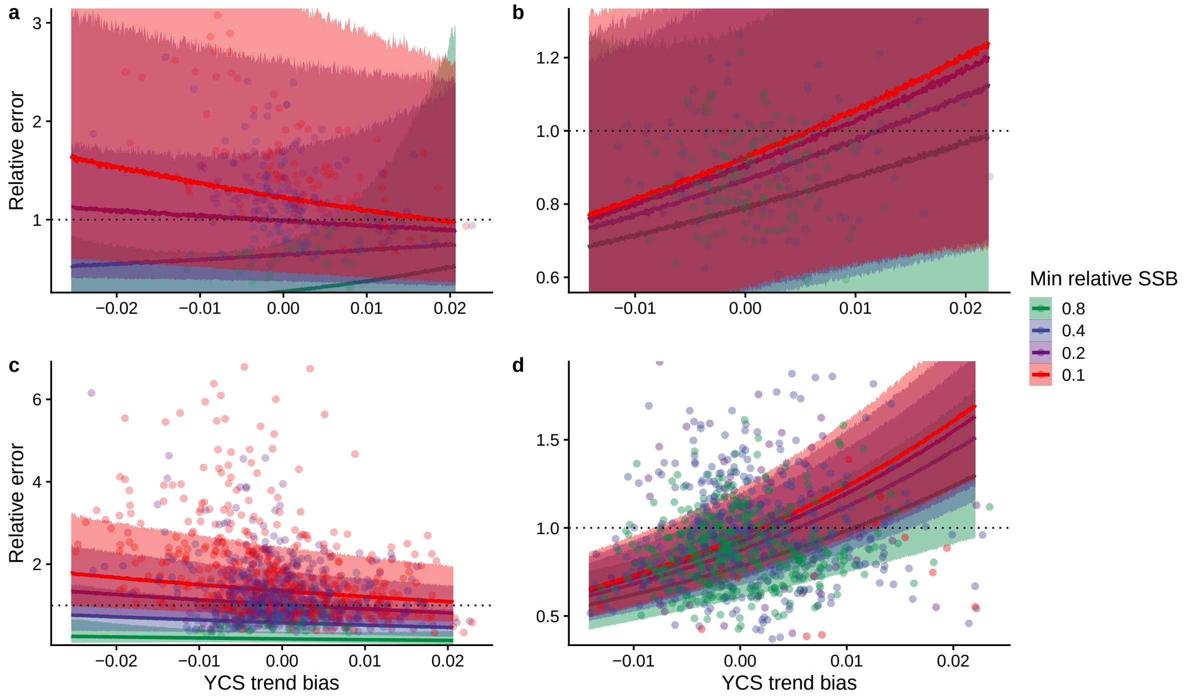
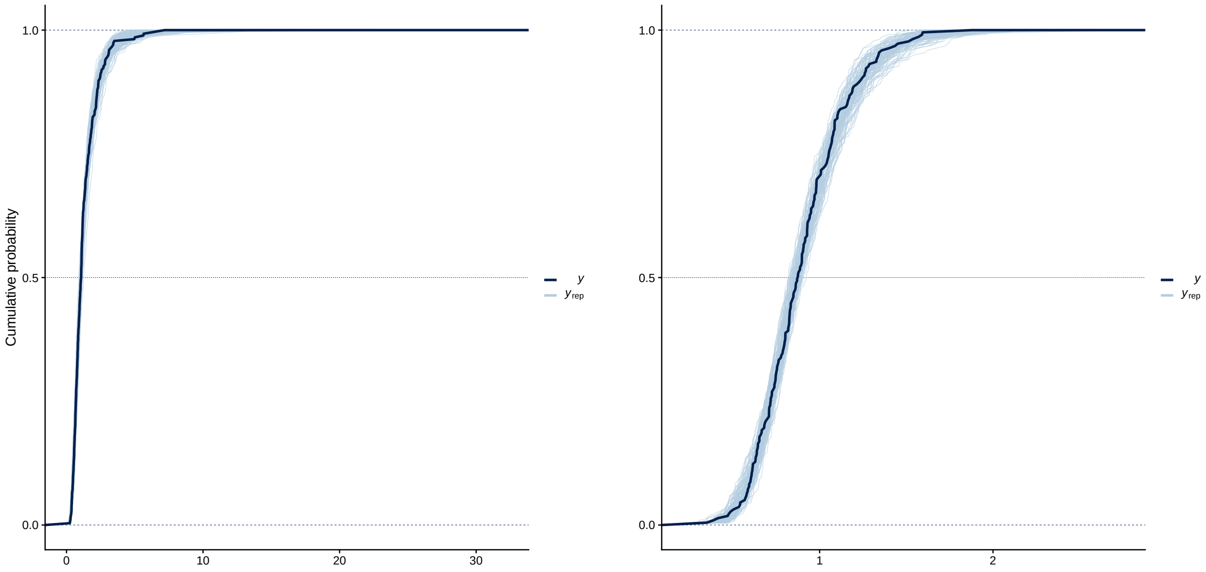


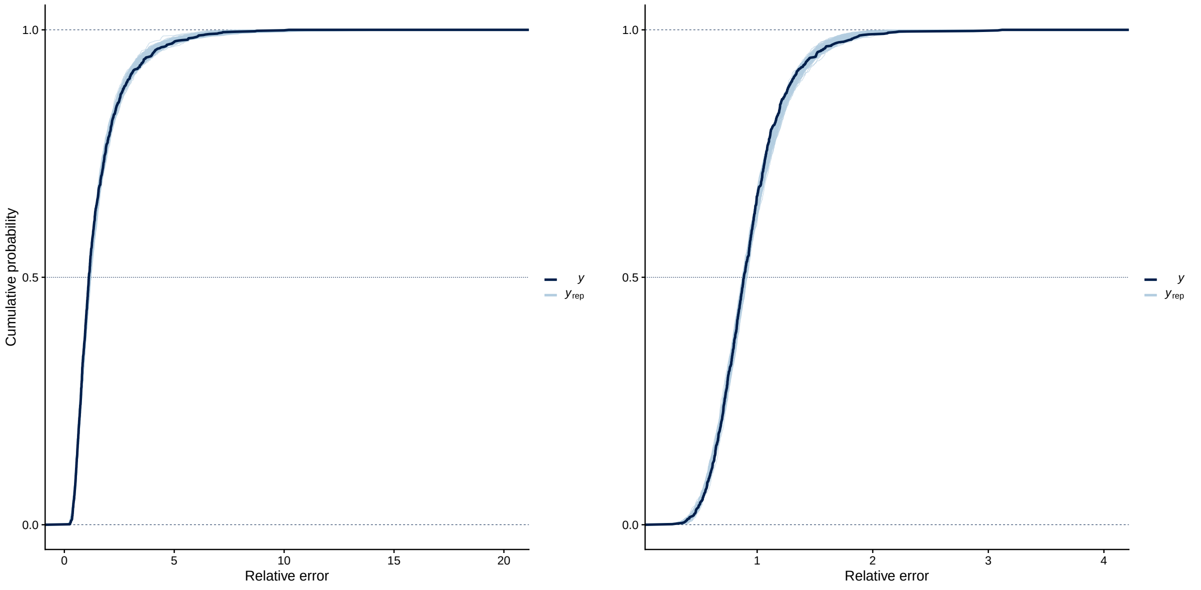
Figure B-9: Marginal effects of estimated year-class strength bias on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

B.3 Assessment outcomes as indicators of bias



(a) Climate scenarios - fast life history

(b) Climate scenarios - slow life history



(c) Base - fast life history

(d) Base - slow life history

Figure B-10: Model fit for model relating potential indicators of model misfit to assessment bias, assessed by posterior predictive draws from the model (blue lines) against the empirical distribution of data (assessment bias).

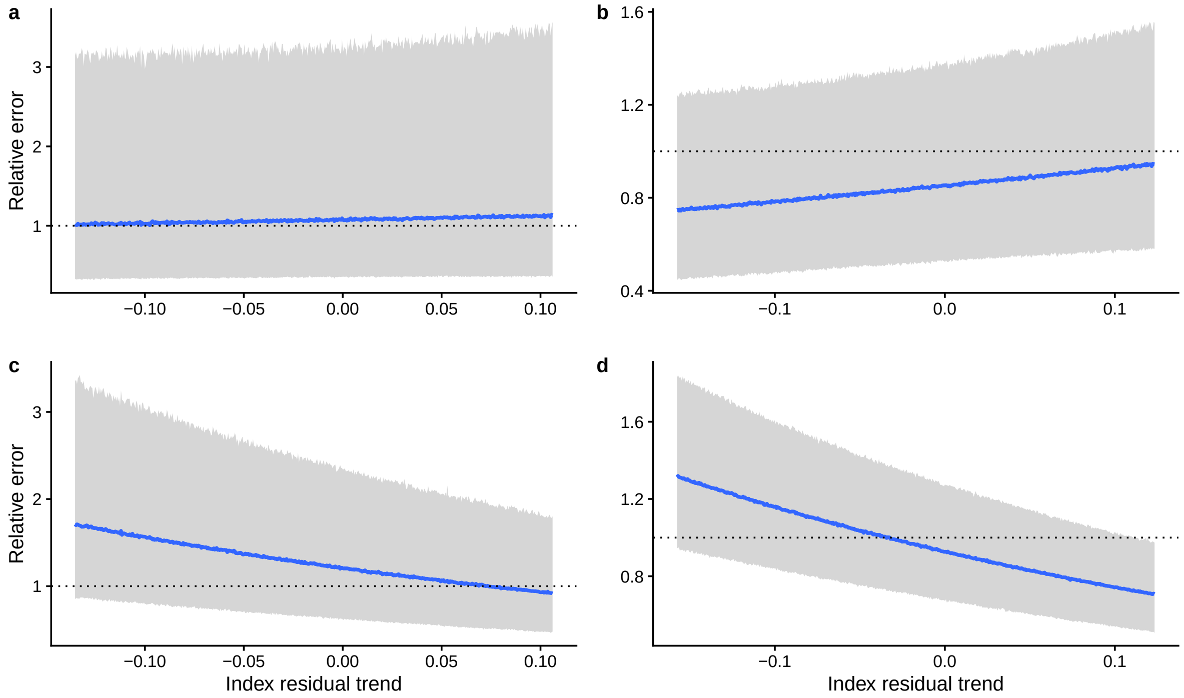


Figure B-11: Marginal effects of abundance index residual trend on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

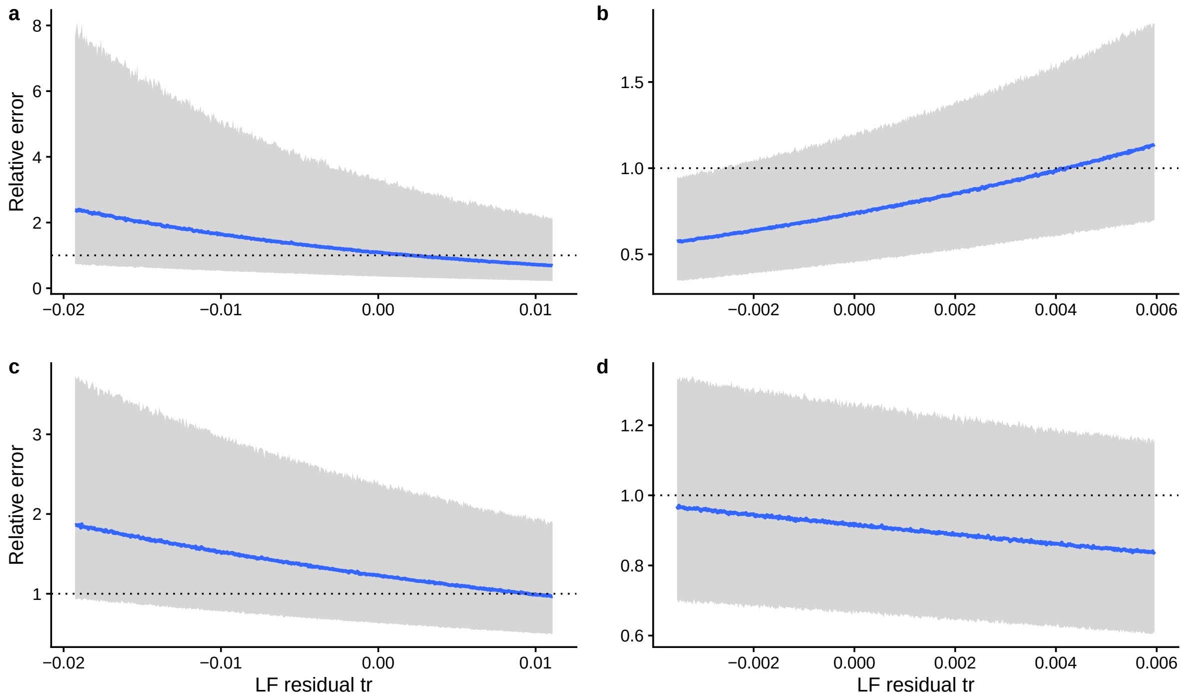


Figure B-12: Marginal effects of estimated length frequency residual trend on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.

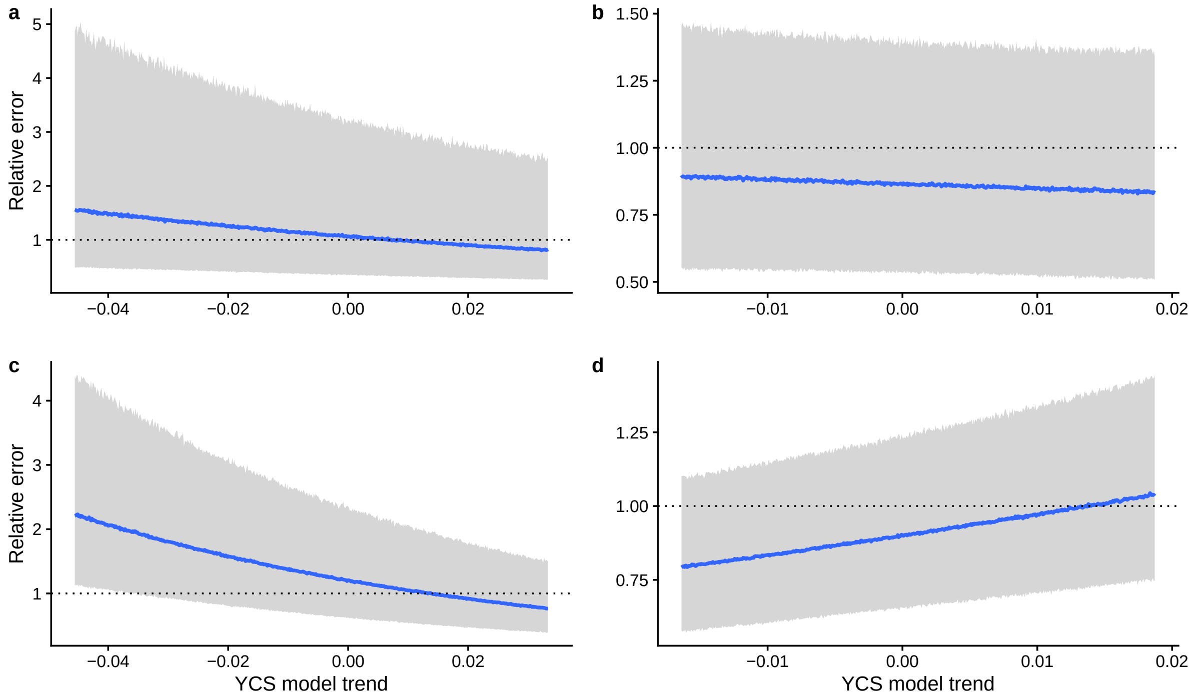


Figure B-13: Marginal effects of estimated year-class strength trend on assessment bias within the base scenario (top row - a&b) and among climate scenarios within replicates (bottom row - c&d) for fast (left column) and slow (right column) life histories.