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Simulation testing recruitment regime shifts based on the 2021 SNA 8 stock assessment

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C. Marsh,
J.R. McKenzie,
A.D. Langley

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Plain language summary

This project used simulation modelling to explore potential bias in snapper SNA 8 stock assessments when there has been a change in stock productivity (i.e., regime-shift), as may be expected under climate change.

Three SNA 8 stock productivity-change scenarios were investigated: the first assumed an upward shift in productivity after 2000; the second assumed a downward productivity shift after 2000; the third had no productivity shift.

Various SNA 8 stock assessment models were run under these productivity shift scenarios including one that explicitly allowed for a post-2000 productivity shift. Assessment bias was investigated specific to two important management metrics: current-stock-biomass; current-stock-status (being the ratio of current-stock-biomass to stock virgin (unexploited) biomass).

All assessment models produced unbiased estimates of current-stock-biomass under the no-regime-shift scenario. Only the post-2000 productivity shift model produced unbiased current-stock-biomass estimates under increasing and decreasing productivity scenarios.

All model current-stock-status estimates were biased under increasing and decreasing productivity scenarios. Although the post-2000 productivity shift model current-stock-status estimates were markedly less biased that those of the other models. An important finding from the study was all models were substantively less biased in their estimates of current-stock-biomass than current-stock-status.

An important conclusion from the simulation work was that we should not be using model predicted stock-status ratios as stock assessment measures when it is suspected that stock productivity is likely to have changed. Instead, we should be placing more ‘faith’ in assessment model predictions of current-stock-biomass and therefore be measuring sustainability solely against these estimates.

EXECUTIVE SUMMARY

Marsh, C.[1]; McKenzie, J.R.[1]; Langley, A.D.[2] (2024). Simulation testing recruitment productivity shifts based on the 2021 SNA 8 stock assessment.

***New Zealand Fisheries Assessment Report 2024/24.* 27 p.**

The effect of a mean recruitment regime shift on a stock with similar productivity dynamics to the west coast New Zealand snapper stock (SNA 8) was investigated using simulation modelling. Agent-based operating models (OMs) were used to generate fishery age compositional and Catch-Per-Unit-Effort (CPUE) observational data sets, which were then used by Stock Synthesis estimation models (EMs) to conduct assessments and explore assessment robustness to recruitment regime shifts.

Three OM scenarios were explored: the first assumed an upward shift in mean recruitment (R_0) after 2000; the second assumed a downward R_0 shift after 2000; the third assumed R_0 was constant (no shift). Three Stock Synthesis EMs were applied to each OM scenario, the EMs were structured as follows: EM-0 assumed R_0 was constant pursuant to the usual fitting constraint that the model estimated recruitment deviates must sum to zero, which is equivalent to constraining year class strengths to average one; EM-1 was structured to estimate a regime shift offset on R_0 (i.e., regime shift B_0) after 2000; EM-2 was structured as per the EM-0 but with the "average to one" constraint relaxed; Assessment results from the nine OM/EM combinations were compared against the "known" OM "realities" on the basis of fits to 100 independently generated datasets from each OM scenario.

All three EMs produced unbiased Spawning Stock Biomass predictions (SSB) from "no regime shift" OM data. SSB estimates from the regime shift EM-1 fitted to regime shift OM data were only slightly biased, whereas SSB predictions for the "average to one" fixed R_0 EM-0 were markedly biased. The SSB predictions from the "fixed R_0 no average constraint" EM-2 were only very slightly biased for regime shift OM data

Of more relevance to New Zealand fisheries management were the EM stock status estimates relative to mean productivity (B_0) thresholds, i.e., the Fisheries New Zealand harvest strategy standard $SSB^{y}_{\%B0}$ target reference points. When OM mean productivity was constant over time, $SSB^{y}_{\%B0}$ estimates from all three EMs were relatively unbiased. However, all three EM estimates of current stock status ($SSB^{current}_{\%B0}$) were biased under both dynamic R_0 OM scenarios. Although, bias in the $SSB^{current}_{\%B0}$ estimate was lowest with regime shift EM-1 as only this model could estimate a regime-shifted B_0 reference value. However, SSB predictions from two of the EMs (EM-1 & EM-2) were relatively robust (unbiased) to the recruitment shifts in our OMs. The lack of bias in SSB predictions from the explicit regime shift estimation model (EM-1 type) and the relaxed R_0 averaging constraint model (EM-2 type) is strong justification for using these types of models to assess SNA 8 and other stocks where it is suspected that productivity has been changing over the model history, and for adopting F-based (exploitation rate) reference points.

[1] National Institute of Water and Atmospheric Research (NIWA), New Zealand.
[2] Trophia Ltd., New Zealand.

1. INTRODUCTION

New Zealand snapper (*Chrysophrys auratus*) is a high-value commercial finfish species and important recreational species that has been managed under the Quota Management System (QMS) since 1986 (Fisheries New Zealand 2023). It occurs predominantly within North Island coastal and near-shore waters out to 200 m. Snapper quotas are set relative to four Quota Management Areas (QMAs). The west coast North Island SNA 8 QMA (Figure 1) is New Zealand's second largest biological snapper stock.

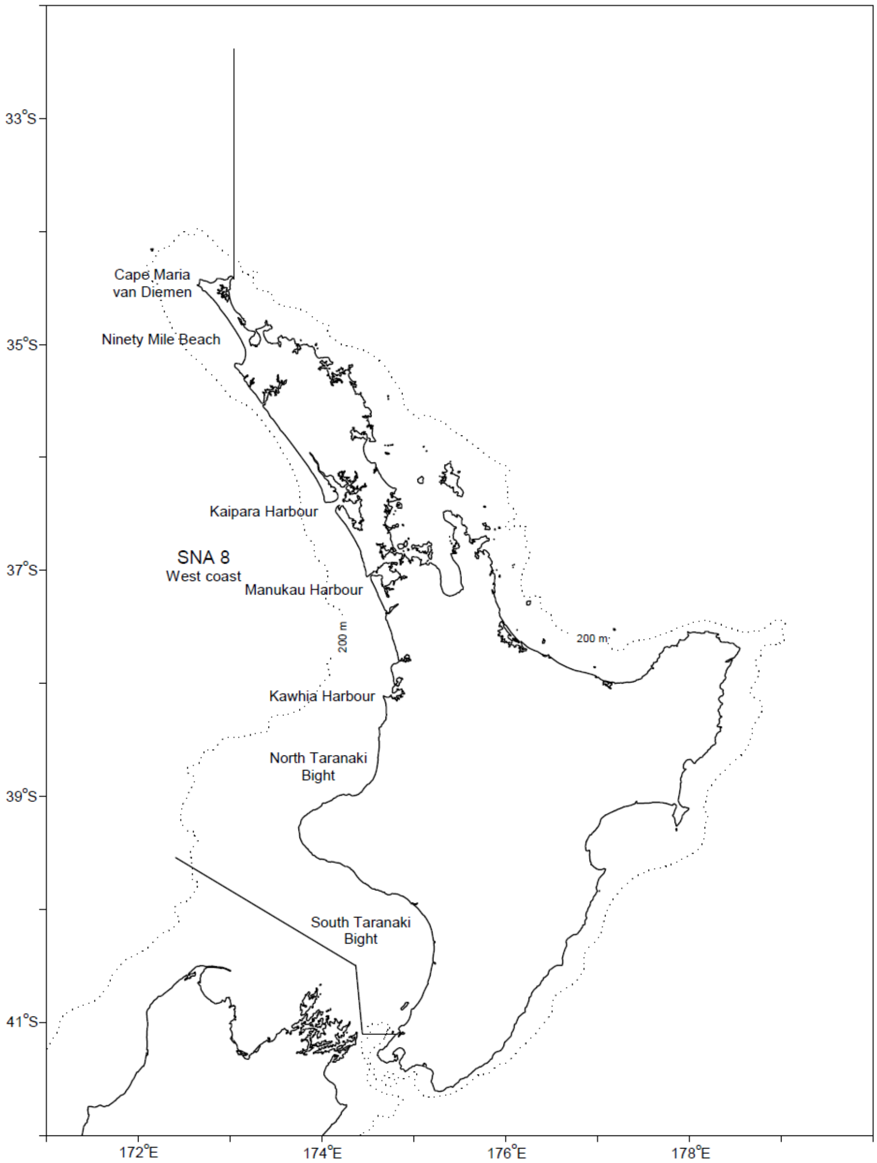

Figure 1: SNA 8 Quota Management Area spatial extent.

Commercial exploitation of SNA 8 dates to at least the start of the 20th century. Catch records exist from 1931 onwards (Fisheries New Zealand 2023). These records suggest annual commercial catches (taken mostly by trawlers) were relatively low (<100 t) up to the early 1950s, after which the trawl fishery began to expand its operations. From the mid-1950s to the mid-1960s the annual SNA 8 commercial catch had stabilised at around 1300 t. Annual catch increased after 1965 to around 4000 t, mostly due to the operation of Japanese longliners outside New Zealand territorial waters (i.e., beyond 12 miles). SNA 8 catches then increased further during the early 1970s with the introduction of domestic pair trawling, peaking at over 6000 t in the mid-1970s. Japanese longliners were excluded from the fishery after 1975 with the establishment of the 200 nautical mile New Zealand Exclusive Economic Zone. Domestic catches fell sharply in the early 1980s due to falling catch rates. In recognition that SNA 8 was highly exploited, a Total Allowable Commercial Catch (TACC) of 1300 t was established for SNA 8 when it was introduced to the QMS in 1986. Since 1986 the SNA 8 TACC has fluctuated in response to quota appeals and stock assessment advice. The current TACC of 1600 t, set in 2022 in response to increasing biomass largely driven by above average recruitment after 2005, is the highest since 1986.

The SNA 8 recreational catch history is uncertain before surveys began in the early 1990s but is thought to have been significantly lower prior to 1990 (Langley 2021). Surveys suggest SNA 8 annual recreational catches (mostly lining) were in the order of 300 t between 1990 and 2005. The recreational catch appears to have mirrored the significant increase in SNA 8 biomass after 2005; recent annual recreational catches are believed to be in the order of 800 t (Langley 2021).

SNA 8 stock monitoring data (age composition, trawl survey, CPUE, tagging) date from 1963 onwards (Davies et al. 1993, Langley 2021). There are two recognised CPUE relative abundance series: a pair trawl series covering the period 1974–1991; a bottom trawl series covering the period 1997 to current day (Langley 2021). Commercial catch at-age observations are available from the mid-1970s but age collection prior to 1989 was sporadic. Annual catch at-age sampling of the spring-summer peak trawl fisheries began in 1989 and continued to 2010, after which a triennial sampling regime was adopted.

Research trawl surveys within the SNA 8 stock boundary date from the 1970s. Lack of comparability in the design of these early surveys means the time series of comparable surveys only dates back to 1990 (Langley 2021). Four SNA 8 surveys were conducted between 1990 and 2000, after which surveys were curtailed and were not resumed until 2018. Four surveys have been conducted since 2018, the latest being in October 2023. The spatial extent of the recent surveys has been compromised by bans on trawling within near-shore Māui dolphin habitat areas that were first introduced in 2008 and subsequently extended in 2020. Not being able to survey with the Māui exclusion zones has cast doubt on the utility of the recent surveys to monitor adult stock abundance (Langley 2021). The full trawl survey series does, however, appear to adequately monitor relative cohort abundance for ages two to five (Langley 2021).

Tagging programmes conducted in 1990 and 2002 provide estimates of absolute spawning stock biomass for those years (Davies et al. 2013).

The most recent accepted SNA 8 stock assessment was conducted by Langley (2021) using Stock Synthesis (SS) software (Methot & Wetzel 2013). The Langley (2021) SNA 8 assessment model was a fully age-structured total catch history model and covered the period 1932–2021. The model assumes the SNA 8 stock to have been in a relatively virgin unexploited state in 1932. The model age structure covers ages 1–30 (both sexes combined with the sex ratio assumed to be 1:1 and time-invariant) with the 30-year age class being a plus group. The model uses externally derived von Bertalanffy (vB) growth curves to calculate mean weight at-age and to derive growth transition matrices for fitting to length observational data (largely recreational fishery data). The model accounts for three time periods of differing growth (1931–1979, 1980–2005, 2005–2021) by applying different vB parametrisations to each. The model assumes a Beverton and Holt stock recruitment relationship with steepness (h) value of 0.95. Natural mortality is assumed to be 0.075 and time-invariant. Maturity (both sexes) is assumed to be knife-edged at age three.

The model catch history recognises five fisheries: Japanese longline fishery, bottom trawl fishery, bottom pair trawl fishery, outside harbours recreational line fishery, inside harbours recreational line fishery.

Observational abundance data fitted in the model were: 1990 and 2002 tag biomass estimates, bottom pair trawl CPUE indices, bottom trawl CPUE indices, and trawl survey abundance indices for 2,3,4, and 5 year-old cohorts. Observational compositional data fitted in the model were: bottom pair trawl annual catch at-age, bottom trawl annual catch at-age, outside harbours recreational annual length frequency, inside harbours recreational annual length frequency, tagging programme length frequency.

Parameters estimated by the Langley (2021) base-case model were: R_0 mean number of one year-olds entering the model in the absence of fishing; recruitment deviates 1960–2019 (N = 60); bottom trawl and pair bottom trawl selectivity function (five parameter double normal plateau function); five abundance series catchability coefficients (q), one for each of the trawl survey pre-recruit cohorts and the two CPUE series. All the other model parameters were fixed having been derived outside the model. Model parameter estimates were constrained by suitable priors; for example, recruitment deviates were constrained in log-space to come from a distribution with a mean of 0 and a standard deviation (*sigmaR*) of 0.6. An important point is that the model estimate of R_0 was strongly determined by length of interval where free recruitment deviates are estimated; specifically, the implicit constraint within the model that the mean of the estimated recruitment deviates should be close to one in natural space.

The 2021 SNA 8 assessment suggested that by 2021 the stock had rebuilt to 54% B_0, up from 10% B_0 in 2002, despite catches being relatively constant over this period (Langley 2021). The main driver of the rebuild appears to have been several strong recruitment cohorts entering the fishery post 2005 (Figure 2), average recruitment over this period being 65% higher than the model predicted equilibrium recruitment level (R_0) (Langley 2021).

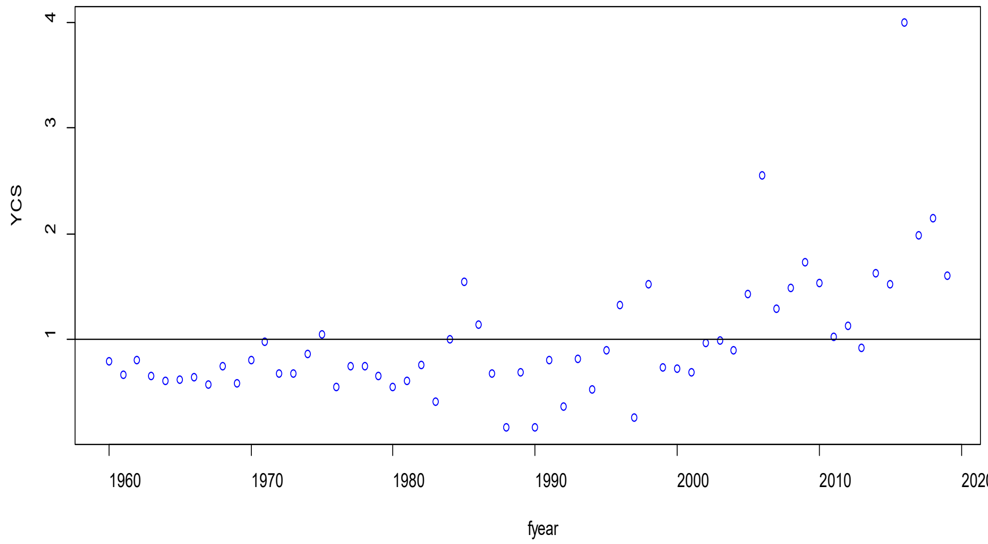

Figure 2: Estimated recruitment deviates from the 2021 SNA 8 assessment model expressed in natural space show a period of higher-than-average recruitment after 2005.

The recent period of above average SNA8 recruitments is consistent with a shift to a higher productivity regime and potentially challenges the validity of using yield-based targets and limits (e.g., % B_0) based on long-term recruitment averages to manage the stock.

This report explores the impact of recruitment regime shift on SNA 8 assessment by fitting a modified version of the 2021 assessment model to simulated data from Agent Based Operating models (ABMs). The ABM incorporated trends in recruitment consistent with those estimated in the 2021 stock assessment (Figure 2), in addition to other trends. The purpose of the simulation work was to investigate the potential for bias in SNA 8 assessments against yield-biased sustainability criteria under mis-specified recruitment assumptions, as well as to explore potential methods to account for regime shifts within the recruitment dynamic.

Simulations were conducted to explore three alternative recruitment scenarios. All three scenarios made different assumptions regarding mean recruitment in the last 20 years of the assessment period, these being: an increase, decrease, and constant mean recruitment. A range of Stock Synthesis (Methot & Wetzel 2013) estimation models (EMs) were developed and they also made different assumptions in the recruitment dynamic. The aim was to identify model assumptions that are robust under regime shifts with respect to estimating spawning stock biomass and related reference points.

This work was conducted under Fisheries New Zealand research project SNA2019-03A.

2. METHODS

2.1 Operating model

The operating model (OM) chosen for this simulation was the C++ agent-based model (CABM) developed by Marsh (2022). CABM is an agent-based model (ABM) that expresses a fish stock as a collection of agents. An agent is defined as one or more fish with homogenous characteristics, i.e., length, weight, and sex. When an agent represents a single individual, the ABM becomes an individual-based model (Grimm & Railsback 2013). Given fish stocks consist of millions if not billions of individuals, ABMs are often more practical than individual-based models due to computational limitations; i.e., it requires large amounts of memory to record and modify millions of agents. CABM uses functions to grow, move, create, and kill agents over time, termed agent dynamics. When summaries are made over all agents, stock level quantities are observed. Simulating stocks with this high level of detail allows heterogeneity in key dynamics such as growth and mortality. This is an advantage of ABMs as this heterogeneity is often approximated in other OM frameworks. However, the main advantage of the ABM simulation approach used is that the model is capable of dealing reliably with length-age integrated observational data.

CABM repeatedly applies an annual cycle over a user defined number of years. An annual cycle consists of discrete time steps that contain user defined agent dynamics. The CABM model developed for this simulation assumed a single area with an annual cycle consisted of three time-step with the following agent-dynamics.

- Time step 1
  - Recruitment and Spawning stock biomass calculations
- Time step 2
  - Half annual growth
  - Half natural mortality
  - Fishing mortality
  - Remaining natural mortality
- Time step 3
  - Remaining annual growth
  - Ageing

The agent dynamics outlined in the above annual cycle are described in more detail in Appendix A. The CABM operating model structure was primarily based on the 2021 SNA 8 assessment model (Langley 2021); however, there were four deviations from this assessment model. The first, related to how recruitment was parameterised and was the main dynamic under investigation (Section 2.3). The second related to time-varying growth. The 2021 assessment assumed three periods with different von Bertalanffy (vB) growth parameters (Langley 2021). For this simulation we assumed only a single vB growth curve that was consistent over the entire time series. Third, we converted length-frequency observations and selectivities for the recreational fishery to age-frequency observations and age-based selectivities. Early exploration found the estimation model (EM, see Section 2.2) generated a small bias when simulating length frequency observations with length-based selectivities for the recreational fisheries from CABM. Due to resource constraints this small bias was never fully resolved, and the compositional data were changed from length to age by use of appropriate age-length keys derived from commercial catch sampling (Walsh et al. 2019). The fourth change dropped the tag abundance observations. The resulting changes meant the OM specifications, although 'similar' to the SNA 8 2021 assessment model in productivity assumptions, did not exactly replicate the assessment.

The remaining OM dynamics were consistent with the 2021 stock assessment with parameter values set to the estimated (i.e., selectivity parameters as MCMC median values) and fixed values (i.e., *M*, steepness, maturity, etc). The sex ratio in the OM was 50:50 with equivalent growth and maturity for male and female fish (i.e., unisex).

The CABM OM fisheries were as per the 2021 SNA 8 assessment model (Figure 3). The OM similarly commenced in an assumed virgin equilibrium state in 1932 extending to a terminal or current fishing year of 2020. CABM applies an annual fishing mortality and, due to the stochastic nature of CABM, produces varying catches for the same fishing mortality.

The CABM OM was tasked with producing stock assessment observational and catch history simulated data consistent with those used by the 2021 SNA 8 assessment model (Figure 3). The OM simulated data were generated at a higher precision than was assumed in the 2021 assessment model with age-compositional data simulated with an effective sample size of 500 and abundance data with a coefficient of variation (CV) of 0.1. We do not anticipate the main results to differ if the simulation was rerun with less precise data. However, we would expect more variable results.

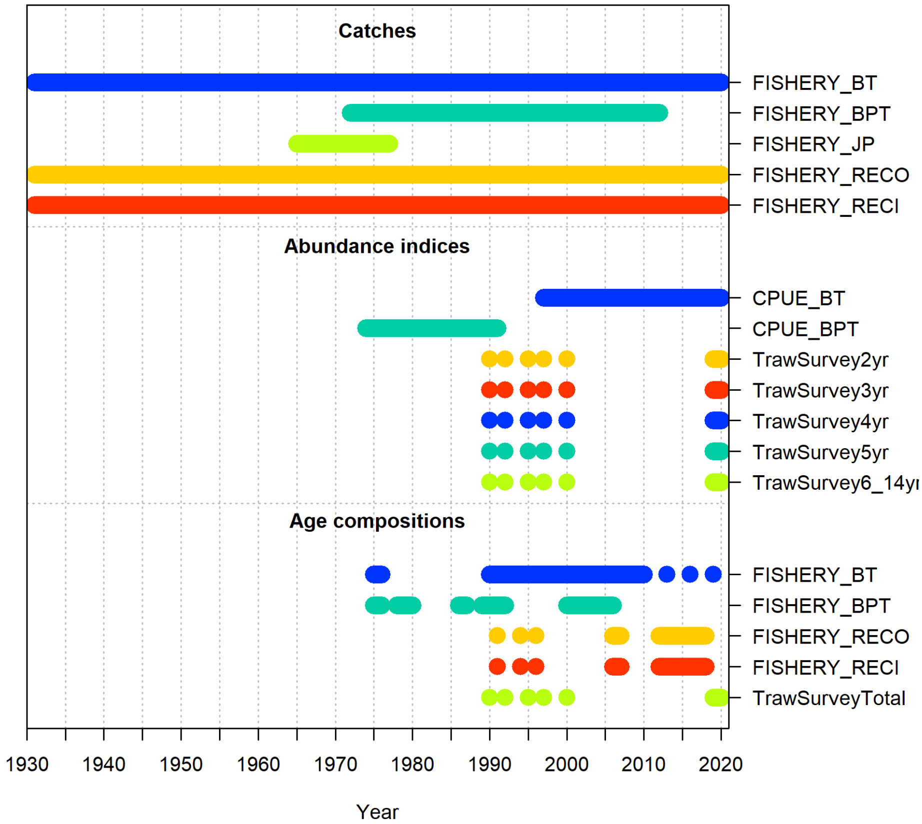

Figure 3: Observation and catches generated from CABM OM. BT = bottom trawl fishery, BPT = bottom pair trawl fishery, JP = Japanese longline fishery, RECO = outside harbours recreational line fishery, RECI = inside harbours recreational line fishery.

2.2 Estimation model

The estimation model (EM) framework used for the simulation was Stock Synthesis (version V3.30.17.00) (Methot & Wetzel 2013) as this was the modelling software used for the 2021 assessment (Langley 2021). The EM structural configuration and parameterisation was the same as the CABM OM (Section 2.1 and Appendix A), with the exception of recruitment. The three EMs made different assumptions regarding recruitment.

EM-0: Assumed a constant R_0 and applied a hard constraint that the mean of the observed recruitment deviates is zero ($\sum_y \varepsilon_y = 0$). This is the most common assumption in age-based stock assessments (Marsh et al. 2021). This is equivalent to applying the Haist parameterisation for year class strength parameters in the CASAL modelling platform (Bull et al. 2012).

EM-1: Assumed a regime shift occurred in 2000. SS allows users to apply a regime shift for R_0 by introducing a multiplier denoted by γ_y

$$R_0^y = R_0 \exp(\gamma_y)$$

where, γ_y is the regime parameter (Methot 2000). From 1932 to 1999, γ_y was set equal to 0; i.e., it had no contribution. Whereas between 2000 and 2020 a single parameter was estimated and assumed for all γ_y.

EM-2: Like EM-0 but without the hard constraint $\sum_y \varepsilon_y = 0$. There is a note in the SS user manual that "the [recruitment] deviations do not have an explicit constraint to sum to zero, although they still should end up having close to a zero sum. The difference in model performance between options $\sum_y \varepsilon_y = 0$ or not has not been fully explored to date". This suggested that this was experimental functionality in SS.

2.3 Simulation scenarios

Three CABM OMs were developed, each representing a different mean recruitment regime-shift dynamic: 'increasing R_0' scenario; 'decreasing R_0' scenario; 'constant R_0' scenario (Figure 4). The 'constant R_0' was primarily added for validation purposes, and the 'decreasing R_0' scenario was added to explore the 'other side of the coin' in terms of regime shifts. Although this trend is not observed in SNA 8, with climate change there are expected to be both winners and losers (Free et al. 2019), where the decreasing trends explore a decreasing shift in recruitment productivity.

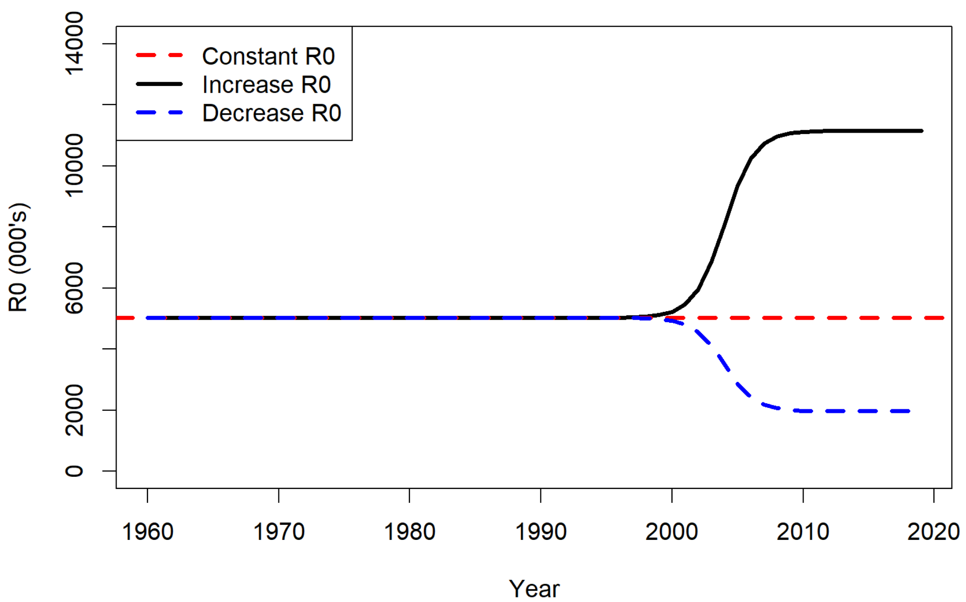

Figure 4: Assumed values for time-varying mean recruitment (R_0^y), for three CABM OMs used in the simulation.

Estimated recruitment from the 2021 SNA 8 assessment was consistently higher during the later years when compared with earlier estimates (Figure 2). A Fisheries New Zealand Inshore Working Group suggested that a logistic step-change was a plausible representation of the upward trend seen in year class strength deviates from the 2020 SNA 8 assessment model (Figure 2) for simulation purposes. Therefore, a logistic curve was fitted to the 2020 SNA 8 assessment model recruitment deviates

(Appendix B). The fitted curve was then rescaled to have a starting estimation year (1960) scalar factor of 1.0 (Appendix B). The final scaled logistic curve ($\hat{\varepsilon}_y$) was then multiplied by the median MCMC estimate for R_0 from the 2020 SNA 8 assessment model, to derive the OM's time-varying mean recruitment parameter

$$R_0^y = R_0 \ \exp(\hat{\varepsilon}_y).$$

This was input to a CABM OM which created the 'increasing R_0' scenario (Figure 4). Two other recruitment assumptions were explored which were the 'constant R_0' scenario and 'decreasing R_0' scenario. The estimated values of $\hat{\varepsilon}_y$ from the 'increasing R_0' scenario were used to derive values of 'decreasing R_0' scenario which were denoted as $\hat{\varepsilon}_y^*$ this was to ensure the magnitude was similar

$$\hat{\varepsilon}_y^* = 1 - 0.5 \times (\hat{\varepsilon}_y - 1)\,.$$

This formula was somewhat arbitrary but resulted in the shift in R_0 shown in Figure 4, which is close to an inverse relationship. In the future it is recommended to use the inverse

$$\hat{\varepsilon}_y^* = \log\left(\frac{1}{\exp\,(\hat{\varepsilon}_y)}\right).$$

Each OM scenario was run 100 times with a different set of year class strengths generated for each simulated a data set. This resulted in 300 simulated data sets (three CABM models × 100 simulations) that were then used by three SNA 8 estimation models (Section 2.2) to estimate and assess the assessment models bias, accuracy, and robustness.

Each simulated data set was re-estimated by all three EMs (Section 2.2) and a range of summaries are provided in Section 3. These included spawning stock biomasses (SSB) along with relevant reference points. We also explored model fits for some realisations of the EMs to ensure we were not presenting results from models that are not plausible due to poor fits to the data.

Relative error was used to describe bias in parameters and derived quantities,

$$RE(\vartheta) = \frac{\hat{\vartheta} - \vartheta}{\vartheta} \times 100.$$

SS static SSB reference point has the following formula,

$$SSB_{\%B0}^{y} = \frac{SSB^y}{B_0}.$$

SS regime shift SSB reference point has the following formula,

$$SSB_{\%B0}^{y} = \frac{SSB^y}{B_0 \exp\,(\gamma_y)}$$

where γ_y is the estimated R_0 regime shift multiplier as described above.

3. RESULTS

All EMs produced unbiased SSB estimates under the constant R_0 scenario (Figure 5), as were the $SSB_{\%B0}^{y}$ estimates from all three EMs (Figure 6).

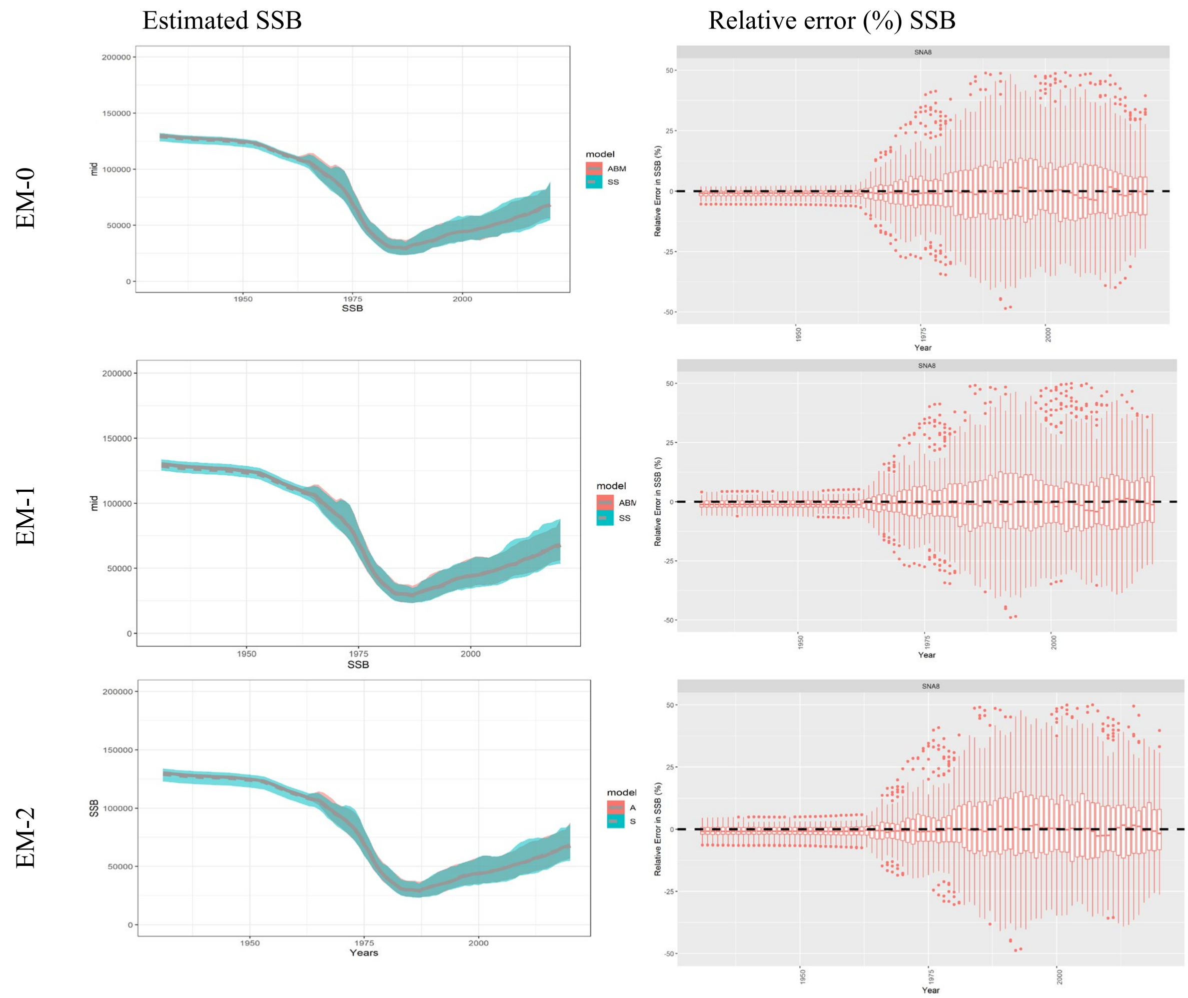

Figure 5: EM SSB estimates and relative error under constant R_0 scenario (EM-0 mean recruitment deviance constrained to zero ($\sum_y \varepsilon_y = 0$); EM-1 mean recruitment scalar (estimated) applied after 2000; EM-2 mean recruitment error unconstrained).

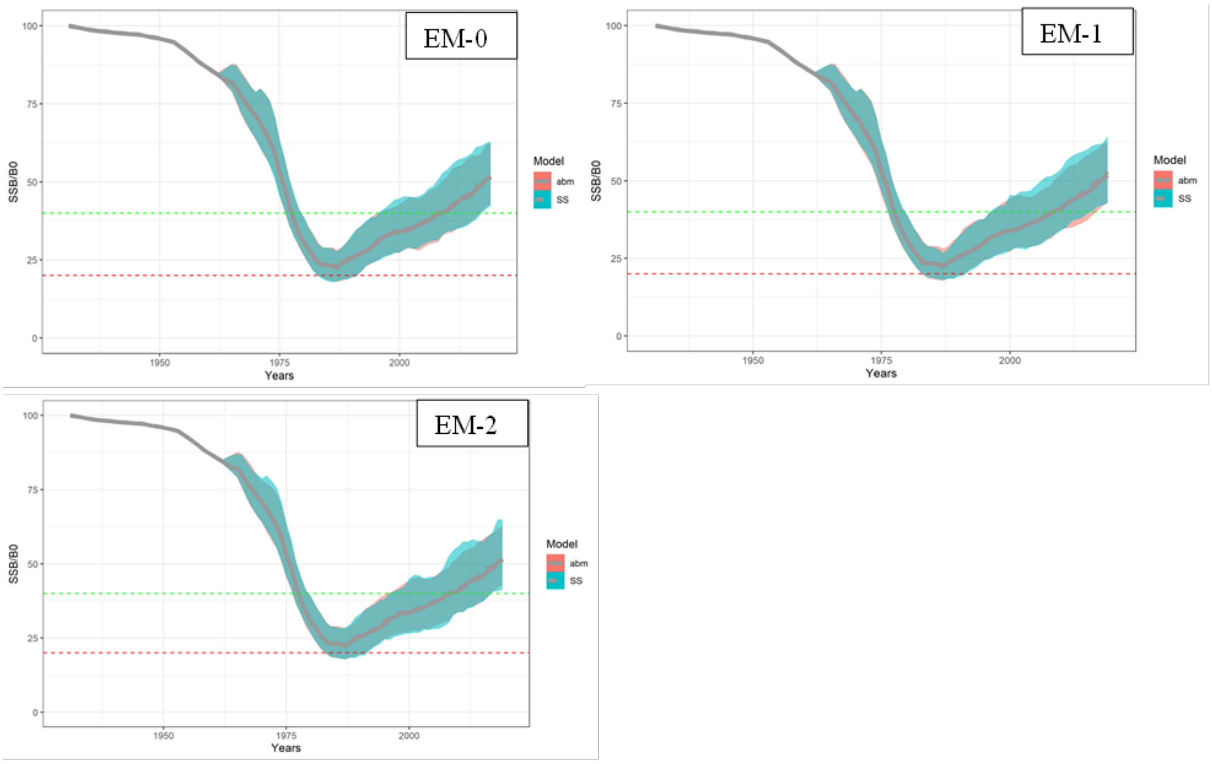

Figure 6: Comparisons of $SSB^{y}_{\%B0}$ using a static R_0 scenario. Median (line) and 95% confidence intervals (shaded) from SSB median posterior density fits to 100 OM data simulations (EM-0 mean recruitment deviance constrained to zero ($\sum_y \varepsilon_y = 0$); EM-1 mean recruitment scalar (estimated) applied after 2000; EM-2 mean recruitment error unconstrained).

For the increasing dynamic R_0 scenario the zero-mean constraint EM (EM-0) was markedly biased with respect to estimating SSB, recent SSBs being biased low (Figure 7), the level of bias observed likely proportional to the degree recent recruits depart from the long-term average (in this case ~64%). As expected, the recruitment scalar EM (EM-1) produced the least biased SSB trajectory; the final 2020 model estimate being virtually unbiased (Figure 7). However, the unconstrained recruitment error EM (EM-2) SSB predictions were almost as good as the recruitment scaler EM (EM-1), SSB being only marginally biased low in 2020 (Figure 7).

All three EMs over-estimated stock status in the 2020 model year ($SSB^{2020}_{\%B0}$; Figure 8). The level of over-estimation in the recruitment scalar EM (EM-1), however, was not as extreme as the other two models (Figure 8). Despite being only marginally biased in its SSB predictions (Figure 7), the recruitment scaler EM (EM-2) produced the most biased 2020 stock status prediction ($SSB^{2020}_{\%B0}$) of the three EMs (Figure 8). The reason why EM-0 2020 model year 2020 stock status prediction is less biased than the unconstrained mean EM-2 model is due to the EM-0 model over-estimating B_0 and under-estimating B_{2020} which results in a 2020 stock status prediction closer to the "true" operating model stock status biomass ratio.

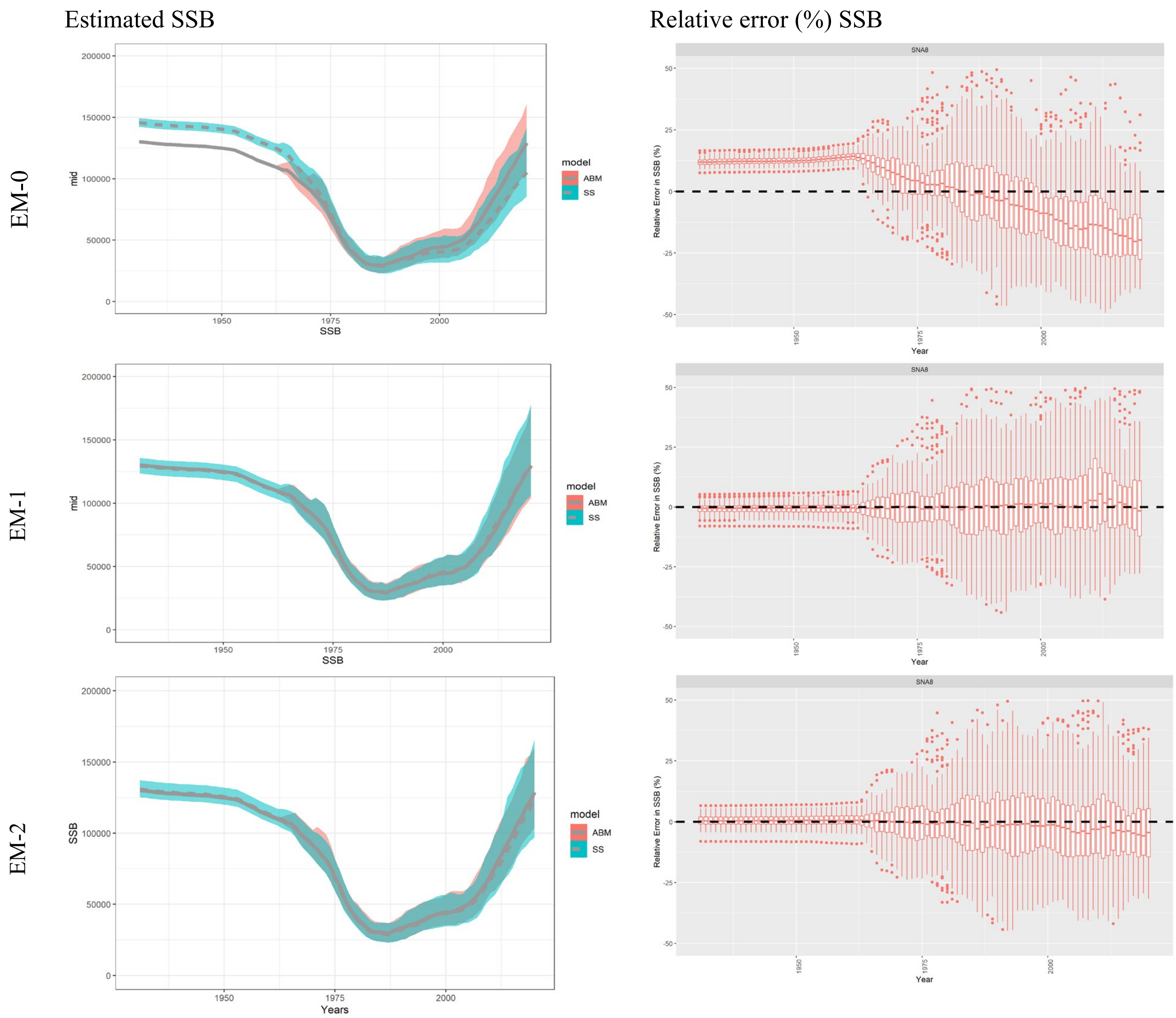

Figure 7: EM SSB estimates and relative error under the increase R_0 regime-shift scenario (EM-0 mean recruitment deviance constrained to zero ($\sum_y \varepsilon_y = 0$); EM-1 mean recruitment scalar (estimated) applied after 2000; EM-2 mean recruitment error unconstrained).

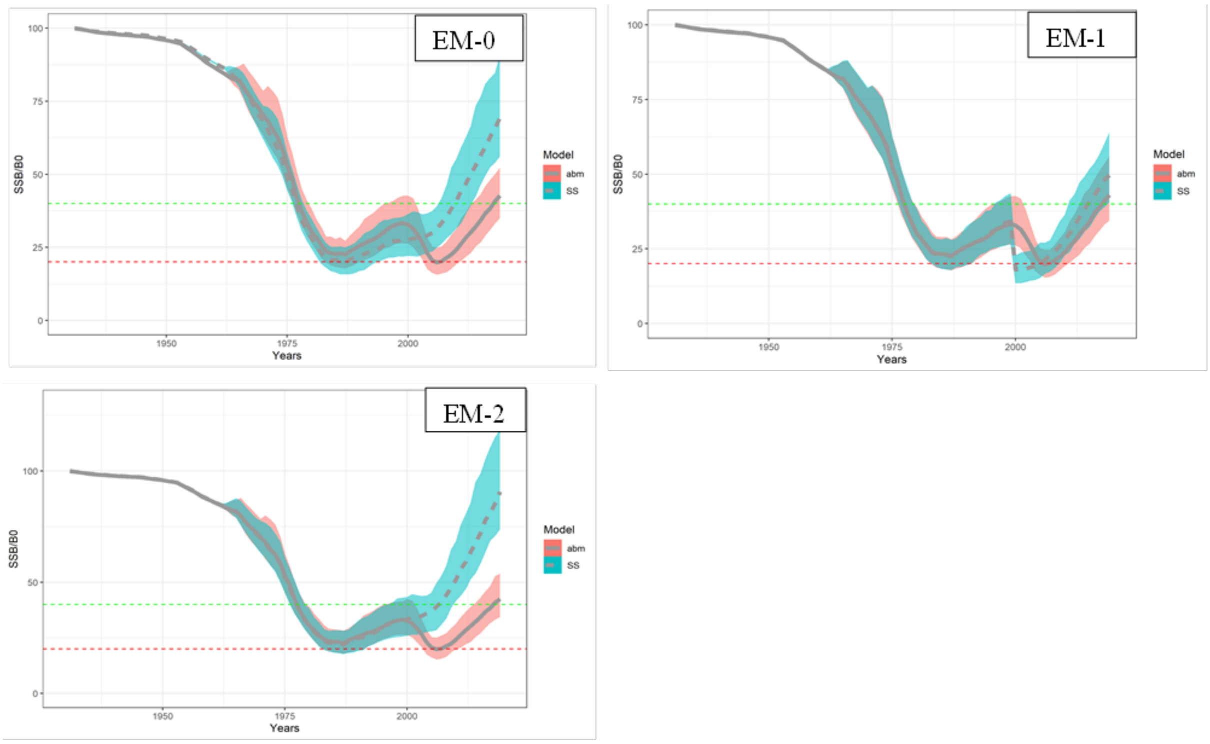

Figure 8: Comparisons of $SSB^{y}_{\%B0}$ under the increase R_0 regime-shift. Median (line) and 95% confidence intervals (shaded) from SS3 median posterior density fits to 100 OM data simulations (EM-0 mean recruitment deviance constrained to zero $(\sum_y \varepsilon_y = 0)$; EM-1 mean recruitment scalar (estimated) applied after 2000; EM-2 mean recruitment error unconstrained).

The SSB and 2020 stock status bias patterns seen in the EM fits to decreasing dynamic R_0 OM scenarios were of similar magnitude to those of the R_0 increasing OM scenarios but, understandably, in the reverse direction (Figures 9 & 10).

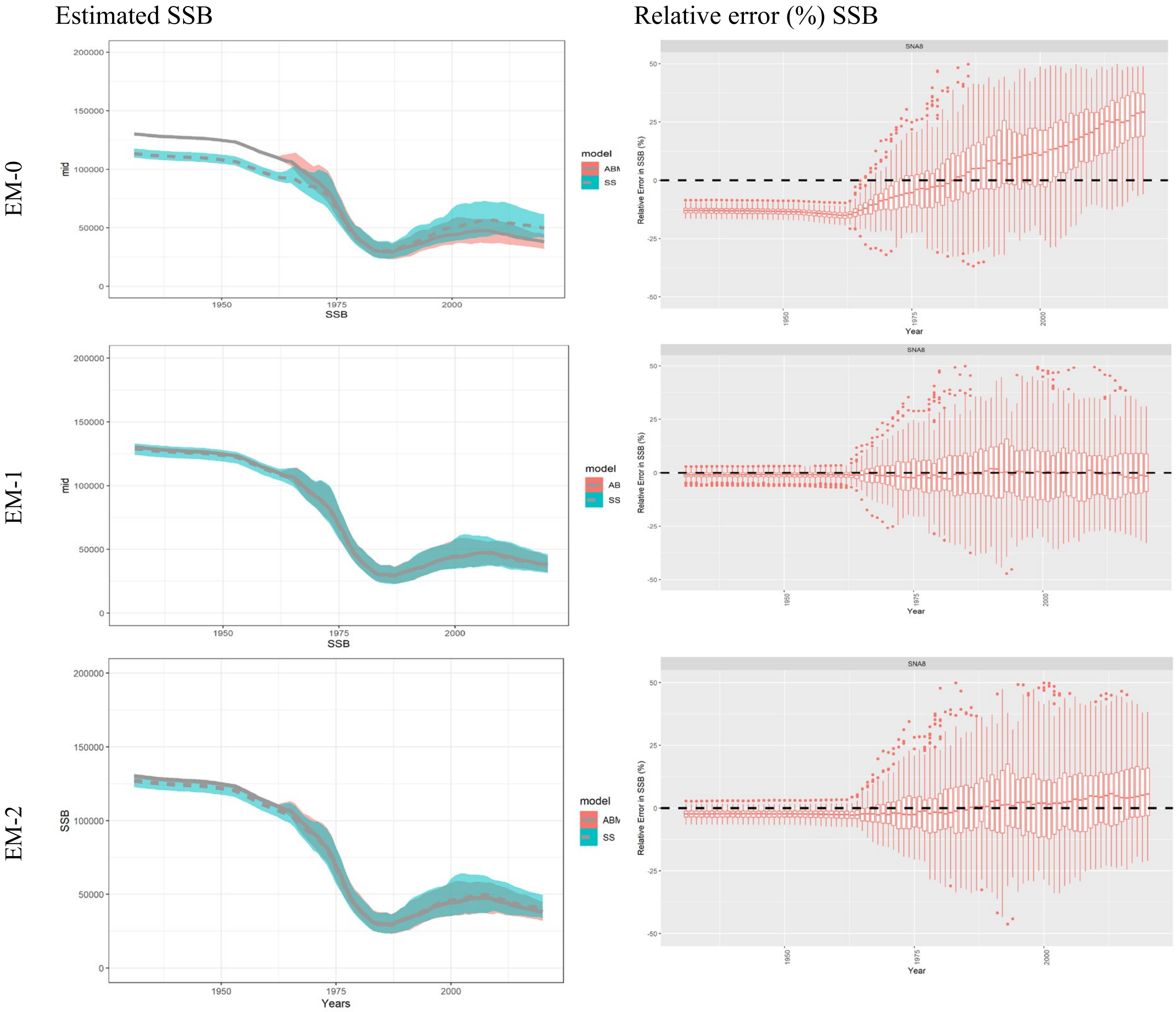

Figure 9: EM SSB estimates and relative error under the decrease R_0 regime-shift scenario (EM-0 mean recruitment deviance constrained to zero ($\sum_y \varepsilon_y = 0$); EM-1 mean recruitment scalar (estimated) applied after 2000; EM-2 mean recruitment error unconstrained).

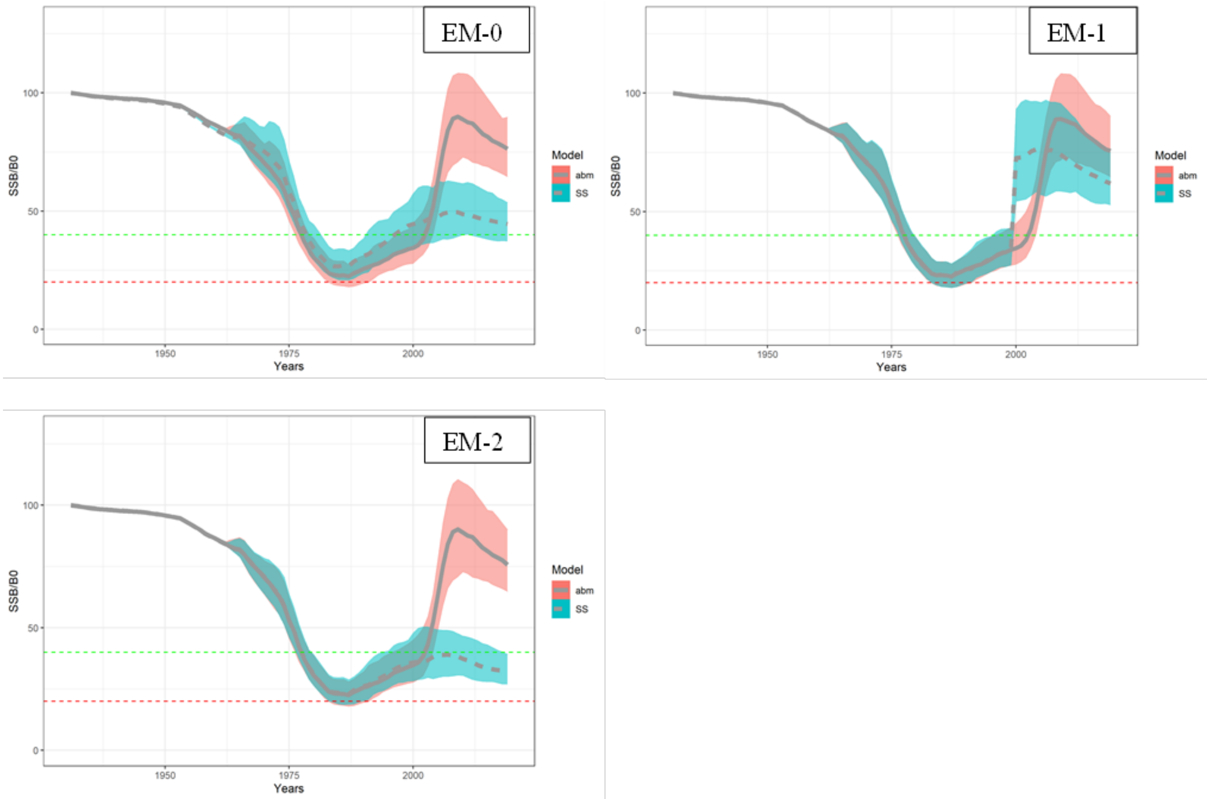

Figure 10: Comparisons of $SSB^{y}_{\%B0}$ under the decrease R_0 regime-shift scenario. Median (line) and 95% confidence intervals (shaded) from SS3 median posterior density fits to 100 OM data simulations (EM-0 mean recruitment deviance constrained to zero ($\sum_y \varepsilon_y = 0$); EM-1 mean recruitment scalar (estimated) applied after 2000; EM-2 mean recruitment error unconstrained).

4. DISCUSSION

This work explored three alternative recruitment assumptions that are readily available in stock assessment models and investigated how well they estimated abundance and biological reference points (BRPs) under varying recruitment assumptions using simulations.

Most stock assessments (SA) are predicated on equilibrium productivity assumptions, specifically that recruitment, growth, natural mortality, and steepness, although sometimes variable or cyclic when viewed over the relative ‘short term’ (e.g., multiple years), are adequately represented in SA models by ‘long-term’ (e.g., multiple decades) averages; e.g., mean recruitment under unexploited conditions (R_0). If we accept the equilibrium assumptions for a given stock by inference, we also must accept that these in combination give rise to a **static** B_0 (Appendix C) being the largest average biomass a stock can be expected to attain under unexploited conditions. Violation of the equilibrium assumption in respect to one or more model productivity parameters could result in B_0 being **labile** which may call into question the validity of using static B_0 BRPs for making sustainability decisions (Berger 2019).

In most stock assessment models, R_0 and B_0 are linearly related such that if R_0 doubles, the model prediction of B_0 also doubles (see Appendix C). Consequently, most dynamic productivity research focus has been on detecting and accounting for dynamism in stock recruitment (e.g., A’mar et al. 2009, Haltuch et al. 2009, Hollowed et al. 2009, Punt et al. 2012, Szuwalski et al. 2015, Perälä et al. 2017, Berger 2019, Maunder & Thorson 2019, Holt & Michielsens 2020, Tang et al. 2021).

Although synonymous with the dynamic productivity concept, it should be noted that the term “dynamic-B_0” has a specific BRP definition in the literature (MacCall et al. 1985, Punt et al. 2014a, Berger 2019). The derivation of dynamic-B_0 BRPs requires re-running the final “accepted” stock assessment model in the absence of fishing ($F = 0$) after fixing model recruitment and other productivity parametrisations at their estimated values, the implicit assumption being that the environmental factors responsible for historical dynamic productivity were independent of fishing (Berger 2019). A logic flaw in the dynamic-B_0 BRP approach, overlooked by most authors, is that the initial starting B_0 in the $F = 0$ in the BPR deterministic model run is the model static B_0 estimate as derived over all observed recruitments under equilibrium assumptions; i.e., that the observed mean recruitment variation is zero in log-space. If we believe recent observed recruitments represent a departure from the long-term average in the model, then bias inherent in the model static B_0 estimate will also bias the model projected dynamic-B_0 BRPs. Specifically, the dynamic-B_0 BRP series will be biased low under increasing recruitment and biased high under decreasing recruitment. Assuming growth, maturity, natural mortality, and steepness are constant under variable recruitment, which they might not be, may serve to exacerbate the level of bias in model predictions.

In this study, SSBs were initially compared with a dynamic ${B_0}^y$ (${B_0}^y|_{F_y=0}$) that was automatically generated by SS. However, it was not clear how this dynamic ${B_0}^y$ was calculated, particularly considering the recruitment bias correction term was turned off during this simulation. Models that had unbiased estimates of SSB and $SSB^{y}_{\%B0}$ with static ${B_0}^y$ generated biased estimates of $SSB^{y}_{\%B0}$ when using a dynamic ${B_0}^y$, which was unexplainable. We recommend bias in SS derived dynamic ${B_0}^y$ BRPs be investigated further in future studies of this nature.

There was no apparent bias in the SSB_{2020} predictions from the regime shift EM-1 under both increasing and decreasing recruitment scenarios. In contrast, the SSB_{2020} predictions from the enforced equilibrium R_0 EM (EM-0) were significantly biased under both increasing and decreasing recruitment scenarios. An interesting finding, however, was that bias in the SSB_{2020} predictions from the two static B_0 models (EM-0 & EM-2) reduced to within 'acceptable' ranges when the mean constraint on R_0 was relaxed (EM-2). These results suggest we should probably not be enforcing equilibrium constraints on R_0 in assessment models where we think mean recruitment has been changing. However, recent exploration of recruitment assumptions did highlight that for some stock assessments, relaxing this constraint can lead to failed model convergence issues due to lack of data and/or large observation error (Marsh et al. 2021).

In contrast to the model SSB predictions, both static B_0 model predictions of current stock status ($SSB^{2020}_{\%B0}$) were strongly biased. These models significantly underestimated the magnitude of increase or decline, which would likely have had serious management implications had these been real assessments. The regime shift EM (EM-1) predictions of current stock status ($SSB^{2020}_{\%B0}$) were also biased under both increasing and decreasing recruitment scenarios, despite being structurally able to account the shift in R_0. However, the important aspects of this model were that the level of bias seen would have been unlikely to have led to poor management advice and, more importantly, the model was able to illustrate that a regime shift had occurred, albeit predicated on specifying when the regime breakpoint occurred in the model.

Overall, the best performing EM across all recruitment scenarios was EM-1 which had an explicit regime shift mechanism in the recruitment dynamic. There was a caveat for this result, that is we did not explore the effect of a mis-specified regime period. There was a slight mis-specification because the CABM model assumed a ramping change (logistic function) in recruitment, whereas the regime shift in SS was knife edge. Also, the period of the regime shift was 'known' by EM-1 in that the shift was fixed to occur in 2000. Allowing estimator models to have more freedom to estimate the shape and period of recruitment regime shifts is something to explore further in future research. Berger (2019) compared static and dynamic-B_0 BRP assessment predictions from hake, sardine, tuna, and rockfish assessment models under random, trending, auto-correlated, and cyclic (predator/prey) recruitment dynamics. Berger (2019) found major differences between static and dynamic model BRPs under trending and regime change recruitment variation. Whereas dynamic and static BRPs preformed similarly under auto-correlated and cyclic recruitment dynamics, this almost certainly was due to the lack of overall trend in Berger's data over the model observation period.

The present study focused on a regime change based on the estimated trends in recruitment from the 2021 SNA 8 assessment. In case of regime shifts, Maunder & Thorson (2019) suggest it is possibly more appropriate to estimate and account for the productivity shift by estimating a new $B_{0,}$ specific to this period, as an alternative to the dynamic-B_0 approach; i.e., EM-1 model in this report. However, this presupposes that the regime shift assumption is appropriate; i.e., sufficiently distinct when viewed in the context of the recruitment history (Szuwalski et al. 2015, Maunder & Thorson 2019). The challenge is to identify when a regime shift has occurred in the recruitment series. Punt et al. (2014) advocate use of the STARS algorithm (Rodionov & Overland 2005) as an appropriate objective method for identifying regime shift interval periods (i.e., periods of uniform average recruitment) in recruitment series.

The shift to higher recruitment in SNA 8 after 2000, seen in Figure 2, is also consistent with a non-equilibrium upward recruitment trend which is a more challenging dynamic for stock assessment models to account for, particularly when undertaking future projections (Punt et al. 2014a, Maunder & Thorson 2019). Options for deriving BRPs differ depending on the type of change being observed; i.e., regime shift or trend (Maunder & Thorson 2019). Punt et al. (2014) suggest that a "moving window" approach to the derivation of "recent" productivity BRPs may perform better than the dynamic-B_0 approach both being preferable to long-term average-based productivity BRPs. Again, the challenge is the choice of an appropriate "moving window" interval.

In situations where there is a strong ecological basis to assume that the observed productivity changes are being driven by environmental factors other than fishing, the use of covariate-based BRPs might be applicable; e.g., water temperature (Maunder & Watters 2003, Haltuch et al. 2009, Punt et al. 2014a, Maunder & Thorson 2019, Berger 2019, Crone et al. 2019). The difficulty with the use of environmental covariates in stock assessment models is that it pre-supposes the relationship between the covariate and model productivity (e.g., recruitment) is both well established and quantifiable (Rose 2000). Maunder & Thorson (2019) state that although there have been numerous studies comparing recruitment estimates from stock assessment models to environmental variables, few have integrated the environmental index into the stock assessment model and very few have been used for management. One of the main impediments to the wider use of covariates in stock assessments is that observed covariate-stock productivity relationships typically breakdown over time (Rose 2000, Maunder & Thorson 2019).

There is also a range of alternative population dynamics that are susceptible to regime shifts that were not considered in this study, such as growth, maturity, natural mortality, and steepness. Shifts in growth and maturity are more easily accounted for in stock assessment models because they can be directly observed (Langley 2021). In contrast, dynamics such as natural mortality and steepness are more difficult to estimate because they are not directly observable and must be estimated/inferred from multiple data sources (Peterman et al. 2000, Punt et al. 2012, Punt et al. 2014b).

Accounting for recent productivity change in stock assessments is a significant challenge for stock assessment, particularly in providing suitable BRPs for management. The number of New Zealand stocks undergoing productivity changes in response to climate change-induced shifting environmental baselines is likely to increase over the coming decades. This project has demonstrated the utility of simulation modelling to illustrate the potential biases in EM model-derived BRPs for SNA 8 under dynamic productivity change, but the finding has general applicability to other New Zealand stocks undergoing productivity shifts (e.g., SNA 7 and SNA 1).

Modelling approaches to account for productivity shifts, their relative merits, and underlying assumptions have been well described in the literature (e.g., Haltuch et al. 2009, Thorson et al. 2015, Perälä et al. 2017, Maunder & Thorson 2019, Holt & Michielsens 2020, O'Leary et al. 2020, Tang et al. 2021, Silvar-Viladomiu et al. 2022). The prerequisites for use of all these models is the need for long time series of observational data, in particular age-composition and abundance. We strongly adocate further use of simulation analysis for SNA 8, and other similarly dynamic stocks, for assessing the utility of alternative BRP assessment approaches. Simulation analysis, when framed in the broader context of Management Strategy Evalaution (Punt et al. 2016), should enable managers to assess the relative robustness of alternative EMs, BRPs, harvest control rule strategies, and, most importantly, appropriate monitoring frequencies (i.e., trawl surveys and catch at-age sampling), under a range of OM dynamic productivity assumptions (Punt et al. 2014a, Punt 2023).

5. POTENTIAL RESEARCH

A key finding from this work is that it illustrates the dangers of providing stock assessment advice pursuant to yield-based (B_0) BRP predictions from equilibrium stock assessment models where there has been clear evidence of recent change in recruitment patterns. This could possibly lead to an inappropriate catch limit that may be either unsustainable under conditions of a decreased mean recruitment productivity, or a missed opportunity during periods of higher productive times of increased mean recruitment. These results highlight the need for further exploration of dynamic reference points.

However, although all three models were biased in their current stock-status predictions ($SSB^{2020}_{\%B0}$) under increasing or decreasing recruitment trends, SSB predictions from two of the EMs (EM-1 & EM-2) were relatively robust (unbiased). This finding is strong justification for using explicit regime-shift estimation models (EM-1 type) or relaxed R_0 averaging constraint models (EM-2 type) and for adopting interim F-based (exploitation rate) reference points for SNA 8 and other stocks where it is suspected productivity has been changing over the model history.

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8. APPENDIX A

Specific equations for CABM OM in the SNA 8 simulations.

8.1 Growth

When the von Bertalanffy growth model is assumed, each agent is assigned an asymptotic length parameter denoted by $L_{i,\infty}$ from the following normal distribution

$$L_{i,\infty} \sim N(\bar{L}_{\infty}, CV),$$

where CV denotes the coefficient of variation, and $\bar{L}_{\infty}$ is the population mean asymptotic length.

When growth is specified in the annual cycle for time step t, CABM will iterate over all agents and increment each agent's length following:

$$l_{i,t+\Delta} = l_{i,t} + p_{\Delta}^{t}(L_{i,\infty} - l_{i,t})(1 - \exp(-k)$$

where k is the global growth coefficient, $l_{i,t}$is the i[th] agent's length in time step t and p_{Δ}^{t} denotes the proportion of annual increment to be added in time step t.

The growth dynamic changes an agent's weight after changing its length using the following allometric length-weight relationship,

$$w_i = \alpha {l_i}^{\beta}$$

where α and β are length-weight coefficients which are equal for all agents in the system.

8.2 Natural mortality

All agents were assumed to have the same natural mortality rate denoted by

$$\begin{aligned} &p_i = \exp(-Mp_{\Delta}^{t}) \quad , \forall\, X_{r,i} \in \boldsymbol{X}_r, \\ &I_i \sim Bern(p_i) \\ &I_i \begin{cases} 0 & \text{agent lived} \\ 1 & \text{agent dies} \end{cases} \end{aligned}$$

p_{Δ}^{t} is the proportion of annual natural mortality that is applied in time step t.

8.3 Fishing mortality

The Baranov catch equation was used to apply fishing mortality (*F*) to agents over time. Annual values of *F* are required for each fishing, denoted by F_y^f along with an assumed selectivity for each fishery denoted by $S^f(.)$. If all selectivity's are age based CABM calculates an annual *F* by age as

$$F_{y,a} = \sum_f F_y^f\, S^f(a)$$

In addition to an annual *F*, the probability of an agent being caught by fishery f at age a is defined as

$$p_a^f = \frac{F_y^f S^f(a)}{F_{y,a}}$$

Fishing iterates over all agents and applies the following

$$
\begin{aligned}
&p_i = \exp\left(-F_{y,a_i}\right) \quad ,\forall\, X_{r,i} \in \boldsymbol{X}_r,\\
&I_i \sim Bern(p_i)\\
&I_i \begin{cases} 0 & \text{agent lives} \\ 1 & \text{agent dies from fishing} \end{cases}
\end{aligned}
$$

If an agent dies from fishing, it is then assigned to a specific fishery using the multinomial distribution denoted by the indicator variable $\boldsymbol{I} = \left(I_1, \dots, I_{nf}\right)$, where nf denotes the number of fisheries.

$$\boldsymbol{I} \sim mulinomial(N = 1, \boldsymbol{p})$$

where, $\boldsymbol{p} = (p_{a_i}^{f}, \dots, p_{a_i}^{nf})$ is the probability that an agent with age a_i. If I_f is assigned a 1, the agent is assigned to the f^{th} fishery. This agent will contribute to reported catch and compositional observations for this fishery.

8.4 Ageing

Ageing is an implicit process in CABM. Each agent that is created or recruited gets assigned a birth year. The age of an agent is a calculation

Age = Current year – birth year

thus, there is no explicit ageing dynamic occurs in CABM.

8.5 Spawning stock biomass (SSB)

$$S_t = S_t^{pre}\, p_\Delta^t + S_t^{post}(1 - p_\Delta^t)$$

The method for calculating SSB for S_t^{pre} and S_t^{post} was the same and is shown below for S_t^{pre}

$$
\begin{aligned}
&p_i = S(a_i) \quad ,\forall\, \boldsymbol{X}_r \forall\, X_{r,i} \in \boldsymbol{X}_r,\\
&I_i \sim Bern(p_i)\\
&S_t^{pre} = \sum_{r} \sum_{\forall\, X_{r,i} \in \boldsymbol{X}_r} w_i n_i I_i\\
&I_i \sim Bern(p_i)\\
&p_i = S(a_i)
\end{aligned}
$$

where, $S(.)$ Is the mature selectivity ogive.

8.6 Recruitment

Recruitment was the dynamic that was of interest during the simulation where multiple recruitment scenarios were explored (see Section 2.3) and was the only dynamic that differed between OM and EM. CABM created the following number of agents each year assuming,

$$R_y = R_0^y\, ycs_y$$

Where, R_0^y was a time-varying parameter and ycs_y are the annual year class strength parameters, where

$$
\begin{aligned}
&ycs_y = \exp\left(\varepsilon_y\right)\\
&\varepsilon_y \sim N(0, \sigma_R^2).
\end{aligned}
$$

See Section 2.3 for details on R_0^y.

8.7 INITIALISATION

CABM calculates the number of individuals that an agent represents during initialisation. It is derived following,

$$\tilde{N} = \sum_{a = a_{min}}^{4\, a_{max}} R_0 \exp\left(-Ma\right)$$

$$\tilde{n} = \frac{\tilde{N}}{n_{agents}}$$

where, a is the age, a_{min} is the minimum age, a_{max} is the maximum age, M is the initial natural mortality rate, R_0 is the average number of individuals expected in the absence of fishing, and n_{agents} is the number of agents assumed from the users to model the initial stock. The choice of n_{agents} is a tradeoff between model run time and agent resolution of the stock. As n_{agents} increases CABM moves towards an IBM ($\tilde{n} \rightarrow 1$) but this comes at computational cost and larger model run times.

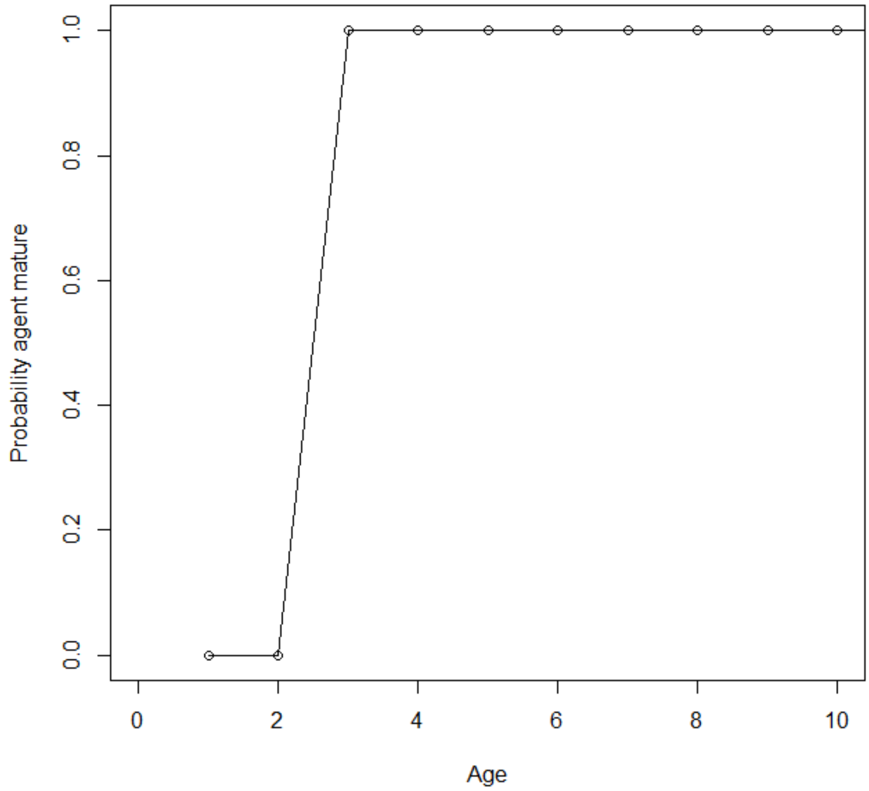
Once CABM calculates $\tilde{n}$, it creates the number of agents for the first age (a_{min}). This is calculated as

$$R_{a_{min}} = round\left(\frac{R_0}{\tilde{n}}\right).$$

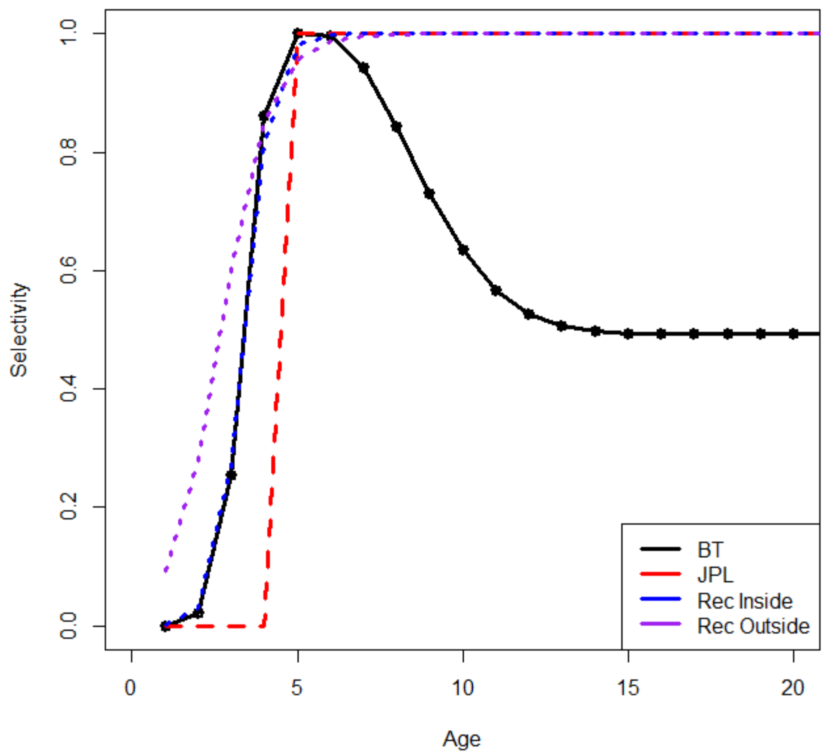
When agents are created, they are also assigned agent attributes based on their age and agent specific attributes. The above actions from CABM assume an equilibrium age structure of agents in each cell, but ignore movement and other dynamics that may affect starting conditions. To account for these dynamics, CABM then iterates over the annual cycle without fishing dynamics for a user defined number of cycles denoted by n_{init}. This populates the agents around the spatial domain according to the annual cycle assumptions.

Appendix Table 1: OM parameters assumed during simulations.

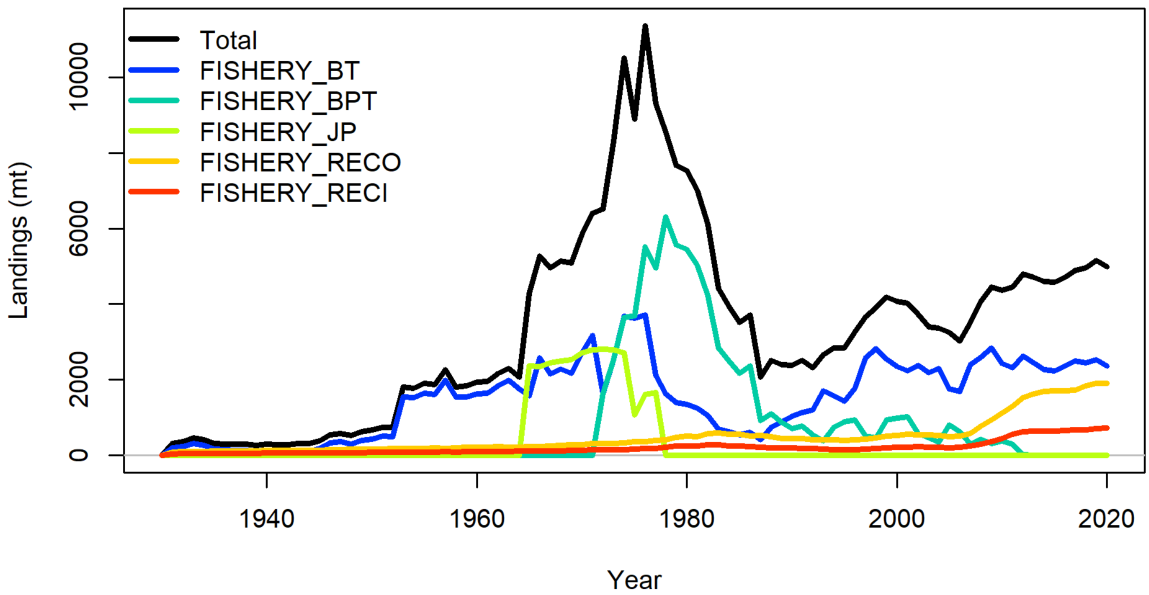
Parameter	Value
n_{agents}	$1e^6$
M	0.075
σ_R	0.6
$\bar{L}_\infty$	57.48
CV	0.08
k	0.146
α	$4.467e^8$
β	2.793



Appendix Figure 1: OM Maturity selectivity.



Appendix Figure 2: OM fishery selectivity. BT = bottom trawl, JPL = Japanese longline.



Appendix Figure 3: Catches produced from OM for one simulated realisation. BT = bottom trawl fishery, BPT = bottom pair trawl fishery, JP = Japanese longline fishery, RECO = outside harbours recreational line fishery, RECI = inside harbours recreational line fishery.

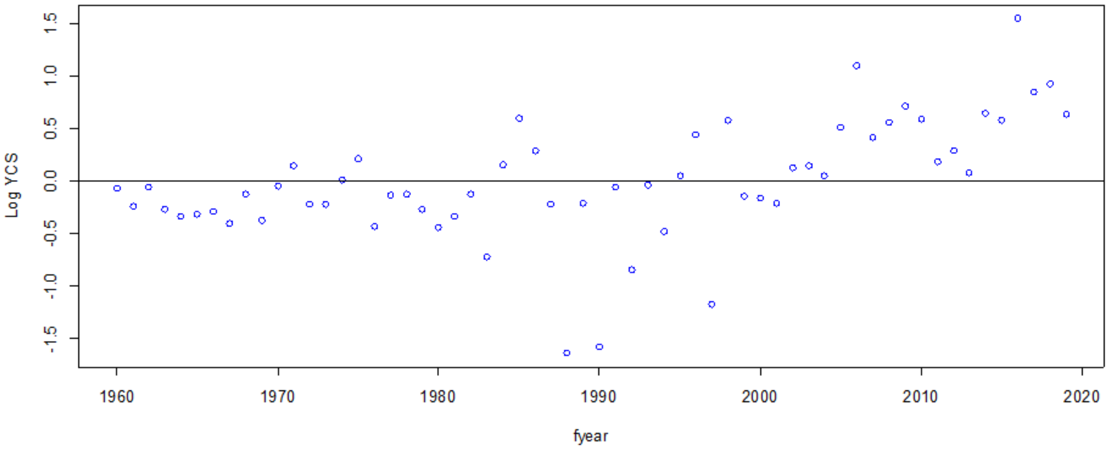
Estimation information for the Stock Synthesis EMs. Catchability coefficients were treated as 'nuisance' parameters and analytically calculated (Appendix Table 2, Bull et al. 2012)

Appendix Table 2: Estimated parameter information. BT = bottom trawl fishery, RECO = outside harbours recreational line fishery, RECI = inside harbours recreational line fishery.

Parameters	Number of estimable parameters	Estimation phase
ln R_0	1	1
$\boldsymbol{\varepsilon} = (\varepsilon_{1960}, \dots, \varepsilon_{2019})$	59	2
BT selectivity	4	3
RECO selectivity	2	1
RECI selectivity	2	1

9. APPENDIX B

A logistic function was fitted using least-squares minimisation to the Stock Synthesis SNA 8 base-case model predicted recruitment deviates, these estimates being in log-space (Appendix Figure 4).

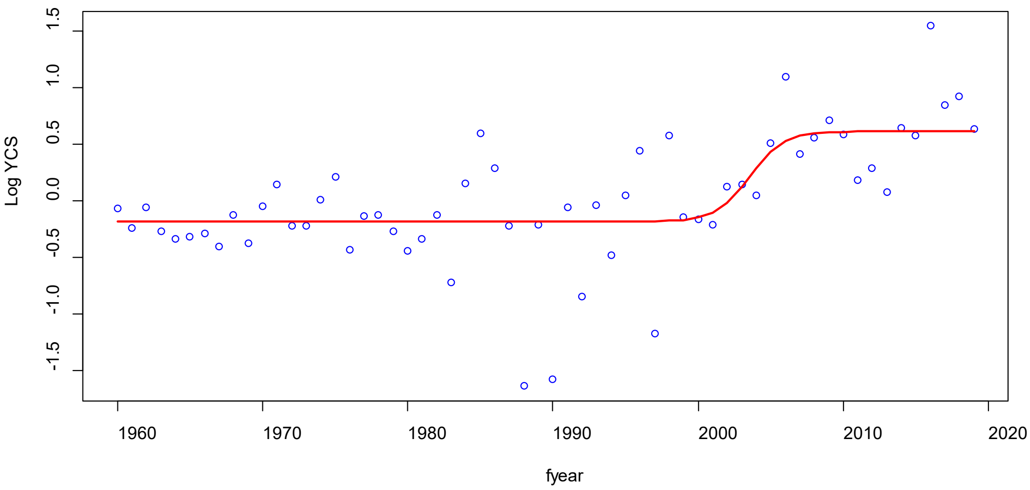


Appendix Figure 4: SNA 8 2021 assessment model predicted recruitment log deviates.

The form of dynamic R_0 logistic curve fitted to SNA 8 model log estimated recruitment deviates had four estimable parameters: *a,b,c,d*.

$$\log{(R0_y)} = a + (1 + \frac{b}{e^{\left(\frac{-(y-c)}{d}\right)}})$$

The dynamic log(R_0) logistic curve least-squares fit to the 2021 SNA 8 model estimated log (year class strength) parameters is given in Appendix Figure 5.



Appendix Figure 5: Fitted log(R_0) dynamic recruitment curve (red line). Circles are estimated recruitment deviates from the 2021 SNA 8 assessment model. Derived Equation 1 parameter values are: a, -0.18562; b, 0.79688; c, 2003.5273; d, 1.17279.

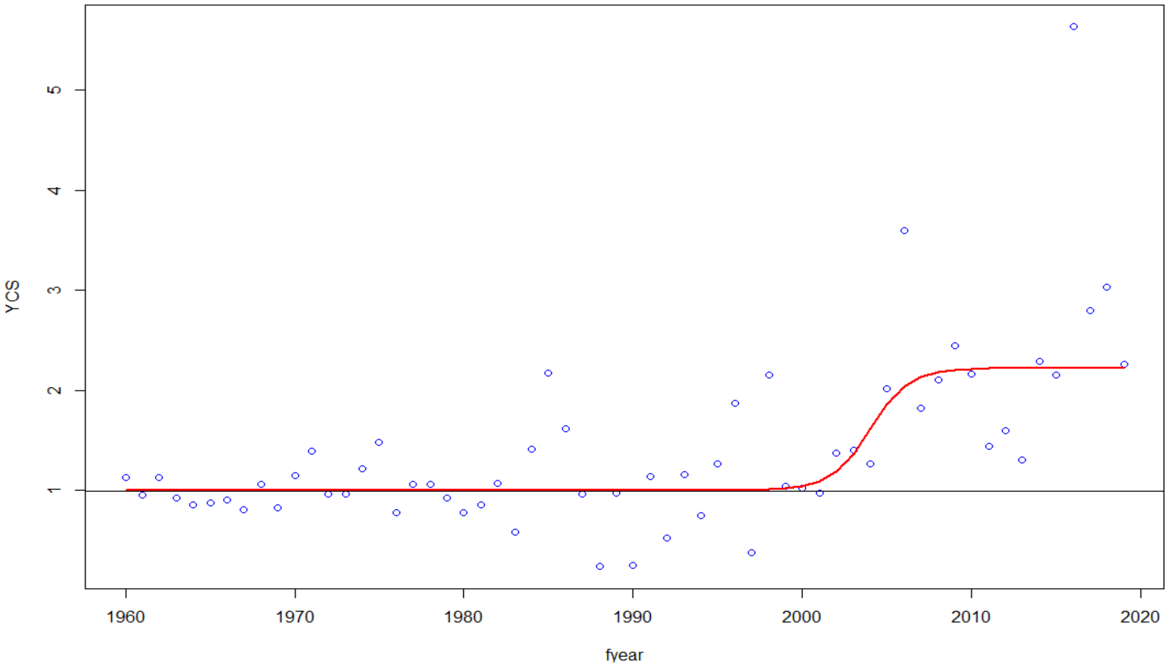
The fitted dynamic log(R_{0y}) curve was converted into natural space in accordance with:

$$R0_y = e^{\left(\log{(R0_y)} + \frac{sigmaR^2}{2}\right)}$$

where $sigmaR = 0.6$. (This $sigmaR$ value is from the 2021 SNA 8 assessment model.)

The ABM input dynamic R_0 scalar vector $\hat{\varepsilon}_y$ (Appendix Figure 6) was derived by rescaling the $R0_{fyear}$ vector to have a scalar value of 1.0 in the 1960 commencing year as follows:

$$\hat{\varepsilon}_y = R0_y * (\frac{1}{R0_{1960}})$$



Appendix Figure 6: Final scaled ABM dynamic R_0 input vector $\hat{\varepsilon}_y$ (red line) and scaled 2020 SNA 8 model recruitment deviates.

10. APPENDIX C

The basic algebra by which B_0 is derived from R_0 in most static equilibrium stock assessment models is as follows:

Unexploited numbers N^0 at age a

$$N_a^0 = R_0 e^{aM}$$

where

M = natural mortality

R_0 = mean number of recruits entering the population at age 0 under un-exploited conditions.

The unexploited population biomass (B_0) is the biomass sum of all age classes 0 and above in the population

$$B_0 = \sum_a^{\infty} N_a^0 \, w_a$$

$$B_0 = \sum_a^{\infty} R_0 e^{aM} w_a$$

where w_a is the mean weight of an age a fish.

It follows from above that a proportional increase Δ in R_0 will result in an equalvalent proportional increase in B_0 such that:

$$\Delta B_0 = \sum_a^{\infty} \Delta R_0 e^{aM} w_a$$