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Tini a Tangaroa

The 2020 stock assessment of pāua (*Haliotis iris*) for PAU 5A

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EXECUTIVE SUMMARY

Neubauer, P.[1] **(2022). The 2020 stock assessment of pāua (*Haliotis iris*) for PAU 5A.**

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The present study conducted a Bayesian length-based stock assessment for pāua (*Haliotis iris*) in pāua quota management area PAU 5A. The assessment model used the same population dynamics model as previous assessments, but the data models that linked the population dynamics (process) model with different data types were significantly updated using changes that were first introduced for PAU 5D in 2018: unlike previous assessments for this area, the present model used only model-derived inputs and did not fit directly to data. It, therefore, represents a Bayesian synthesis of available information rather than an integrated model that fits to data directly. This development is most significant for the growth process as represented in the model, which previously relied on fitting directly to available data from particular quota management areas. In this model, growth information was given in the form of a rather vague prior, and the model used this information with other inputs to estimate stock-level growth. In addition, recruitment variation was not estimated prior to robust commercial shell length frequency data being available in 2001, to avoid the introduction of artefacts by large estimated early recruitment events which appear inconsistent with more recent data.

The assessment was run as a single and multi-area assessment over smaller research strata; however, as all multi-area runs led to near-identical conclusions as the single-area model, the latter was selected to provide a base case and key sensitivity for the assessment. The base case suggested healthy stock levels near 50% of unfished biomass, with slow declines over recent decades. The key sensitivity differed from the base case in that it allowed for increasing efficiency in the fishery. This assumption led to estimates of slow increase in efficiency early in the fishery (pre 2000), but a more substantial increase since 2001, with estimates of stock status at near 40% of unfished biomass, but with more positive recent trends. Projections for both models suggested little change from current stock status over the next three years and into the future at current catch levels, corresponding with previous assessments and management procedure evaluations.

[1] Dragonfly Data Science, New Zealand.

1. INTRODUCTION

New Zealand abalone, pāua (*Haliotis iris*), is commercially fished throughout New Zealand, with its management based on different quota management areas (QMAs). The management of pāua fisheries includes regular stock assessments that determine the stock status in a particular QMA. These stock assessments are based on statistical models that estimate the current and projected stock status, as well as the exploitation rate of the portion of the population that is impacted by fishing.

This report details the 2020 stock assessment of New Zealand abalone, pauā (*Haliotis iris*), in quota management area (QMA) PAU 5A (Figure 1). It describes the data inputs, methods, and results of the 2020 stock assessment. The fishing year for this fishery is defined as the period from 1 October to 30 September the following year (here, unless the range is explicitly stated, a fishing year is referred to by the later year in the corresponding time period).

The PAU 5A pāua substock is part of the southern pāua QMA PAU 5, which was split into three sub-areas in the 1995 fishing year: Fiordland (PAU 5A), Stewart Island (PAU 5B), and the eastern Southland and Otago coast (PAU 5D). The impact of changes in management areas on catch distribution is difficult to identify because new stock boundaries did not consistently align with previous reporting areas. Also, there was a delay in the adoption of new nomenclature in statutory reporting following each change. Starting in 1997, reporting for PAU 5A was split into 17 statistical reporting areas, further refined to 49 areas in 2001 when reporting at the level of fine-scale statistical areas became mandatory on the Paua Catch Effort Landing Return (PCELR) forms (see Figure 1). No changes to the reporting system have occurred since then (see Table 1 for a summary of reporting standards over the assessment period).

The PAU 5A QMA covers all of the Fiordland coast, and its fishery is remote, accessed from the south or via Milford Sound; it uses relatively large vessels due to the extensive distances involved in fishing in this area. Because of access limitations, fishing in PAU 5A between access points (previously reporting stratum 31) is greatly weather dependent. The Total Allowable Commercial Catch (TACC) for the area is currently set at 148.98 t; however, since 2006, 30% of the quota has been shelved by the commercial pāua industry, and only around 105 t are landed each year. In addition, the minimum fishing size was increased in 2006 to 130 mm shell length in the southern areas of PAU 5A, and to 126 mm shell length for areas north of Milford Sound (more details on the fishery and its development are provided by Fu et al. 2017).

Data inputs to the stock assessment consisted of commercial, recreational, customary, and illegal catch (reconstructed for part of the assessment period), catch-per-unit-effort (CPUE), commercial catch sampling length frequency (CSLF), and growth and maturity estimated from a meta-analysis of pāua growth data. In addition, the current assessment explored the use of a spatial model next to the commonly used non-spatial model. This approach was used to explore if small-scale trends inferred in the spatial model were consistent with large-scale trends inferred in the single-area model.

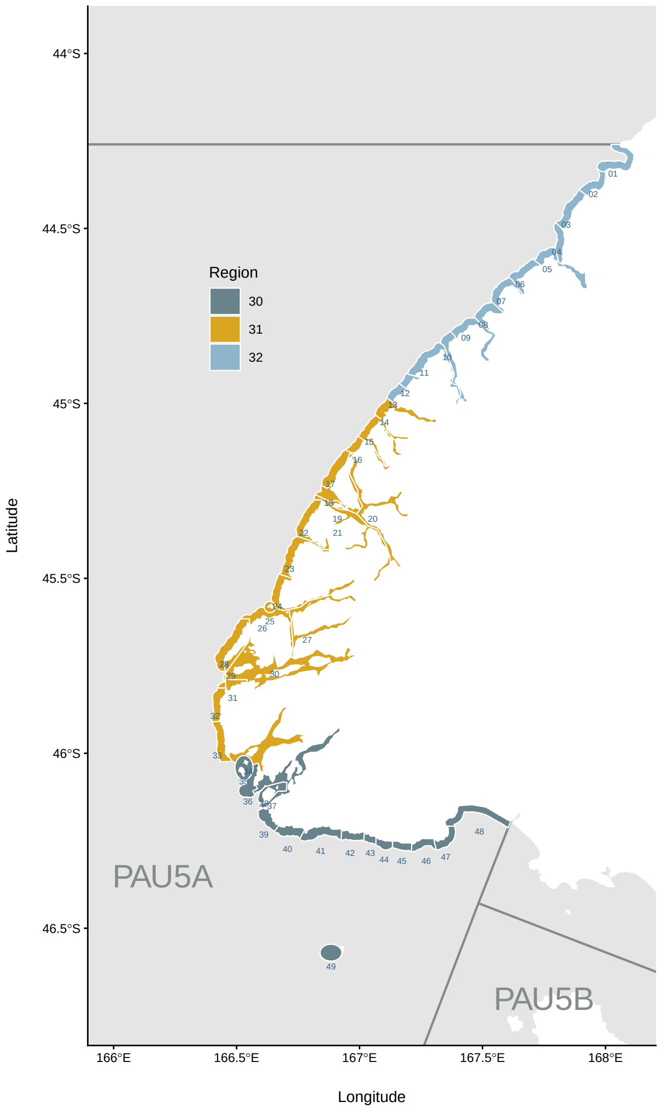


Figure 1: Pāua quota management area PAU 5A, southwestern South Island, and key spatial divisions within PAU 5A. Catch reporting was initially at a lower spatial resolution of General Statistical Areas (030, 031, and 032), and subsequently changed (in 2001) to 49 Pāua Statistical Areas.

2. METHODS

2.1 Inputs

2.1.1 Commercial catch

The commercial catch history for PAU 5A is uncertain prior to 1996, owing to changes in the spatial resolution of the reporting framework in this year (Table 1) and non-overlapping areas between reporting frameworks. From 1974 to 1995, catch was reported at the unit of research strata within the PAU 5 QMA covering the south of South Island from Awarua Point on the west coast to Waitaki River on the east coast. Catches within this area could have occurred in any of the sub-areas now attributed to the PAU 5A, PAU 5B, or PAU 5D substocks. Considerable effort by stock analysts in previous years, in consultation with the Fisheries New Zealand Shellfish Working Group (SFWG), has led to a reconstructed pre-1996 catch history under the following assumptions:

- 23% of the catch in PAU 5 between 1974 and 1983 was from the PAU 5A sub-area;
- 40% (low: 18%; high: 61%) of the catch attributed to Statistical Area 030 between 1984 and 1996 was from PAU 5A (Statistical Areas 031 and 032 are entirely within PAU 5A).

Although the previous (pre-1996) statistical areas are generally referred to with a zero preceding the research stratum code, the zeros were subsequently omitted here for convenience. These statistical areas are referred to as research strata or as area with number (e.g., "area 30") compared with the current fine-scale statistical areas, which generally carry a P and QMA letter before the statistical area number.

Table 1: History of the spatial extent and resolution for pāua stock in sub-area PAU 5A, after quota management area (QMA) PAU 5 was split into three sub-areas including PAU 5A.

QMA	Statistical areas		
Oct 1995–present	1983–1995	1996–2001	2002–present
PAU 5A	032 (North)	A1–A5	P5AH01–P5AH13
	031 (Middle/Central)	A6–A12	P5AH14–P5AH34
	030 (South)	A13–A17	P5AH34–P5AH49

Components of the catch reconstruction included data reported by Murray & Akroyd (1984), from the Fisheries Statistics Unit (FSU) database, from Quota Management System (QMS) reporting (assembled by the National Institute of Water and Atmospheric Research, NIWA), and catch effort data supplied by Fisheries New Zealand (Figure 2). Based on these data sources, the catch history was reconstructed, consisting of customary, recreational, commercial, and illegal fishery components and as the sum of all components (Figures 3 and 4) (see additional detail of the catch reconstruction provided by Fu et al. 2015).

For the 2019 fishing year, the catch was set to 104 t in accordance with the 30% TACC shelving agreed by the pāua industry. Since 2001–02, catch has been reported at the level of fine-scale Pāua Statistical Areas (on PCELR forms; see Figures 5 and 6 for the spatial and temporal distribution of recent commercial catch over fine-scale statistical areas for the period when the forms were implemented).

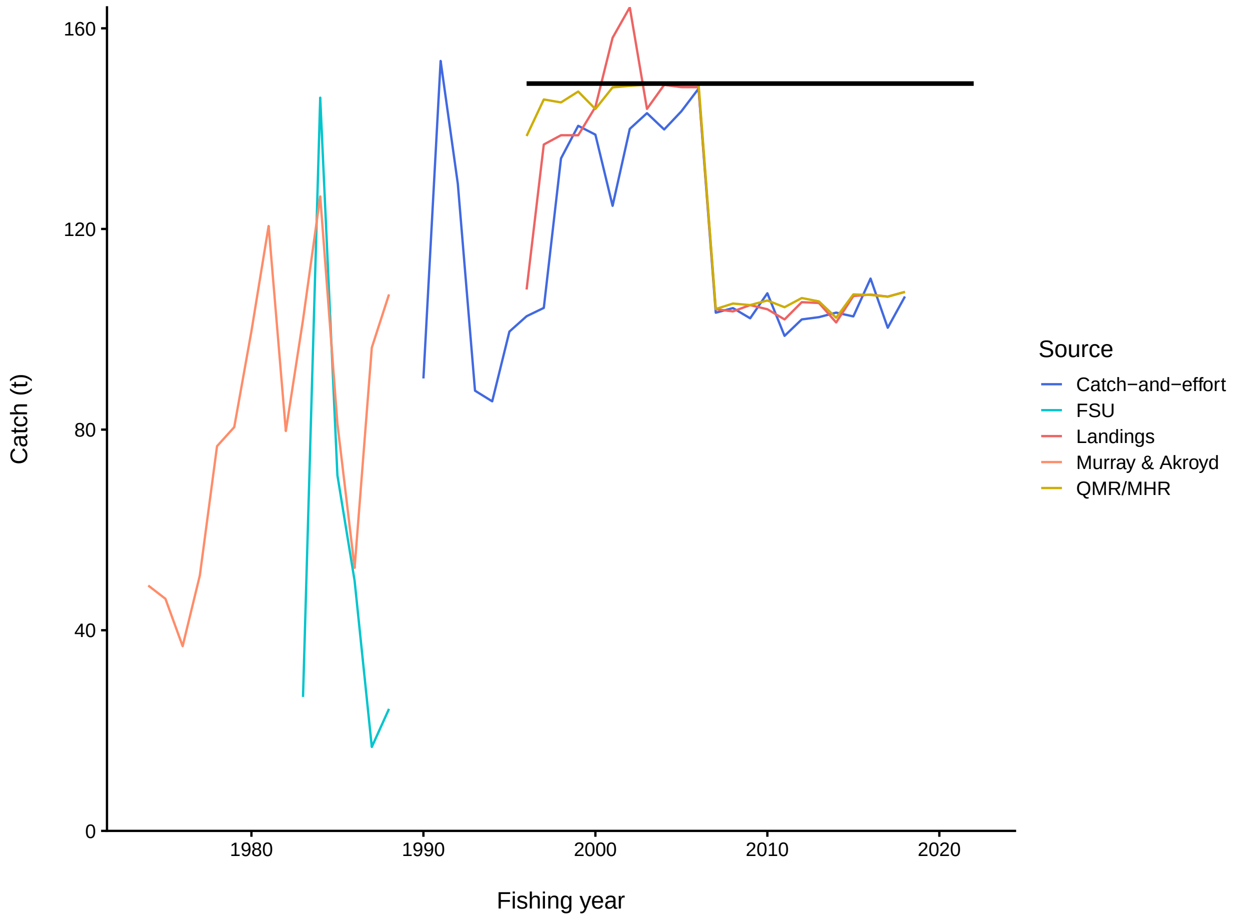


Figure 2: Estimated commercial catch history for PAU 5A from 1974 to 2019. Catch to 1983 was reconstructed from data reported by Murray & Akroyd (1986), from the Fisheries Statistics Unit (FSU) database (orange; 1983–1989), Quota Management System (QMS) reporting data assembled by NIWA (red; 1990-2016), and catch effort data supplied by Fisheries New Zealand (blue). NIWA data were used prior to 1996, data supplied for QMS landings were used thereafter. Proportions by area calculated from catch-effort data were used to calculate catch scenarios. Scenarios show low and high presumed proportions of catch from reporting area 30 for the Catch Effort Landing Return (CELR) reporting years. The TACC is shown as a solid black line.

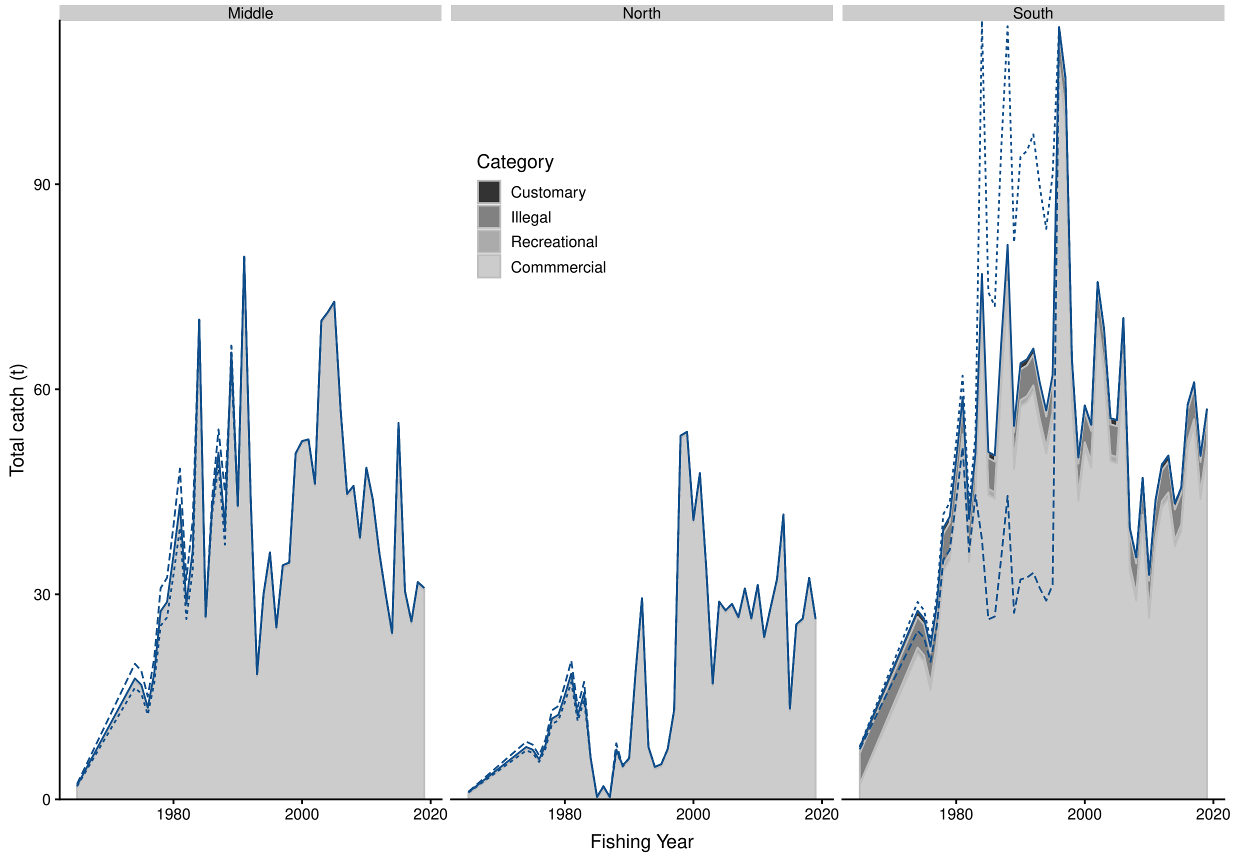


Figure 3: Estimated total catch history for quota management area (QMA) PAU 5A from 1974 to 2019 by fishery component and reporting area. Fishery categories were customary, illegal, recreational, and commercial (Total Commercial Catch, TCC) catch. Commercial catch was reconstructed up to 1995 when the QMA was created, and based on landing records thereafter. Dashed lines show alternative low and high catch scenarios for periods of uncertain catch from PAU 5A prior to the division of PAU 5 into smaller QMAs.

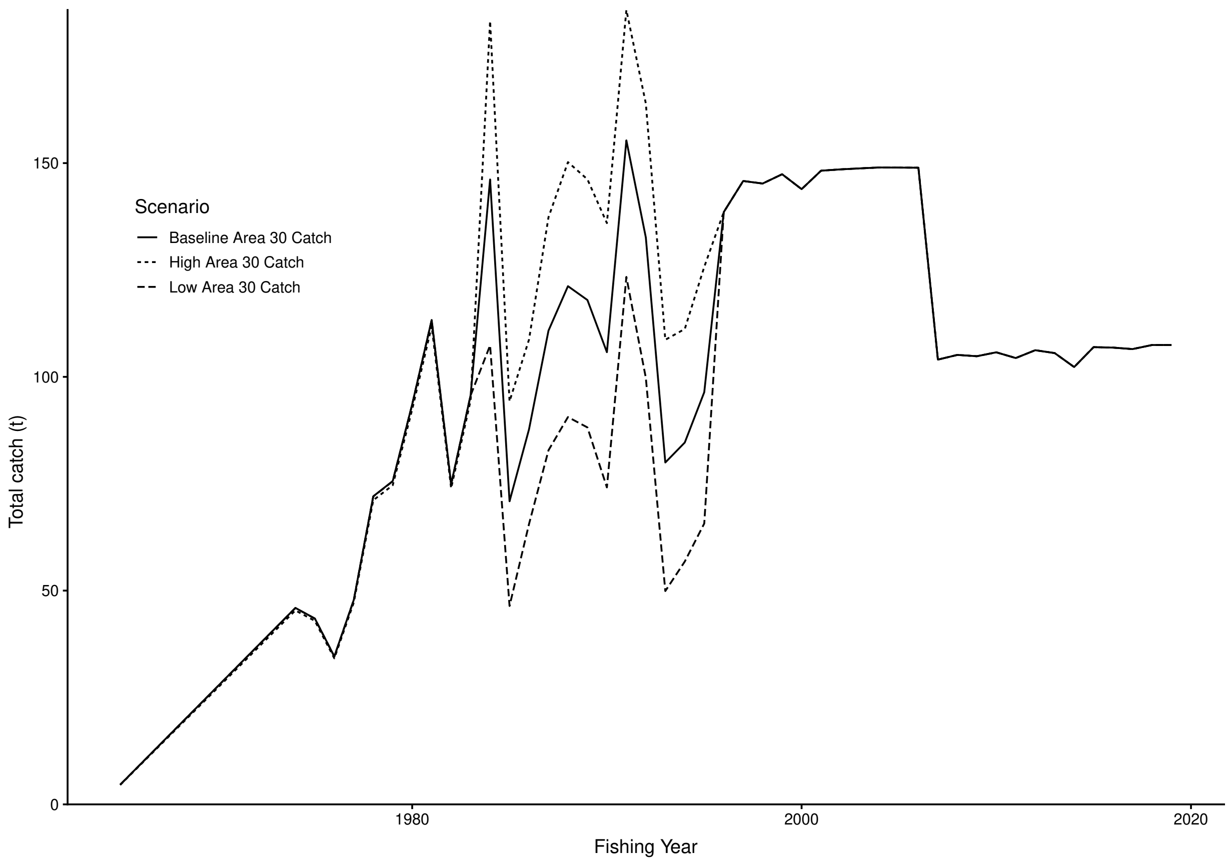


Figure 4: Total pāua catch history used in the single area stock assessment for PAU 5A from 1974 to 2019 as the sum of all catch components (customary, illegal, recreational, and commercial catch). Dashed lines show alternative low and high catch scenarios for periods of uncertain catch from PAU 5A prior to the division of PAU 5 into smaller QMAs.

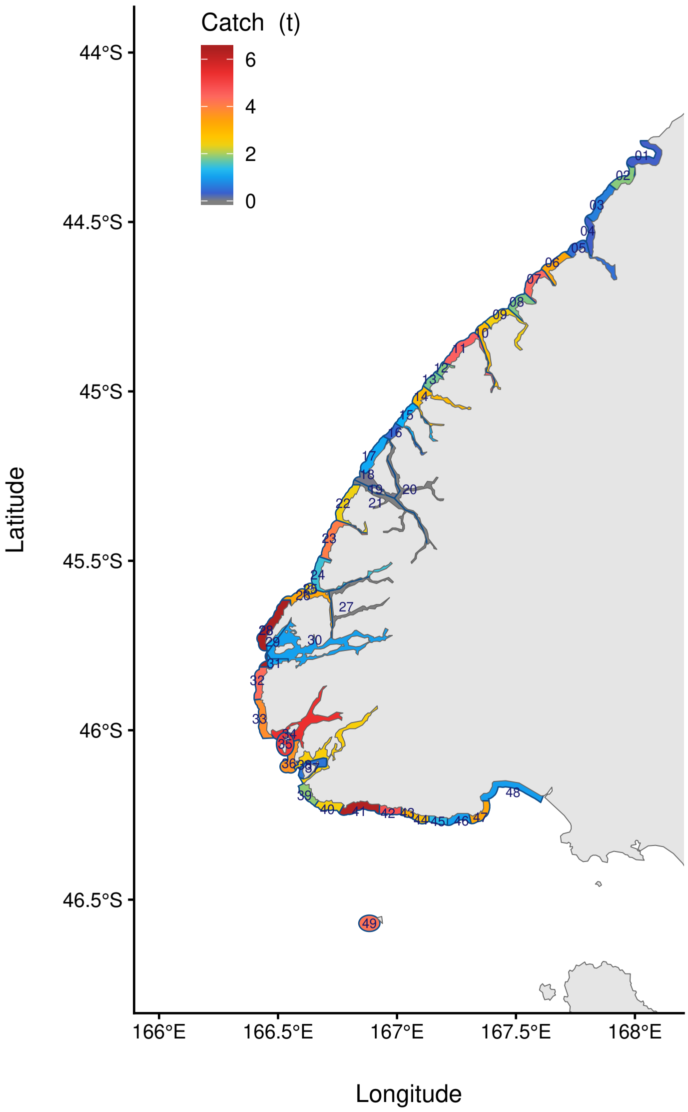


Figure 5: Distribution of catch used in the current stock assessment of pāua in PAU 5A. Colours show the relative proportion of catch from each statistical area (averaged since 2002).

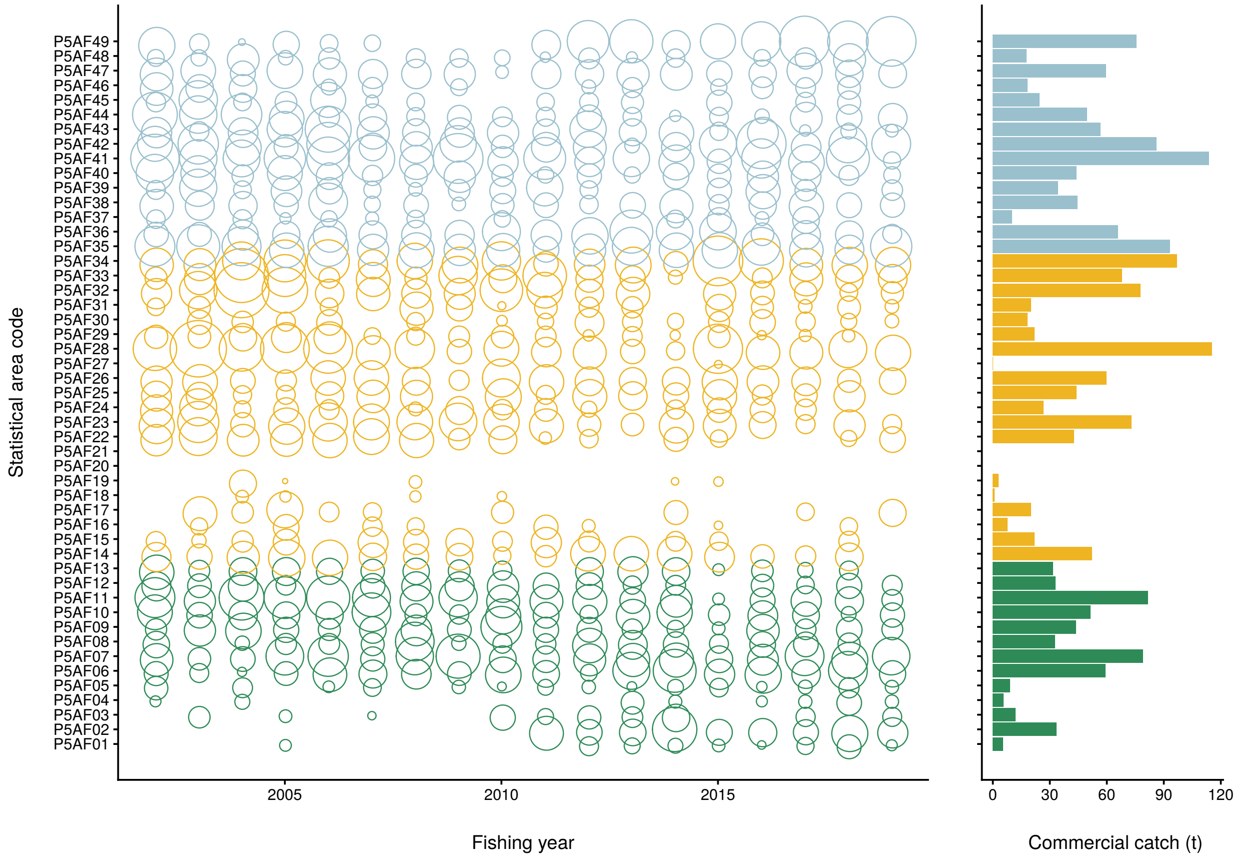


Figure 6: Relative trend in pāua catch (kg) over time by statistical areas in PAU 5A for the period from 2002 to 2019, with total catch over the same time period (right-hand side). Key areas within PAU 5A: South (south coast & Chalky Sound) in blue, Middle (Dusky Sound & central) in orange, and North (George & Milford sounds) in green.

2.1.2 Recreational, customary, and illegal catch

Unlike previous assessments, which assumed 5 t of recreational catch, the recreational catch was assumed to increase linearly to 1 t in 1974, subsequently staying constant, with 90% of all recreational, customary, and illegal catch assumed to occur in the southern area (area 30; see Figure 3 for the PAU 5A catch history by catch category and area). This assumption was agreed upon by the SFWG based on two national panel surveys. The customary and illegal catch were set to a constant 1 t and 5 t for PAU 5A, respectively, as agreed upon by the SFWG for previous assessments.

2.1.3 Catch-per-unit-effort (CPUE)

In addition to both Catch Effort Landing Return (CELR; 1989 to 2001) and PCELR (2002 to 2019) data, the stock assessment used data from the Fisheries Statistics Unit (FSU) period to construct a single CPUE index for the assessment. The FSU data were omitted from all recent previous assessments on the basis that they covered a relatively small proportion of the assumed catch at the time, and had poor recording of fisher identification numbers.

A review of the FSU data suggested that the lack of records in previous data preparation procedures had been due to the exclusion of data from reporting area 30; however, these data were included for CELR and PCELR standardisation. For consistency, FSU data from area 30 were retained here, leading to a total amount of records that was *a priori* considered sufficient to derive a standardised index. Nevertheless, some anecdotal evidence suggests that reporting was poor in early years in some QMAs, leading to the omission of early years with few records in the process of developing the current base case —in this case, 1983 was omitted for PAU 5A. In addition, the relatively infrequent recording of Fisher Identification Numbers (FINs) in FSU data (and inconsistent numbering with later reporting regimes) led to the exclusion of FINs from FSU data in the model for FSU data.

The preparation of FSU data led to a 15% reduction in the number of FSU records from a total of 892 (excluding 1983) to 758 records (Table 2). The number of records was also low towards the end of the FSU period; however, because this period was in-between periods with higher reporting, this low number was considered to be less limiting, because higher observation error ensures that points with few records are less important in fitting CPUE.

Table 2: Summary of data preparation steps and number of records removed from Fisheries Statistics Unit (FSU) data by year and in total.

Data preparation	1983	1984	1985	1986	1987	1988	Total
All	129	424	201	114	59	94	1021
Fishing method: diving	106	414	183	107	58	94	962
Fishing duration $\leq$10 h	92	380	157	92	46	83	850

Data preparation procedures for CELR and PCELR data generally followed established protocols detailed by Fu et al. (2017). Nevertheless, a vessel correction factor was introduced here to remove records for which the difference between estimated and landed green weight exceeded 20%. Discrepancies can arise for a number of reasons, such as draining of water from animals, misreporting, and also data transcription errors. The vessel correction factor is commonly used in New Zealand rock lobster assessments to ensure that these errors do not unduly affect the CPUE. The data preparation steps can be summarised as follows (see the outcome of the data preparation in Tables 3 and 4):

1. Use only events with “diving” as method.
2. Remove items with missing fields needed for standardisation.
3. Remove events with a correction factor of >0.2.
4. Remove client/Fisher Identification Numbers (FINs), diver identifications and statistical areas that account for fewer than 20 dive events over all years.
5. Retain only events with less than eight recorded divers, and a recorded fishing duration of $\leq$12 h.

Table 3: Data preparation steps and number of records removed for data from Catch-Effort-Landing-Return forms by year and in total (as number and percentage of records retained). DI, diving; VCF, vessel correction factor; Stat area dives, dive events in a statistical area; FIN, Fisher Identification Number. The number of records with diving method as the reference was used to calculate proportion of records retained.

Data preparation	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	Total	% retained
All	94	332	436	377	393	347	425	425	382	354	251	237	201	4254	119.43
Fishing method: ”DI”	94	307	383	319	289	265	337	318	305	286	242	227	190	3562	100.00
Missing fields	94	304	382	318	286	265	335	312	282	260	236	219	187	3480	97.70
VCF$<$0.2	87	291	344	268	212	223	252	287	218	151	188	170	145	2836	79.62
Stat area dives $>$ 20	87	291	344	268	212	223	252	287	218	151	188	170	145	2836	79.62
FIN records $>$ 20	59	201	256	218	195	212	246	272	210	141	177	155	127	2469	69.31
Diver records $>$20	59	201	256	218	195	212	246	272	210	141	177	155	127	2469	69.31
No. of divers $\leq$8	59	201	256	208	192	212	246	272	210	141	176	155	127	2455	68.92
Fishing duration/diver $\leq$12 h	58	200	256	208	192	212	246	270	208	141	176	155	127	2449	68.75

Table 4: Data preparation steps and number of records removed for data from Paua Catch-Effort-Landing-Return (PCELR) forms by year and in total (as number and percentage of records retained). DI, diving; VCF, vessel correction factor; Stat area dives, dive events in a statistical area; FIN, Fisher Identification Number. The number of records with diving method as the reference was used to calculate proportion of records retained.

Data preparation	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	% retained
All	558	618	663	626	731	537	570	484	476	370	461	436	450	439	429	423	392	277	8940	100.00
Fishing method: ”DI”	558	618	663	626	731	537	570	484	476	370	461	436	450	439	429	423	392	277	8940	100.00
No spatial subsetting	558	618	663	626	731	537	570	484	476	370	461	436	450	439	429	423	392	277	8940	100.00
Missing fields	558	616	657	619	731	537	570	484	471	359	457	436	447	439	429	423	391	277	8901	99.56
VCF$<$0.2	393	485	536	519	556	407	455	366	356	253	374	325	341	348	346	327	314	249	6950	77.74
Stat area dives $>$ 20	392	485	527	518	556	407	451	366	354	253	374	321	341	344	346	323	310	248	6916	77.36
FIN records $>$ 20	386	485	520	517	554	407	441	366	354	253	374	321	339	344	346	317	306	248	6878	76.94
Diver records $>$20	217	297	367	420	434	331	335	276	291	224	315	261	264	256	297	239	230	140	5194	58.10
No. of divers $\leq$8	217	297	367	420	434	331	335	276	291	224	315	261	264	256	297	239	230	140	5194	58.10
Fishing duration/diver $\leq$12 h	217	297	367	420	434	331	335	276	291	224	315	261	264	256	297	239	230	140	5194	58.10

For CELR data, records were required to be recorded as combined effort, but were usually recorded as individual effort (i.e., hours per diver instead of hours for all divers). In the data preparation of recent assessments, this aspect was addressed by using a cut-off time for fishing duration. For fishing durations above this threshold time, data were considered to represent combined effort. The threshold value was set by the SFWG upon inspection of fishing duration times recorded for individual divers and comparison with fishing duration records for events with more than one diver (Figure 7).

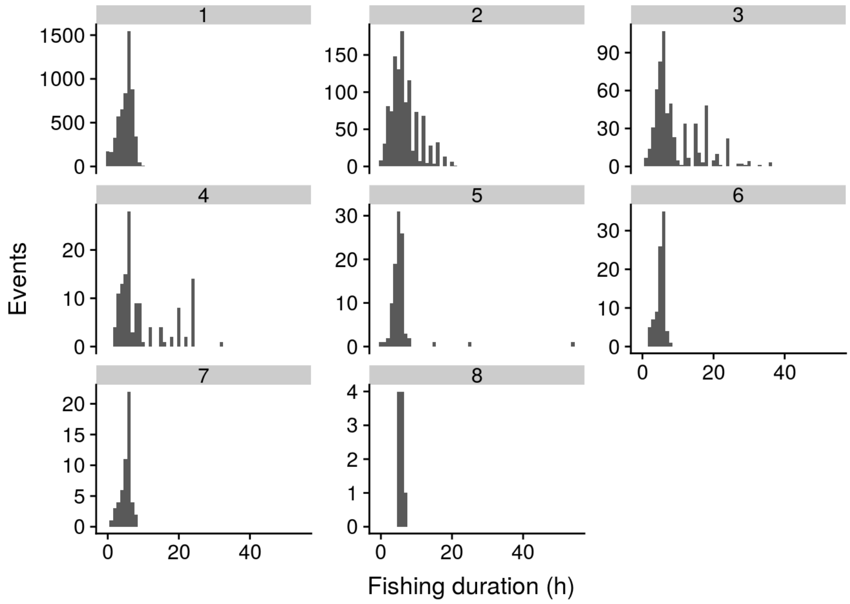


Figure 7: Fishing duration recorded on (Paua) Catch Effort Landing Return forms by number of divers recorded (as indicated above each panel).

In the 2019 assessment for PAU 5A, the effort classification model that was applied was first developed for the 2018 stock assessment for PAU 5D. Briefly, the procedure classifies reported effort for each record to one of two reporting types (by diver/by crew) based on reported fishing times for events with single divers for each crew. The model employs year- and crew-specific effects for dive times to capture potential changes in reporting over time (see details of this method provided by Neubauer & Tremblay-Boyer 2019a).

In the preparation of CPUE data, one or the other reporting type was applied (i.e., direct use of duration per diver or reported effort divided by the number of divers in a crew), depending on classification outcomes. For any crew/year combination where $p_{c,y}$ was $p > 0.05$ and $p < 0.95$, data were not used for standardisation because the reporting type was considered too uncertain.

For most crew and year combinations, the estimated reporting regime had high certainty (Figure 8) and the data were, therefore, retained for CPUE analysis (Figure 9). For some crews, the reporting regime changed over time, and for some records, the classification was ambiguous—these records occurred most often for crews with few records overall or for single years for some crews.

The present assessment of PAU 5A used methods developed previously (Neubauer & Tremblay-Boyer 2019a) to partition the observed variance in CPUE across reporting datasets; it was estimated how much of the residual variance in FSU (CELR) data was due to factors accounted for in CELR (PCELR) data. All PCELR variables commonly used in the standardisation were nested within CELR variables, which in turn were nested in FSU data: divers were nested within Fisher Identification Number, fine-scale statistical areas were nested within larger research strata. The residual variance in FSU (CELR) data was, therefore, due to variance explained by CELR (PCELR) factors plus a common residual (see detailed model configuration provided by Neubauer & Tremblay-Boyer 2019a). Here, the model was applied both with and without FSU data, and in a spatial (including area-year effects) and non-spatial configuration.

The log-normal CPUE index model fitted the data reasonably well (Figure 10), and produced an index that diverged relatively strongly from the raw CPUE in recent years (Figure 11). Dive conditions and FIN had the largest effect in the standardisation model (Figure 12). The standardisation effect (i.e., lower standardised CPUE in recent years compared with raw CPUE) was mainly owing to a larger proportion of catch being caught by more efficient crews and divers, and in more favourable dive conditions, whereas the statistical area had relatively little effect (Figures 13 to 16).

The spatial model provided similar results to the non-spatial model in terms of standardisation (see Figures 11 and 17); there were initial declines during the FSU years in all areas (and in the aggregated model), but sparse data in the northern area led to a highly variable index. Effect sizes were similar in both models. The model without FSU data was nearly identical to the full model in all aspects, corresponding with the FSU data having relatively few records and no variables for standardisation.

The CPUE and estimated observation error (σ_{OBS}) were used as direct inputs to the model without further modifications, because process error is estimated within the model, based on relative weights for CPUE and commercial sampling length-frequency (CSLF) data.

2.1.4 Commercial sampling length-frequency (CSLF) data

The present assessment used a standardisation model for composition data (developed by Neubauer 2020) that adjusts the length-frequency samples based on spatial and temporal variability. This adjustment is similar to adjustments in CPUE applied during the standardisation of CPUE. This procedure has the advantage that reasonably smooth length-frequency distributions (i.e., filtering out variance from highly multi-modal LF distributions that result from low sample numbers) for sparsely sampled strata can be extracted, even if individual samples in those strata are unlikely to provide a reliable estimate of the true length-frequency distributions. Random effects formulations ensure the sharing of information across strata (see Neubauer 2020 for more detail about the procedure).

Composition standardisation was performed for CSLF data from 2001–02 using small-scale statistical area, reporting area (areas 30 to 32), and area-year as standardising variables. Area and year were entered as fixed effects, and area-year and statistical area were entered as random effects. The standardisation led to small adjustments based on statistical areas and areas fished (Figure 18). For example, in 2013–14, a considerable number of samples was from the northern area (area 32) compared with the other areas, which tended to be fished more regularly. The model downward-adjusted the lower limb of the LF distribution in this year (and, by extension, upward-adjusted the tail of the LF distribution). Adjustments owing to small-scale statistical areas within larger reporting areas were generally small (the estimated year and area-year effects from the model are shown in Figures 19 and 20, respectively). The error bars were comparatively large when few samples were available for any particular area-year combination, e.g., the northern area in 2008–09.

2.1.5 Growth and maturation

The present assessment did not fit to data from individual growth tagging sites (i.e., three sites in PAU 5A), because the sample size was generally insufficient to adequately estimate mean growth and variability across a fishery with high spatial heterogeneity in growth. Recent developments for pāua growth models suggest that flexible growth models based on energy balance equations (e.g., Ohnishi et al. 2012) can describe observed growth and maturation differences across pāua QMAs (Neubauer & Tremblay-Boyer 2019a). Here, an informed prior was derived from a meta analysis of pāua growth, allowing the model to adjust growth in accordance with other sources of information (priors on natural mortality M, CSLF, and CPUE input). For the priors for mean growth and growth standard deviation, at each length l, a proportion $z(l)$ of the population grows according to a log-normal growth prior, and a proportion $(1 - z(l))$ of pāua is located in areas with no growth at length l (Figure 21). Maturation was estimated simultaneously with growth in the meta-analysis.

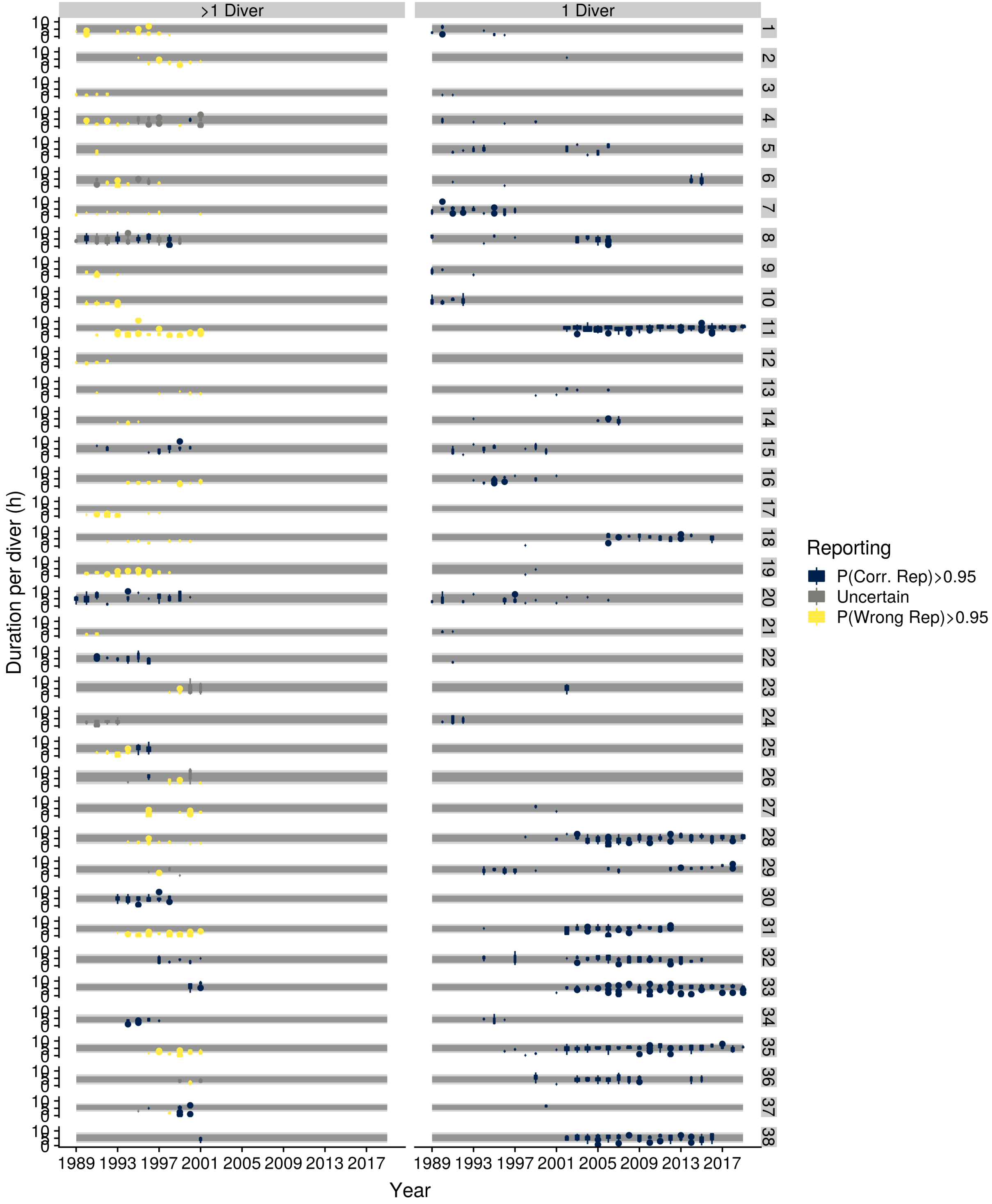


Figure 8: Classification of pāua fishing duration records into reporting by diver ($p \approx 1$; yellow) and by combined time in water ($p \approx 0$; blue) for events with more than one diver (left column). The right column shows the "training data" with single-diver records. Each line corresponds with one fishing crew (Fisher Identification Number), with the estimated distribution of fishing duration per single diver in grey (dark grey: 80% confidence; light grey: 95% confidence). For events with more than one diver (left column), the reported fishing duration was divided by the number of crew (boxplot), so that for records reported by crew (i.e., correct; blue), the boxplot should be within the distribution indicated by the grey ribbon. Yellow boxplots are outside the grey distribution with >95% certainty, and show records reported incorrectly by diver rather than as combined total effort.

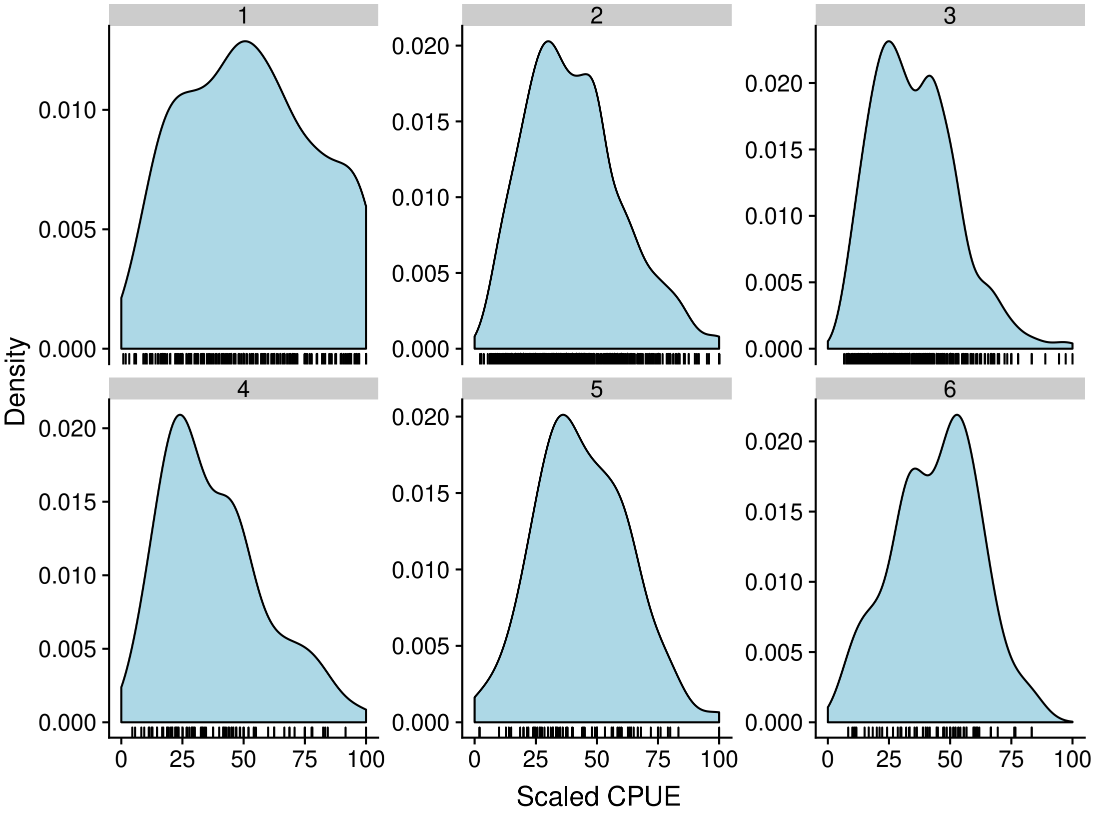


Figure 9: Densities of corrected pāua catch-per-unit-effort (CPUE) in PAU 5A by diver, for records with one to six divers in the crew.

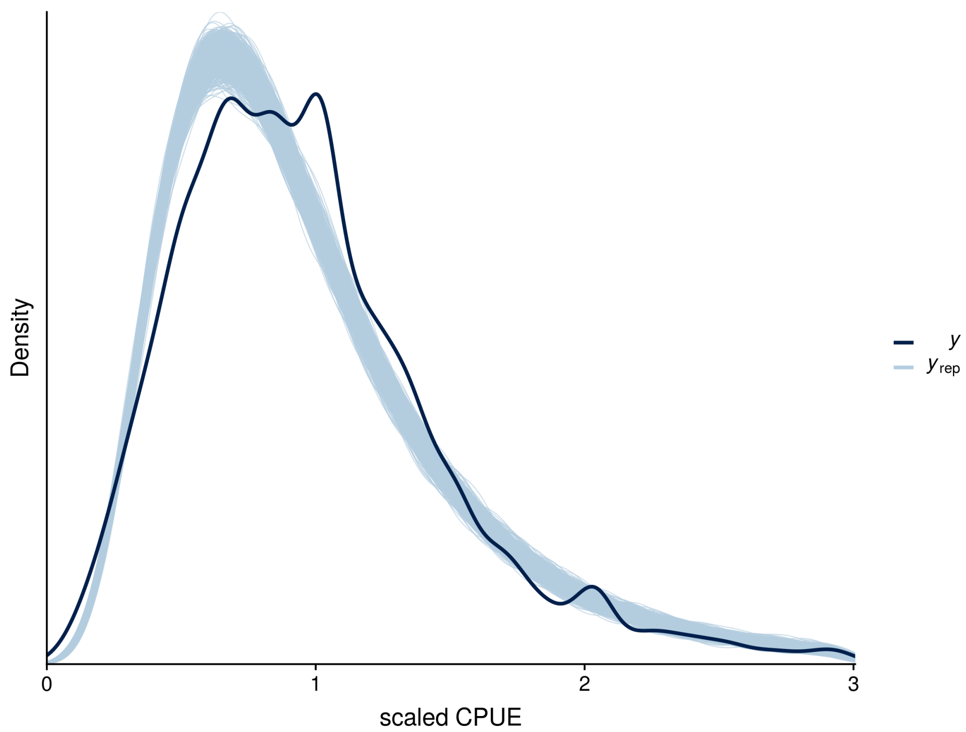
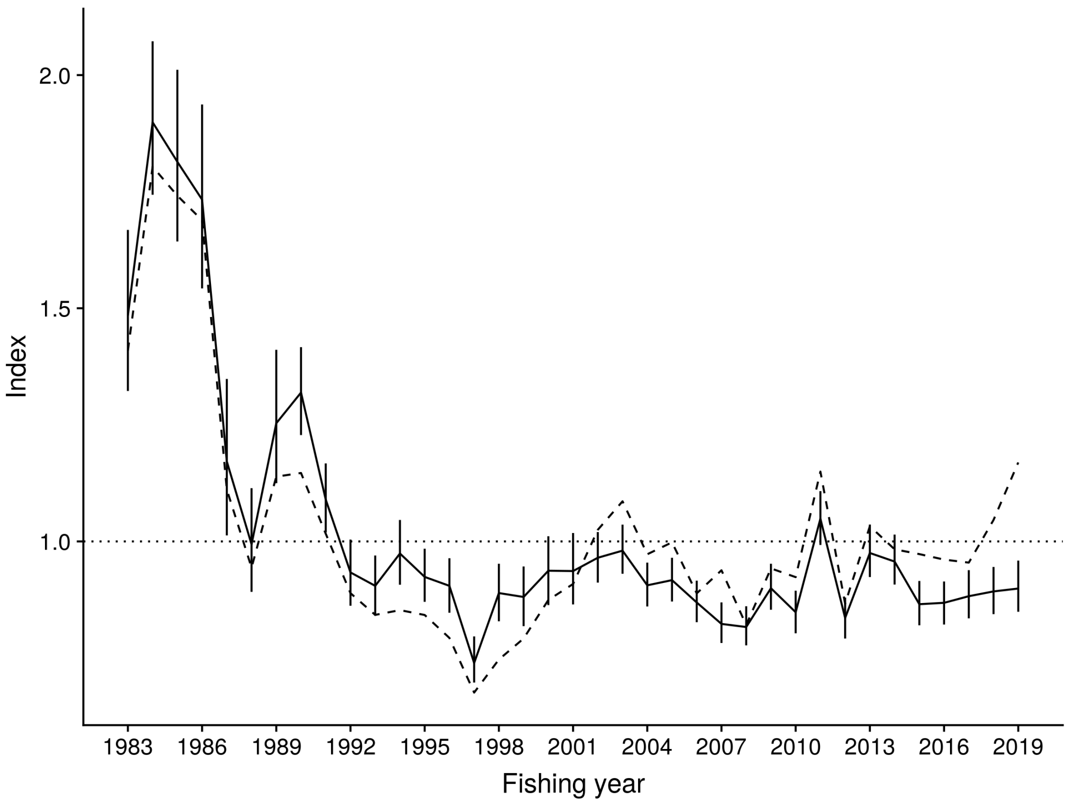


Figure 10: Fit of the log-normal generalised linear mixed model used for catch-per-unit-effort (CPUE) index standardisation. Shown is the cumulative distribution from posterior predictive draws from the model (i.e., predicting each data point; blue) compared with the empirical cumulative distribution (black line).



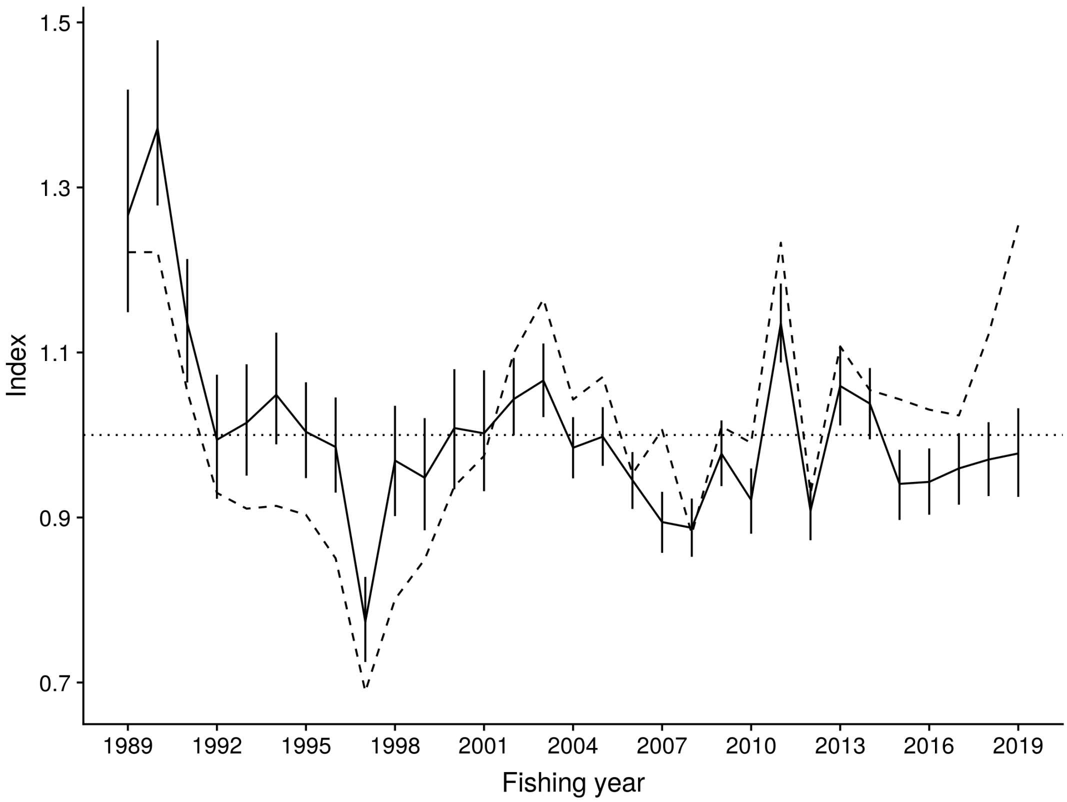


Figure 11: Standardisation of catch-per-unit-effort (CPUE) data using a generalised linear mixed model for CPUE index standardisation. The model was applied to data with (top graph) and without (bottom graph) data from the Fisheries Statistics Unit. Black lines and points with error bars show estimated CPUE index and 95% posterior quantiles. Unstandardised geometric mean CPUE included for reference (dashed line). All models were applied to data corrected by the classification procedure.

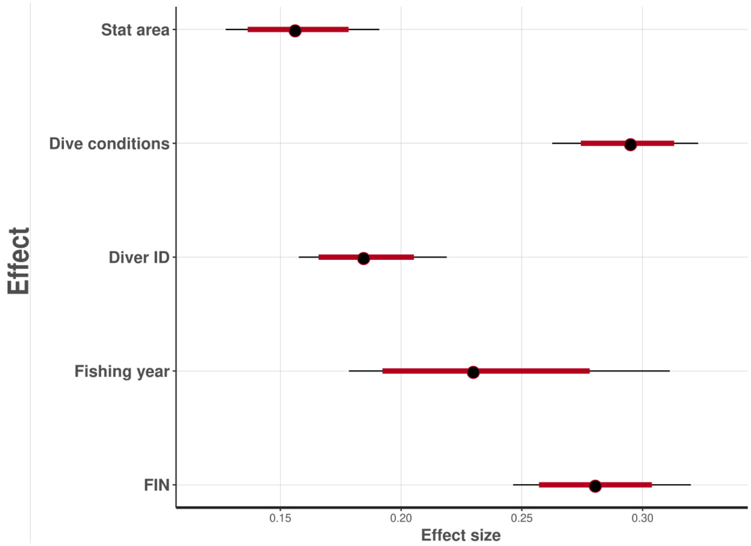


Figure 12: Effect size as variance explained for variables included in the random effects standardisation model; Stat area, statistical area; FIN, Fisher Identification Number.

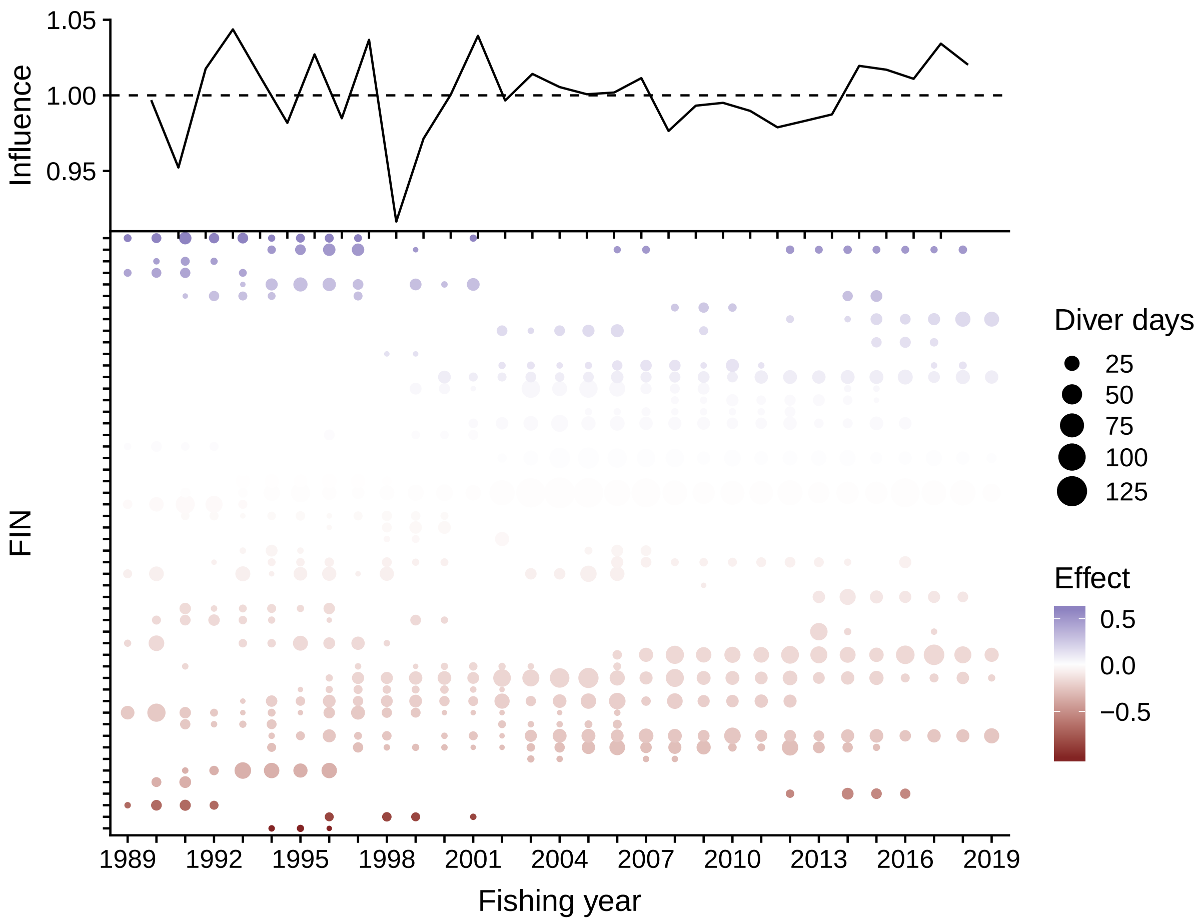


Figure 13: Influence plots for Fisher Identification Number (FIN) effect, showing the effect on raw catch-per-unit-effort (CPUE; top graph) of applying estimated effect sizes (bottom graph) from the factor levels encountered each fishing year. (A positive (>1) influence for a given time period means that the unstandardised index was increased due to the relative distribution of the covariate.)

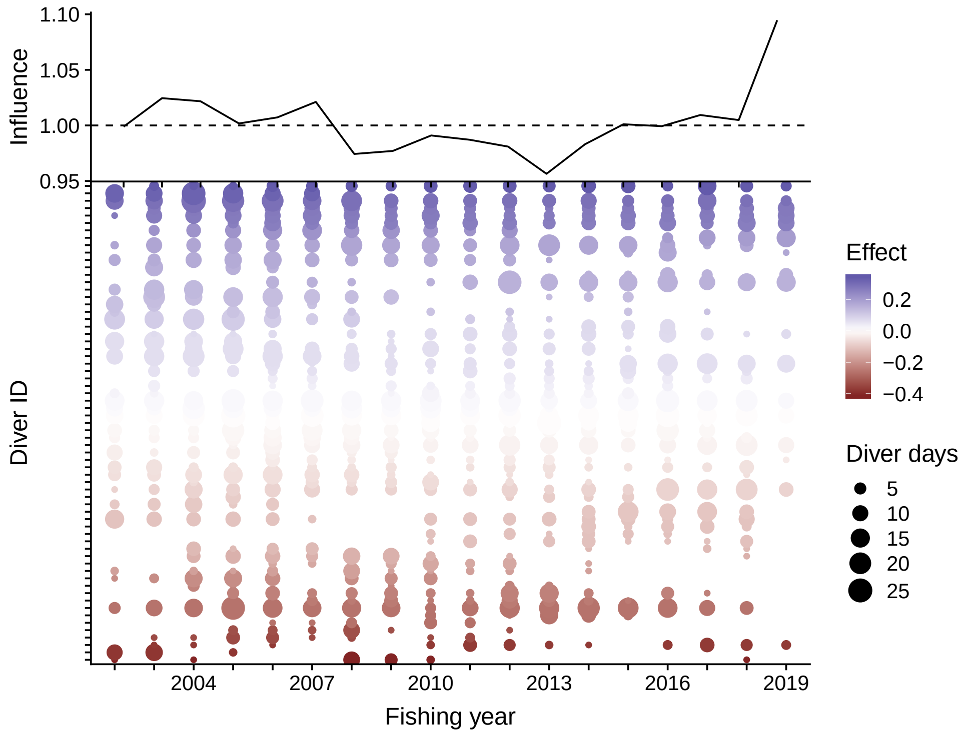


Figure 14: Influence plots for diver random effects, showing the effect on raw catch-per-unit-effort (CPUE; top graph) of applying estimated effect sizes (bottom graph) from the factor levels encountered each fishing year. (A positive (>1) influence for a given time period means that the unstandardised index was increased due to the relative distribution of the covariate.)

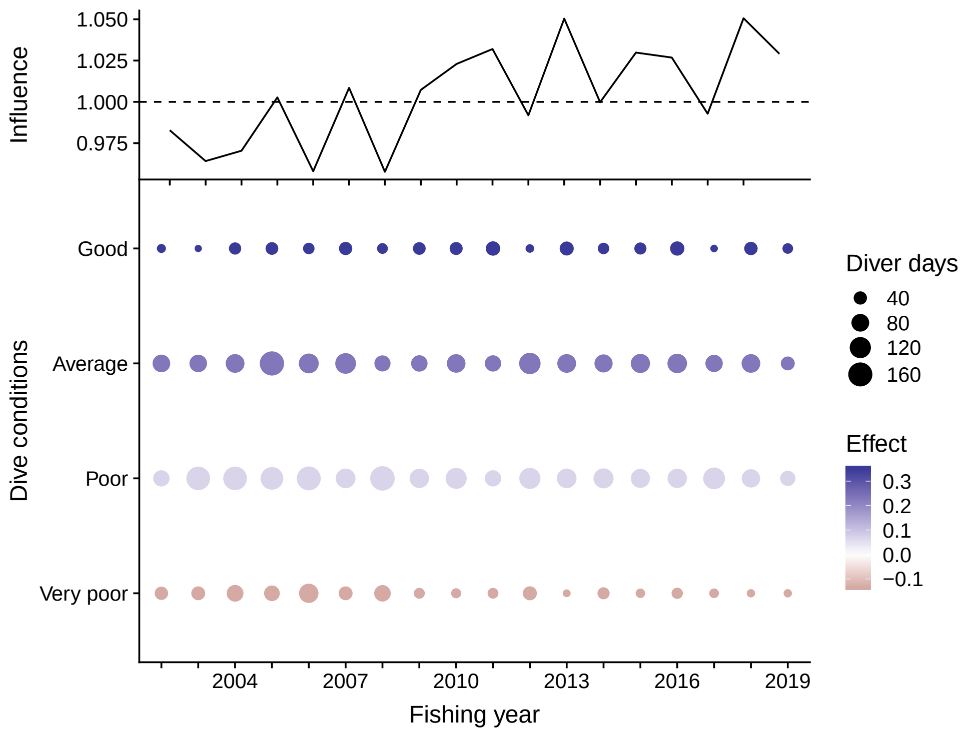


Figure 15: Influence plots for dive condition, showing the effect on raw catch-per-unit-effort (CPUE; top graph) of applying estimated effect sizes (bottom graph) from the factor levels encountered each fishing year. (A positive (>1) influence for a given time period means that the unstandardised index was increased due to the relative distribution of the covariate.)

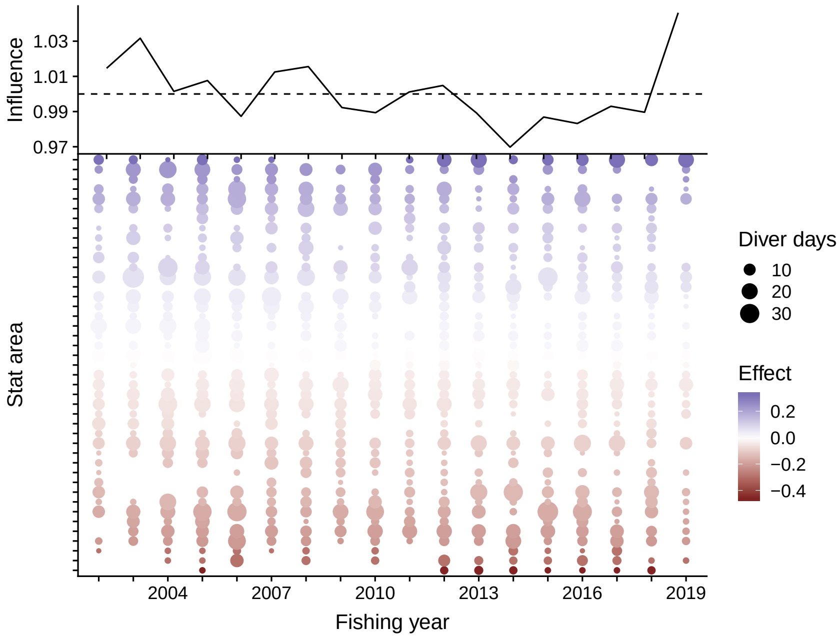


Figure 16: Influence plots for statistical (stat) area effect, showing the effect on raw catch-per-unit-effort (CPUE; top graph) of applying estimated effect sizes (bottom graph) from the factor levels encountered each fishing year. (A positive (>1) influence for a given time period means that the unstandardised index was increased due to the relative distribution of the covariate.)

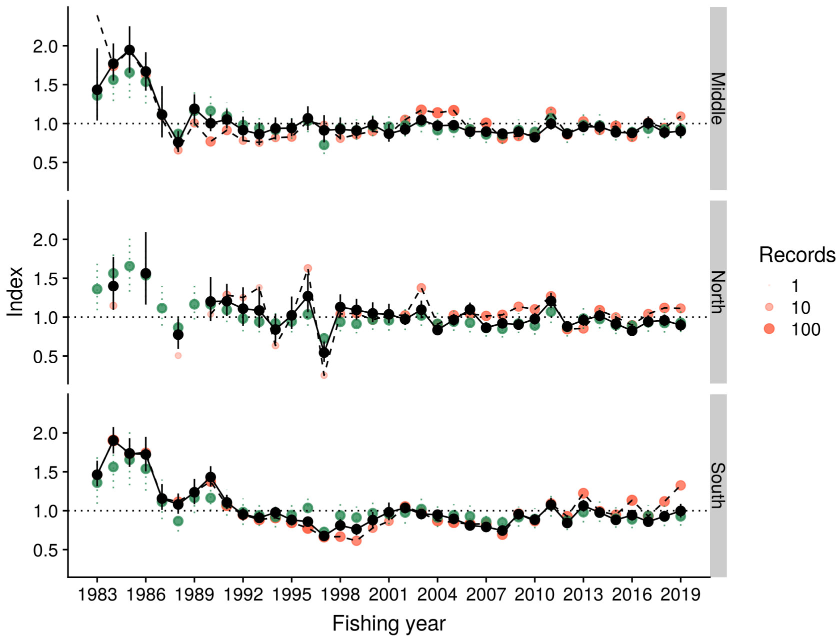


Figure 17: Standardisation of catch-per-unit-effort (CPUE) data using the generalised linear mixed model used for CPUE index standardisation using a model with area-year interaction; showing CPUE by area with FSU data included. Black points with error bars show estimated CPUE index and 95% posterior quantiles. Unstandardised geometric mean CPUE included for reference (dashed line). Red points show raw geometric mean CPUE with size and shading to indicate the number of records per year. Green points and intervals are estimated year effects across all of PAU 5A.

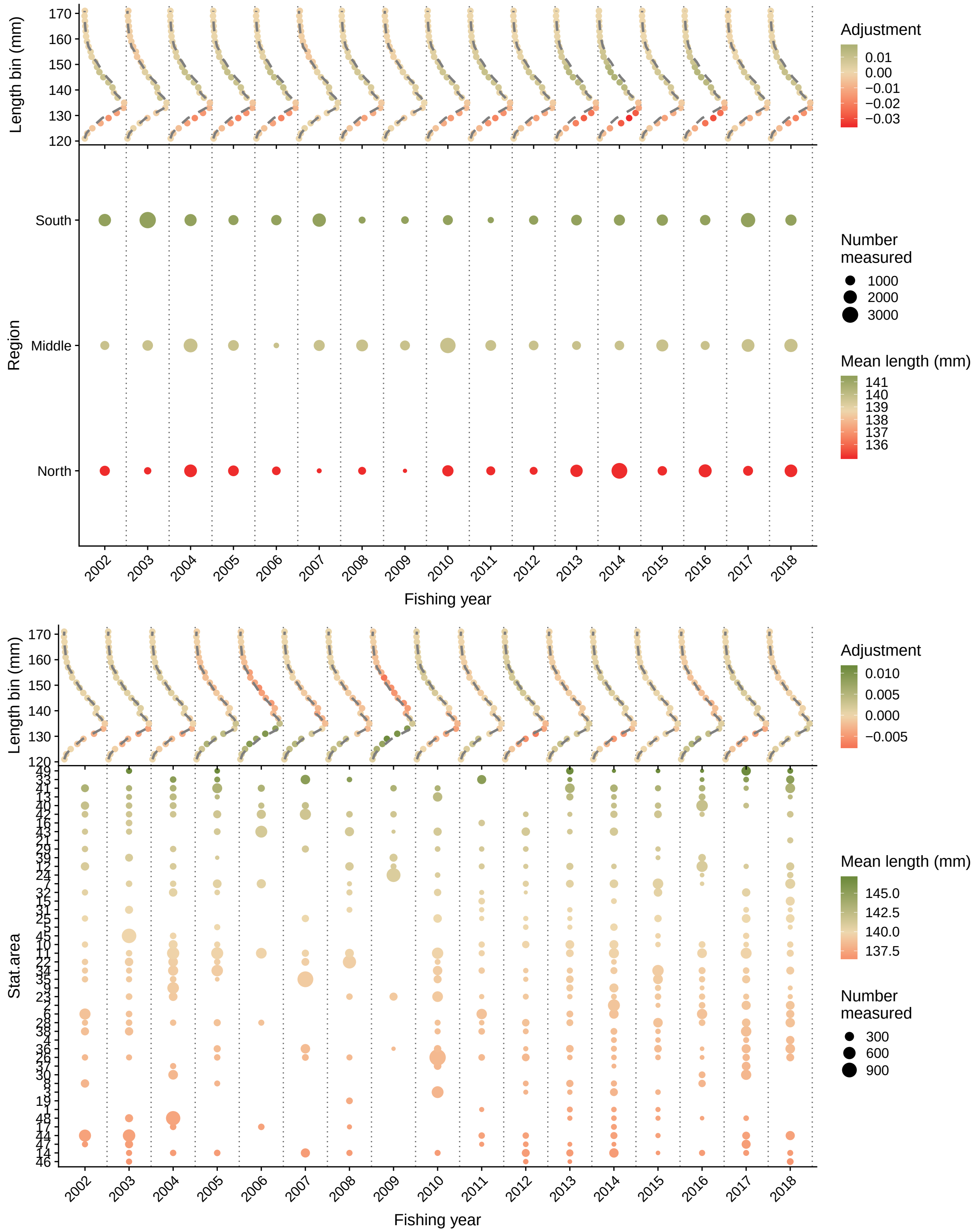


Figure 18: Effects plot for reporting area (top graph) and for small-scale statistical area (bottom graph) for pāua management area PAU 5A. For each graph, the top panel displays the direction of the adjustment from the raw catch sampling length frequency (LF; coloured points for LF classes) in each year and length class in relation to the fishing pattern (shown in the lower panel). Strata in the lower panel are sorted by the observed mean length to allow comparisons of their influence on estimated deviations in the upper panel.

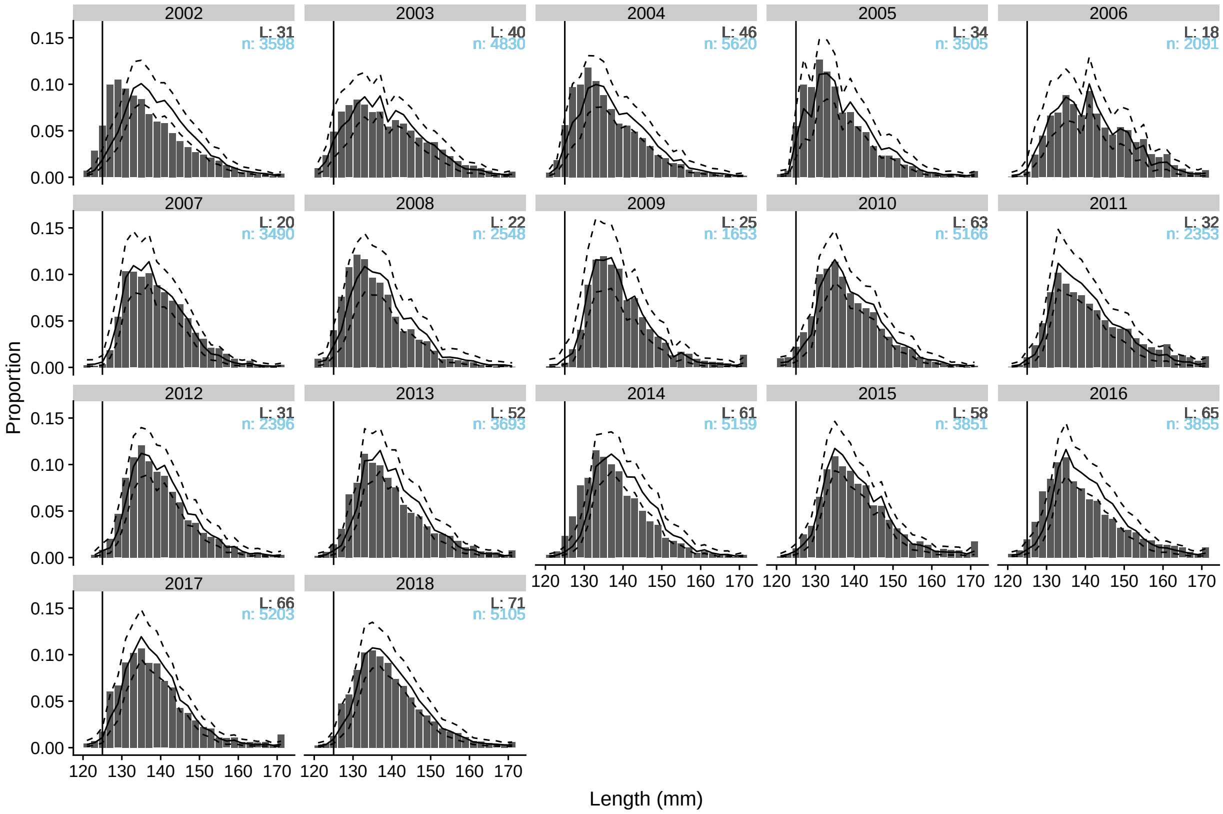


Figure 19: Dirichlet-Multinomial posterior distributions for yearly proportions π_y (black line) in pāua management area PAU 5A, with 95% confidence intervals (dashed line). Raw catch sampling length frequency proportions are in grey; number of landings (L) in black; number of measurements (n) in blue.

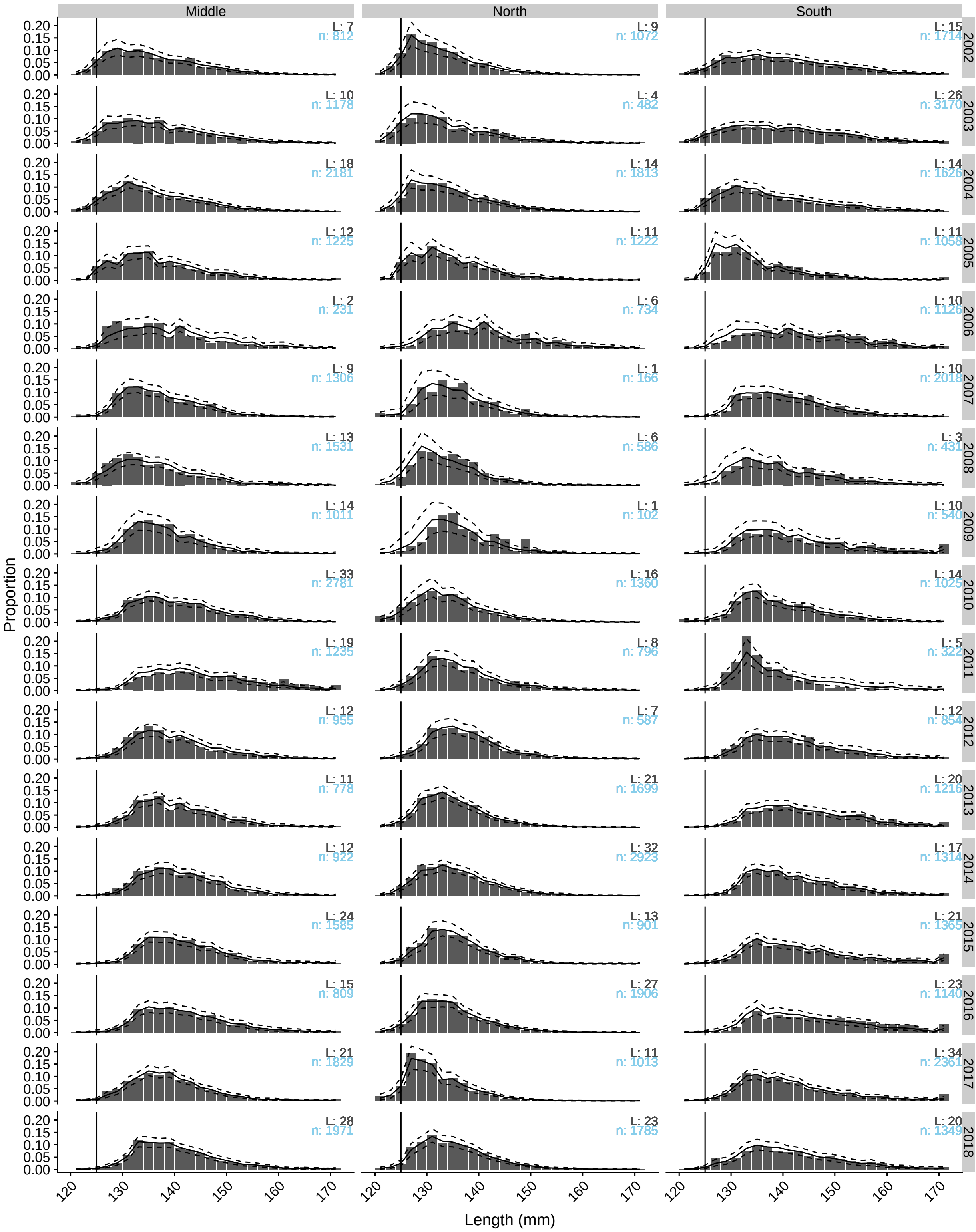


Figure 20: Dirichlet-Multinomial posterior distributions for yearly proportions $\pi_{r,y}$ (black line) in each of three areas in pāua management area PAU 5A, with 95% confidence intervals (dashed line). Raw catch sampling length frequency proportions are in grey; number of landings (L) in black; number of measurements (n) in blue.

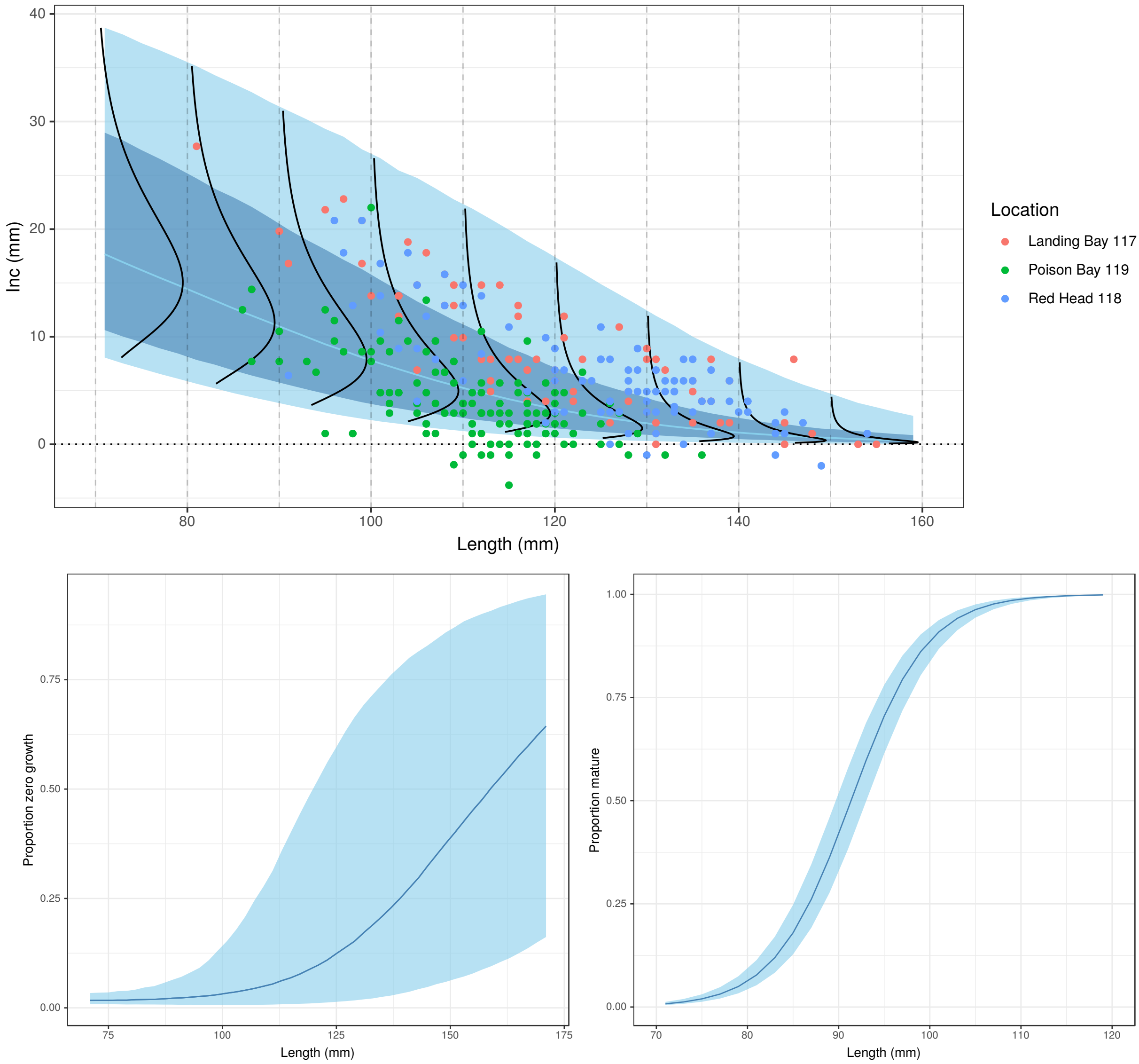


Figure 21: Priors implied from a meta-analysis of growth of pāua, based on model-fitting to all tag-increment data. Shown is the joint prior for positive growth increments (inc) and tag-recapture data from three sites in PAU 5A (top graph), proportion of local populations not growing at a particular size l (left bottom graph), and population level maturity (right bottom graph). For positive increments, dark blue shading shows uncertainty of mean growth, light blue line indicates posterior median of mean growth; light blue area shows the posterior median for the population standard deviation applied to mean growth; black line indicates the implied distribution of growth at the median of the prior.

2.2 Assessment model

The stock assessment model in this assessment used the general length-based population dynamics model that was developed by Breen et al. (2003) and used in subsequent stock assessments (e.g., Marsh & Fu 2017), with changes introduced in the 2018 pāua stock assessment for PAU 5D (Neubauer & Tremblay-Boyer 2019b).

2.2.1 Summary of changes from recent assessments

Key developments in the current analysis included:

- Restricting the estimation of recruitment deviations to years with CSLF data to avoid over-fitting CPUE in early years and introducing spurious patterns in other parts of the model (e.g., estimated increases in catchability).
- Estimating time-varying and dome-shaped selectivity: although diver-level selectivity is likely determined by minimum harvest sizes, population-level selectivity likely varies with spatial fishing patterns (Waterhouse et al. 2014). Because the latter patterns are variable, large pāua may be left in the water in some areas and years. For this reason, the present assessment trialled a dome-shaped selectivity and also a time-varying selectivity as a process error term for both logistic (variable size at 50% maturity) and dome-shaped (variable doming) selectivity to explore potential effects.
- Increases in catchability q were estimated either across the entire period for which CPUE data were available, or for CPUE reporting epochs (i.e., fitting separate selectivity q_s).
- A spatial assessment model of the same form as the single area model, but split by region, was employed alongside the single-area model to ensure that differences in regional dynamics do not bias the large-scale assessment (Neubauer 2020).

2.2.2 Assessment specification

The main pāua population dynamics are described by Breen et al. (2003), but some changes were recently implemented following recommendations by an international expert review panel for the stock assessment (Butterworth et al. 2015). Detailed equations for the most recent version of the population dynamics model are provided by Neubauer & Tremblay-Boyer (2019b).

2.2.3 Prior distributions

The CPUE process error on log CPUE was estimated in the model using a half-normal prior distribution (N^0), with prior standard deviation $\tau_{\mathrm{PE}_{\mathrm{CPUE}}}$:

$$\mathrm{PE}_{\mathrm{CPUE}} \sim \mathrm{N}^0(\tau_{\mathrm{PE}_{\mathrm{CPUE}}}).$$

Similarly, the multiplicative CSLF process error was estimated in the model using a half-normal prior distribution on the log of the process error, standard deviation $\tau_{\mathrm{PE}_{\mathrm{CSLF}}}$.

Recruitment deviations (R_{dev}), equilibrium recruitment (R_0), natural mortality (M), catchability ($\log(q)$), length at 50% selectivity (D_{50}), and 95% selectivity offset (D_{95}) were assigned log-normal priors, parameterised in terms of mean and standard deviation (sd; on the log-scale), with the sample mean for R_{dev} forced to one.

Steepness h was estimated in this iteration of the assessment model; it was assigned a beta distribution prior with parameters a and b, with $a = 10$ and $b = 4$ the default prior, leading to a wide prior that put most of the weight at $h > 0.5$ (see Table 5 for other default priors).

Table 5: Default priors used in the pāua stock assessment model (LN=Lognormal, N=Normal, N^0=half-normal), with prior standard deviation (SD) shown on the log-scale and on the positive scale (CPUE, catch-per-unit-effort; CSLF, catch sampling length frequency).

Parameter	Symbol	Prior	Mean	SD	SD (pos)
Equilibrium recruitment	R_0	LN	13.5	0.5	4.4×10^5
Recruitment deviations	R_{dev}	LN	0	2	54.1
Natural mortality	M	LN	log(0.1)	0.3	0.03
Catchability	q	LN	-13	2	0
Length at 50% selectivity	D_{50}	LN	log(123)	0.03	3.69
95% selectivity offset	D_{95}	LN	log(5)	0.5	3.02
Selectivity increase	D_a	LN	0	1	2.16
Steepness	h	Beta	0.71	0.12	
CPUE process error	PE_{CPUE}	$N^0(0.05)$	0.04	0.03	
CSLF process error	PE_{CSLF}	$N^0(1)$	0.80	0.6	

Prior predictive simulations were used to assess the impact of different formulations of priors for R_0 for final stock status and maximum depletion. The procedure is similar to stochastic stock-reduction analysis (Walters et al. 2006), and can be considered as deriving a joint prior for R_0 and depletion level in the absence of *a priori* information on R_0 (Poole & Raftery 2000). The procedure is as follows:

1. Draw N values from prior for all parameters.
2. Simulate trajectories using same length-based dynamics used in stock assessment, removing observed catches for each region and year.
3. Compare the parameter space where available biomass >0 for all years with the prior, discard any prior values where available biomass is below zero, retain *n* trajectories simulated from the reduced prior.
4. Inspect the distribution of stock status and maximum depletion implied by all *n* retained draws.

An overly vague prior for R_0 implies a strong prior on current stock status and maximum depletion: at high values for R_0, the resulting scale of the biomass implies that fishing has no impact—the prior markedly favours a stock status that reflects no fishing impact. In contrast, small values for R_0 will lead to the rapid depletion of regional stocks in prior simulations, and these values are thus discarded. The prior for R_0 is then adjusted to obtain a prior on stock status that corresponds with expectation. For PAU 5A, the prior was set at $R_0 = LN(13.5, 0.5)$, which leads to a near-normally distributed prior over stock status that is centred on 0.5 and allows for some prior weight near the soft- and hard-limit reference points of 0.2 and 0.1 of spawning stock biomass SSB_0 (Figure 22). For additional detail about the procedure, see Neubauer (2020).

2.2.4 Data weighting

In this assessment, the Kullback-Leibler divergence (KLD) was used as an alternative method for data weighting *via* a measure of information loss. The method relies on the premise that there should be no *a priori* weight for any one dataset, and that relative weight should emerge as part of the analysis and model

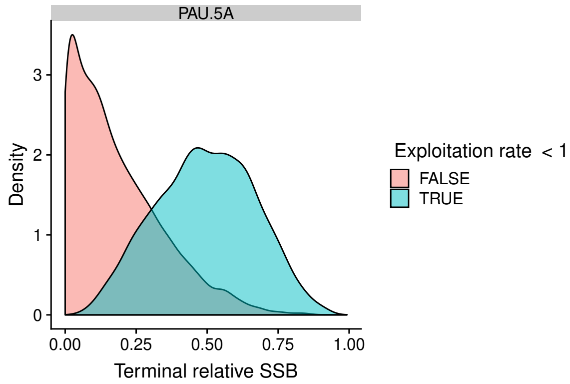


Figure 22: Prior induced on stock status (relative depletion) by the informative prior on equilibrium recruitment R_0 and all other priors in the model. Red shows draws that are discarded *a priori* based on values exceeding the exploitation rate limit.

refinement process. In addition, it makes use of the total distribution for the compositional data instead of only the first moment (e.g., mean length).

The method used previously (in the 2018 stock assessment for PAU 5D, see Neubauer & Tremblay-Boyer 2019b) was slightly modified to calculate the KLD. Previously, the combination of process and observation error was used to calculate the KLD across Y years for the normally-distributed log CPUE index:

$$\text{KLD}_{\text{CPUE}} = 1/Y \sum_y 0.5(\log(\frac{\text{OE}_y^2 + \text{PE}^2}{\text{OE}_y^2}) + \frac{\text{OE}_y^2 + (\text{CPUE}_y - \text{CPUE}_y^M)^2}{\text{OE}_y^2 + \text{PE}^2} - 1), \tag{1}$$

and the multivariate equivalent (scaled to match the univariate KLD) for the CSLF inputs:

$$\begin{aligned}\text{KLD}_{\text{CSLF}} = 1/Y \sum_y 0.5L^{-1}\Big(\log\left(\frac{|\Sigma_y^M|}{|\text{OE}_y|}\right) + \text{tr}((\Sigma_y^M)^{-1}\text{OE}_y) - L + \\ (\text{CSLF}_y - \text{CSLF}_y^M)(\Sigma_y^M)^{-1}(\text{CSLF}_y - \text{CSLF}_y^M)\Big),\end{aligned} \tag{2}$$

with $\Sigma_y^M = \text{OE}_y(1+\text{PE})$ the covariance matrix including OE and PE. The latter terms refer to observation and process error for each data source, respectively.

This previous formulation limits the divergence from the inputs, because the process error will be larger for larger deviations, leading to a smaller KLD. For the present assessment, a parametric (multivariate) normal approximation was assumed instead for the posterior distribution of the log CPUE, and the centred-log-ratio (clr)-transformed model-predicted CSLF compositions. This assumption has the advantage that marked deviations from the inputs that are nevertheless certain (that have low posterior variance, but high process error) lead to larger KLDs. The updated formulation is then:

$$\text{KLD}_{\text{CPUE}} = 1/Y \sum_y 0.5(\log(\frac{\text{var}(\text{CPUE}^M)}{\text{OE}_y^2}) + \frac{\text{OE}_y^2 + (\text{CPUE}_y - \text{CPUE}_y^M)^2}{\text{var}(\text{CPUE}^M)_y} - 1). \tag{3}$$

For the CSLF data, Σ_y^M was redefined to be the empirical covariance matrix of model-predicted CSLF: $\Sigma_y^M = \text{var}(\text{CSLF}^M)$.

The initial data weighting started with a set of weights that had been found to provide reasonable fits for both CPUE and CSLF data in the 2018 stock assessment for PAU 5D and the spatial stock assessment for pāua (Neubauer 2020, Neubauer & Tremblay-Boyer 2019b). These weights were then varied to inspect the effect of weighting of CSLF and CPUE data on model outcomes.

2.2.5 Technical model details

The model was initialised for a period of 60 years with constant recruitment at R_0 and no fishing. All Markov chain Monte Carlo algorithms (MCMCs) were run using the no-u-turn-sampler (NUTS), implemented in Stan (Stan Development Team 2018). The Stan language is more efficient than conventional Metropolis Hastings or Gibbs sampling for MCMC, and also provides diagnostics that can signal biased MCMC transitions (divergences) and potential bias in estimated quantities from these transitions. All MCMC chains were, therefore, monitored for divergent transitions to ensure that they were not biased. Initial models were run with four independent chains for the MCMC configuration, and 500 iterations were kept after discarding the initial 500 iterations. For the final base case and sensitivity, eight independent chains were run over 6000 iterations, with the first 1000 samples discarded for each chain, and a further 5000 samples saved for inference and post-processing.

2.3 Stock assessment

2.3.1 Set 1a: CPUE, catch set, and structural sensitivities

A first set of model runs explored different scenarios:

- including or excluding the FSU CPUE index;
- estimating a trend in catchability q, and forcing hyper-stable CPUE;
- high and low catch scenarios for area 30 prior to 1996;
- low recruitment variability.

The trend in catchability q was implemented as a linear trend, with an intercept of $log(q)$ and slope $\theta_{\log(q)}$. Data weight parameters were set to values that produced reasonable fits in other assessments.

2.3.2 Set 1b–spatial model runs: CPUE, catch set, and structural sensitivities

A variation of the first set of model runs explored the same scenarios as in set 1a, using the spatial model described by Neubauer (2020) for each of the three large-scale reporting strata (areas 30, 31, 32). Natural mortality and steepness were shared parameters, whereas recruitment was estimated independently for each region, and total (PAU 5A-wide) unfished recruitment was partitioned into each of the three regions using a composition vector that is estimated within the model using an informed prior based on relative catch levels.

2.3.3 Set 2: Selectivity, using separate q for epochs, and recruitment estimation for CSLF years only

After running the set 1a models, it was evident that the models were using recruitment to adjust the biomass for increases in CPUE after an initial decline in the late 1980s and early 1990s. Nevertheless, this period of CPUE increase coincided with a period of rapidly increasing efficiency (dive gear, operational aspects, weather forecasting) in all pāua fisheries throughout New Zealand, which all showed some degree of CPUE increase during this period. For this reason, the SFWG decided to fix recruitment for all years until CSLF information was available (2000–01), and to instead use variable catchability by i) splitting catchability into reporting epochs (FSU, CELR and PCELR), and ii) estimating increase in catchability for each epoch.

In addition to fixing early recruitment, the assessment here trialled using variable selectivity to account for spatially-variable fishing patterns that likely determine some of the CPUE variation (instead of variation being determined by recruitment): if fishers only fish a subset of available areas in any given year (due to weather or market constraints), variable (and potentially dome-shaped) selectivity would be expected given small-scale variation in growth and fishing pressure. In the present assessment, both variable logistic selectivity (variable length at 50% selection) and fixed and variable dome-shaped selectivity (with variable right-hand limb of the inverted quadratic curve used for the dome-shaped selectivity) were trialled. Models with variable dome-shaped selectivity did not converge and were, therefore, excluded from this assessment.

In addition, owing to uncertainty about the accuracy in early FSU reporting and implausible scenarios resulting from the exclusion of FSU data, the present study trialled different scenarios, with the second set of models set up as follows:

- including the CPUE index from the FSU data, but starting CPUE in 1984, or estimating initial depletion in 1984 (starting catch and CPUE in 1984);
- estimating a trend in catchability by CPUE reporting period (using separate initial catchability q for FSU, CELR, and PCELR data).
- baseline catch scenarios for area 30 prior to 1996;
- fixed recruitment prior to CSLF data availability (estimated from three years prior to first year of CSLF data);
- variable logistic selectivity and dome-shaped selectivity (fixed; variable dome-shape selectivity did not converge).

2.3.4 Set 3: Data weights and recruitment estimation for CSLF years only

The robustness of models from the first two sets that were considered plausible (baseline catch with FSU CPUE from 1984, with or without recruitment deviations for pre-CSLF period, with or without variable selectivity) was investigated by varying model weights. Three sets of weights were trialled in addition to weights used in sets 1 and 2: all sets down-weighted CPUE by a factor of 2 relative to sets 1 and 2, and either doubled (0.2) or halved (0.05) CSLF weights.

3. RESULTS

3.1 Initial model runs

3.1.1 Set 1a: CPUE, catch set, and structural sensitivities

The initial set of model runs produced three distinct outcomes (see Appendix A.1, Figures A-1 to A-9): models that did not include FSU data suggested little depletion since the start of the fishery (final stock status above 60% of SSB_0; Figures A-8 and A-9), whereas models with forced hyperdepletion in the CPUE index or estimated increase in catchability led to higher depletion levels (final stock status near 40% of SSB_0). The baseline model that included FSU data, and scenarios with low or high catch from area 30, produced intermediate status estimates, as did the model with reduced recruitment variability. The latter model was also distinct in that it estimated markedly faster growth (Figure A-3) and also high natural mortality ($M>0.1$; Figure A-1; with $M\leq0.1$ for all other runs).

Based on these model runs, the SFWG decided that model scenarios without FSU data were unlikely to adequately capture biomass declines over the initial phase of the fishery; the estimate of a stock near 75% of un-fished biomass in the early 2000s did not appear compatible with a voluntary 30% shelving of the quota in 2006. Because models with estimated increase in catchability q produced similar results to models with forced hyperdepletion, the latter models were not pursued further.

3.1.2 Set 1b: Spatial model for PAU 5A

Spatial model runs were able to partition the initial biomass decline and demographic variability into the three pre-1996 research strata (see Appendix A.2, Figures A-10 to A-20). The northern region had the lowest depletion level owing to sporadic fishing in the region, which had significantly slower growth than the other regions (Figures A-12 to A-14), but a similar proportion of the overall recruitment (see values for p[2] in Figure A-10).

Overall, aggregate values from the spatial model were almost identical to the non-spatial model (e.g., Figure 23), and the more parsimonious single-area model was, therefore, preferred by the SFWG.

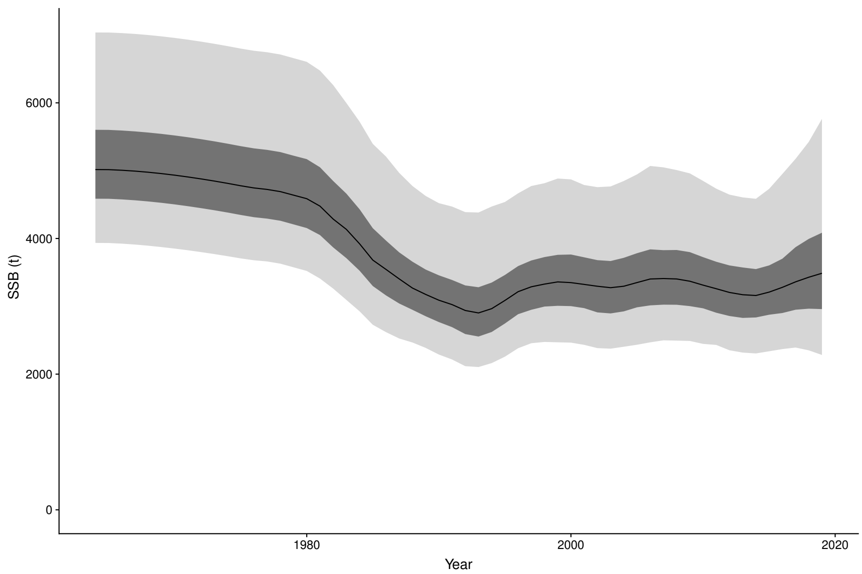


Figure 23: Trend in predicted relative spawning stock biomass (SSB) for pāua for the baseline spatial stock assessment model in quota management area PAU 5A (black line and 95% confidence interval).

3.1.3 Set 2: Selectivity, using separate q_s for CPUE epochs, and recruitment estimation for CSLF years only

All models in the second set of model runs produced similar outcomes, except the model with variable selectivity; this model appeared to over-fit and produce implausible selectivity patterns (see Appendix A.3, Figures A-21 to A-29): starting CPUE in 1984 (i.e., excluding the first year, 1983) produced similar results to model runs that included the first year. Nevertheless, the first year was excluded from subsequent model runs based on concerns about early CPUE reporting. Estimating initial depletion in 1984 invariably led to low estimated initial depletion (i.e., the mode of the posterior distribution for initial depletion was near zero; Figure A-21). This depletion level was considered implausible by the SFWG. Because models with estimated initial depletion led to similar inferences about stock status and productivity, these models were not explored further.

Estimated selectivity in the dome-shaped selectivity model was only slightly domed, with a small increase in the dome after 2006 (Figure A-25). The (invariable) left-hand limb of the curve was estimated near post-2006 selectivity for models with logistic selectivity. The model with variable logistic selectivity suggested highly variable selectivity with selection of large individuals in early years to allow the model to fit a steep CPUE decline in the FSU years (Figure A-25). Nevertheless, this pattern was considered implausible by the SFWG, because it seemed that selectivity was taking the role of other, unknown process error and allowed the model to over-fit.

Models with no time-varying process error (i.e., no yearly variable selectivity or recruitment) prior to availability of CSLF data nevertheless provided reasonable fits to CPUE (which shows some high inter-annual variability).

3.1.4 Set 3: Data weights and recruitment estimation for CSLF years only

Changing the weights for CSLF and CPUE data had comparatively little impact on the stock trajectory (see Appendix A.4, Figures A-30 to A-38): reducing CSLF weights generally led to a lower stock status, but all estimates remaining near or above 40% of B_0. A reduction in CSLF weight also led to less marked variation in estimated selectivity for the variable logistic selectivity model (Figure A-34). Nevertheless, the selectivity still suggested selection of large individuals in early years of the fishery and a decrease in the fully-selected size in more recent years. This outcome is contrary to estimates from a model with a single shift in selectivity in 2006, which suggests a shift in the size-at-50% selection in 2006 corresponding with an increase in the minimum harvest size.

The difference from data weights was small overall compared with differences introduced by estimating (or not) recruitment for pre-CSLF years. Models that included less recruitment for all CPUE years and trends in catchability q suggested a strong recent increase in q over the PCELR period, and a continued decline of the fishery to below 40% of SSB_0. Nevertheless, this recent increase in catchability was considered less likely by the SFWG, especially because most of the significant innovations in the fishery (improved boats and gear) took place in the CELR period, and most likely not in the more recent PCELR period.

3.2 Base case results and agreed sensitivity run

As a suitable base case, the SFWG selected a model with:

- CPUE starting in 1984, removing the initial FSU record,
- estimated recruitment from 2001,
- separate catchability for three reporting periods.

The base case (see Appendix B.1) suggested a relatively slow but steady downward trend since the 1990s, with a more recent downward trend that was attributed to estimates of recruitment being forced low to compensate for early estimated above-average recruitment (Figure B-10 — CPUE is slowly increasing most recently; see Figure B-5). The base case also indicated that the stock is currently near target spawning stock biomass with a high probability (Table 6, Figure B-11), with little to no probability that it is below the soft limit of SSB_0. This inference was supported by the agreed sensitivity run, which included an estimated trend in catchability (Table 6). Projections from the base-case model suggested little movement in spawning stock biomass over the coming years at current catch levels, but a projected decline should catches be increased (Table B-2).

The tested sensitivity led to lower recent stock status, but with a slight recent increase, providing an improved fit to recent CPUE (Table 6; Figure B-25). In addition, projections from this model were slightly more optimistic about future stock trajectory, even at increased catch levels (Table B-4).

Table 6: Final model runs for the stock assessment of pāua in management area PAU 5A. Posterior quantities for natural mortality M, relative available spawning stock biomass (SSB), stock status and and probability of the stock status being below the soft limit ($0.2SSB_0$). Numbers are posterior means, with the 0.025, 0.500, and 0.975 posterior quantiles in parentheses (see detailed results in Appendix B: for the base case, section B.1; for the sensitivity run, section B.2).

Run	M	Available biomass	Stock status	P(SSB>0.2)
Base case	0.10 (0.07;0.10;0.14)	0.40 (0.30;0.40;0.52)	0.52 (0.41;0.51;0.63)	1.00
Sensitivity run	0.09 (0.06;0.09;0.12)	0.26 (0.14;0.25;0.42)	0.41 (0.26;0.40;0.57)	1.00

4. DISCUSSION

In spite of a number of modifications to the model structure and assumptions, the present assessment reached similar conclusions about the stock status in PAU 5A as previous assessments, notably the 2015 assessment (Fu 2015a, 2015b). The present assessment used both single and multi-area models, but both model frameworks led to similar conclusions. In previous assessments, the stock in PAU 5A was assessed using two separate assessments for the South coast and Chalky Sound area (area 30), and for areas 31 and 32, based on *a priori* assumed differences in growth.

Nevertheless, upon re-examination of data, this practice was considered to be incompatible with biological information: length frequencies are similar in areas 30 and 31, but smaller in area 32, which includes areas with the most stunted pāua growth in the QMA. In addition, the only reliable growth data from the QMA came from sites on the South coast, with data from the northern part of the fishery (area 32) previously considered to be non-representative. There was, therefore, no growth data for the previous combination of areas 31 and 32, and South coast data were used for the assessment in these two areas, leading to estimates of almost identical growth.

For the present assessment, the same growth prior was used as in the 2018 stock assessment for PAU 5D (Neubauer & Tremblay-Boyer 2019b). This prior was based on a country-wide meta analysis of growth, and only provides the model with a vaguely informed prior on growth. The growth data for PAU 5A, therefore, entered the model only via the meta-analysis prior; data from individual growth sites were considered to be un-representative, preventing their use for estimating mean growth and growth variation across the entire QMA. With this prior, the spatial model estimated a growth pattern which suggested mainly stunted growth in the northern area (area 32), and average (relative to country-wide mean) growth in areas 30 and 31. These estimates, together with the finding that the spatial model provided almost identical inferences to the non-spatial model, suggest that the previous sub-division of the assessment into two areas was not necessary, and that management can be based on a single-area model. Although, for reasons of model parsimony, the spatial model was not carried forward by the SFWG to assess the stock status, a spatial model which further splits the QMA into fine-scale strata (e.g., individual sound systems in Fiordland) could be explored in the future to aid fine-scale spatial management.

In this assessment, the previous practice of estimating recruitment prior to having available CSLF data was discontinued. The reason for this change was that models with weak constraints on early recruitment deviations tend to estimate considerable recruitment variation to "explain" fluctuations in CPUE that are more likely caused by reporting changes and increases in catchability that are not accounted for in the CPUE standardisation. Assuming constant recruitment prior to CSLF data being available (i.e., 2001) led to a deterioration in fit to CPUE data in earlier years (see Figures B-4 and B-18); however, this lesser fit seems justified given that there is little evidence in length frequencies or CPUE for marked recruitment variations since 2001 (in any pāua fishery).

Although the present assessment tended to estimate a trend in catchability at a later time than is considered to have happened, a linear trend in q was estimated in the key sensitivity here to allow for the possibility that increases in catchability occurred over time. This scenario led to a slightly more pessimistic view of the current status of the fishery, but it led to more optimistic outlooks about future stock trend given current catches. Nevertheless, whether changes in catchability are still occurring is uncertain, and projections with increasing catchability should, therefore, be treated with caution.

5. ACKNOWLEDGMENTS

The author thanks Marine Pomarède, Storm Stanley, Jeremy Cooper, and the members of the Shellfish Working Group. Stimulating discussion with M. Dunn (NIWA) led to various developments in this assessment.

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APPENDIX A: MODEL COMPARISON

A.1 Model runs: Set 1a

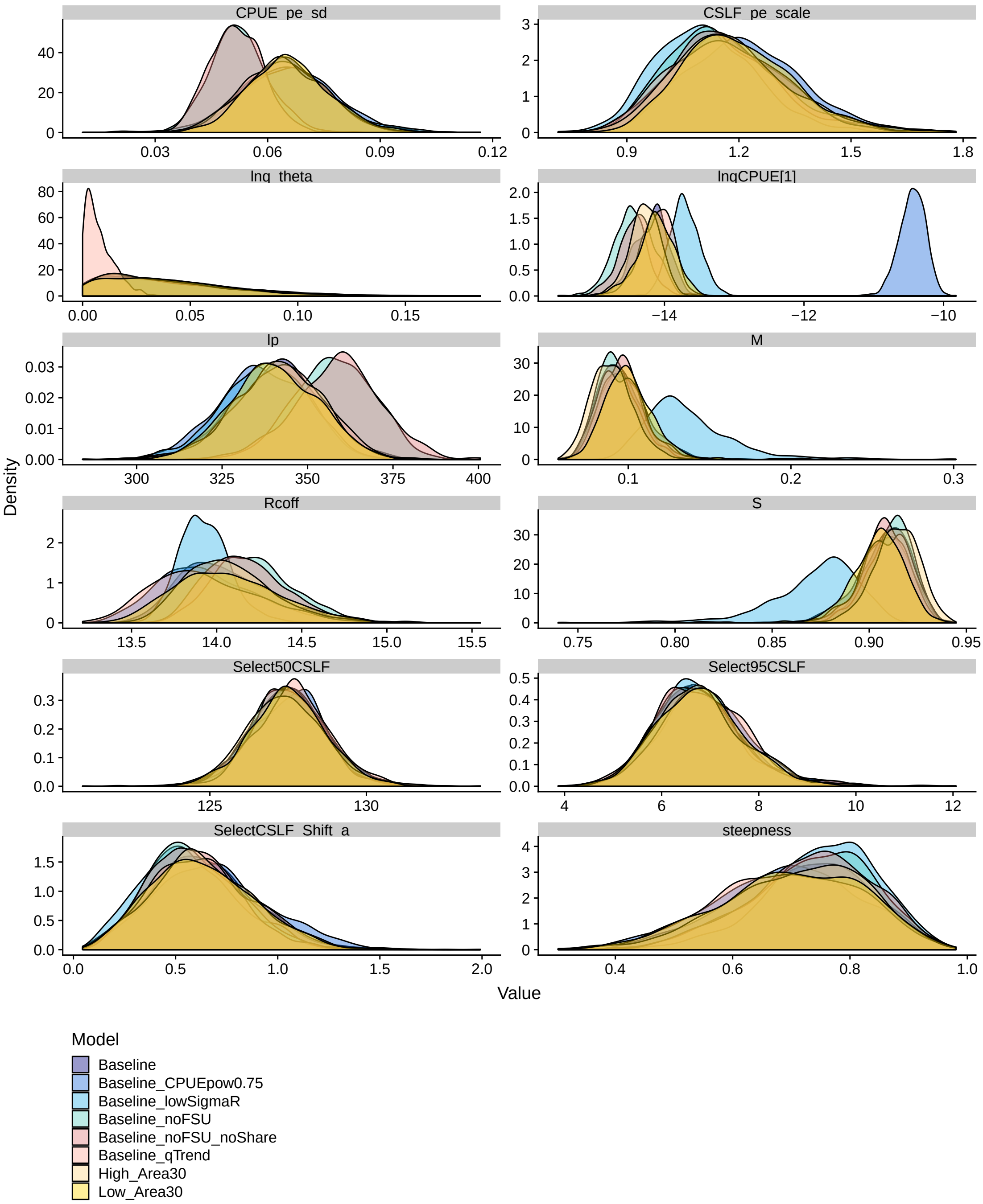

Figure A-1: Comparison of posterior densities for parameters in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit (FSU) data (noFSU), and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

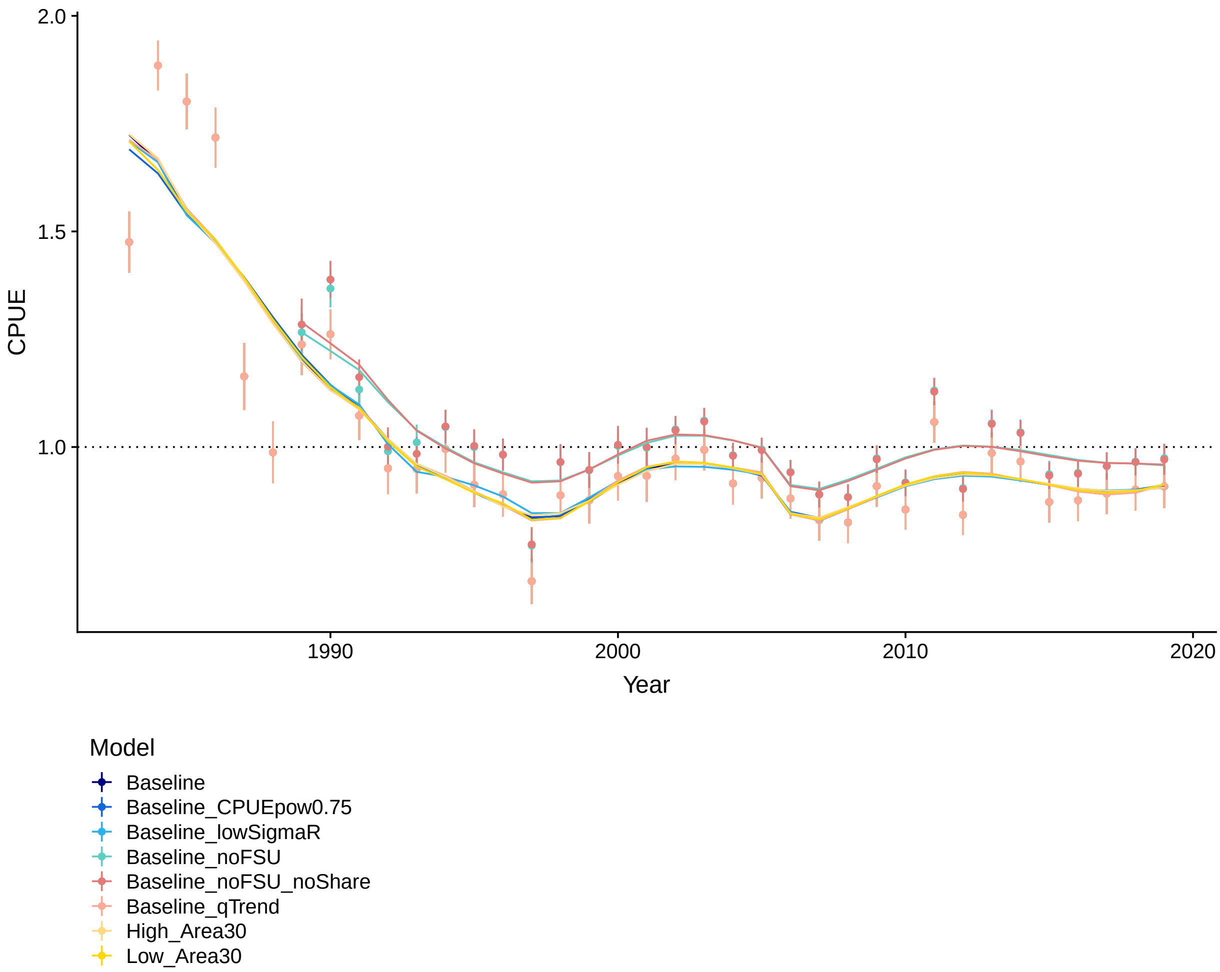

Figure A-2: Comparison of posterior median predicted catch-per-unit-effort (CPUE) in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

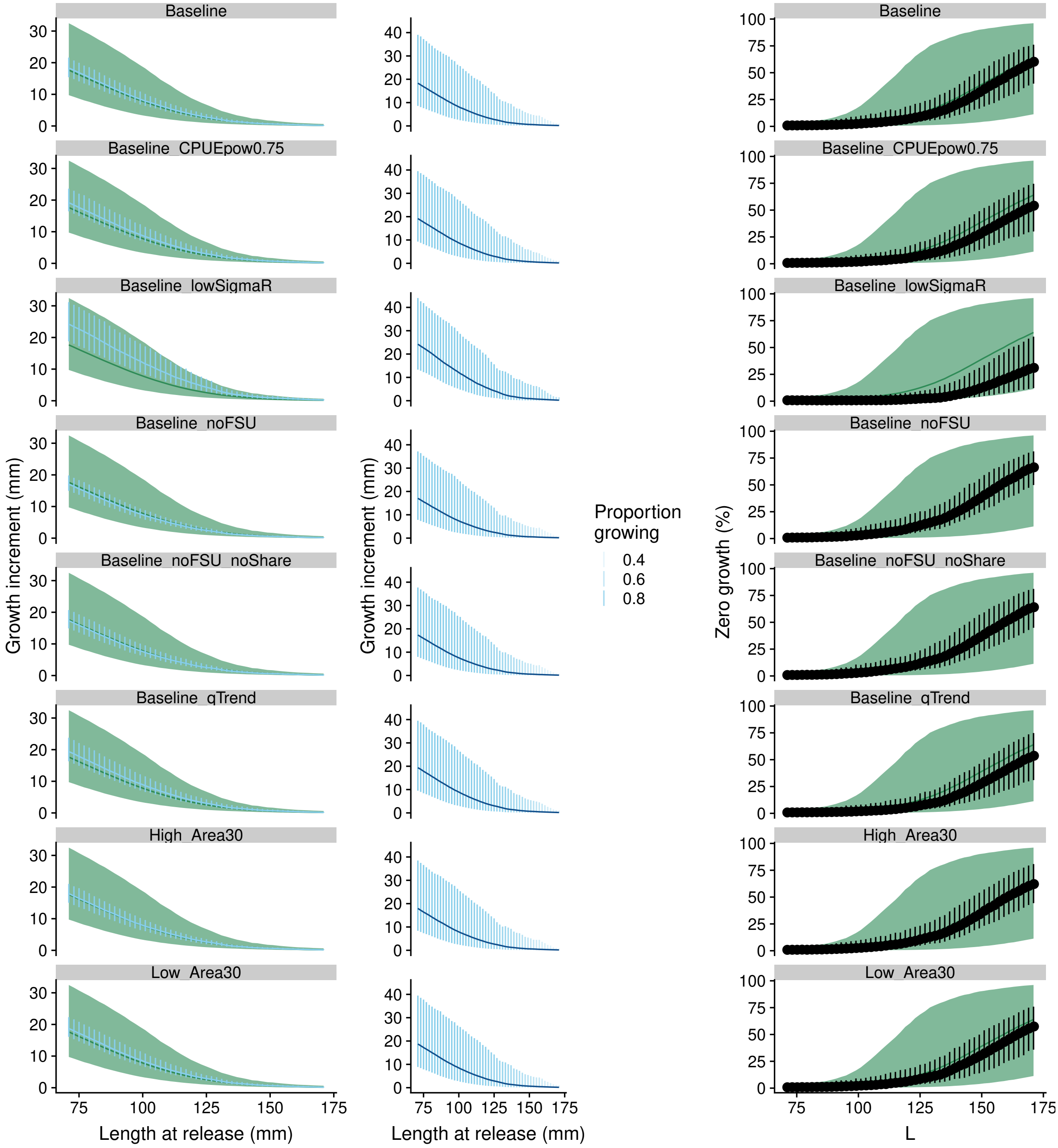

Figure A-3: Comparison of prior and posterior growth in the stock assessment model using parameters for Set 1a. Left graphs: prior for population mean growth (prior mean (green line) and 95% prior interval (green shading)), and posterior mean growth (light blue posterior median and 95% posterior interval). Middle graphs: median distribution of population somatic growth by size class with posterior mean (dark blue line) and 95% growth intervals. Right graphs: prior for proportion of pāua not growing at each length class (prior mean (green line) and confidence interval (green shading)) and posterior distribution (black dots and 95% posterior confidence). Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

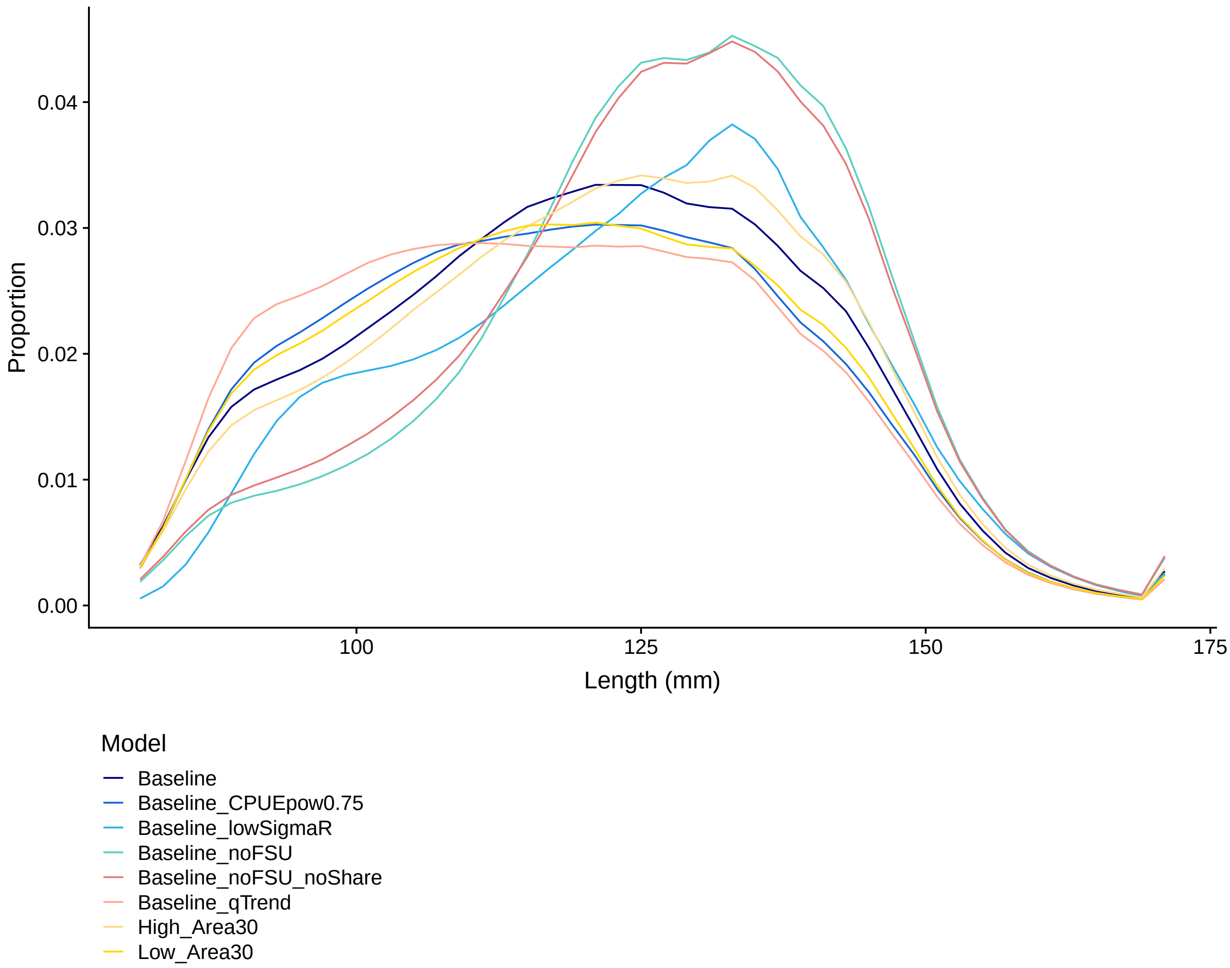

Figure A-4: Comparison of posterior mean proportions-at-length in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

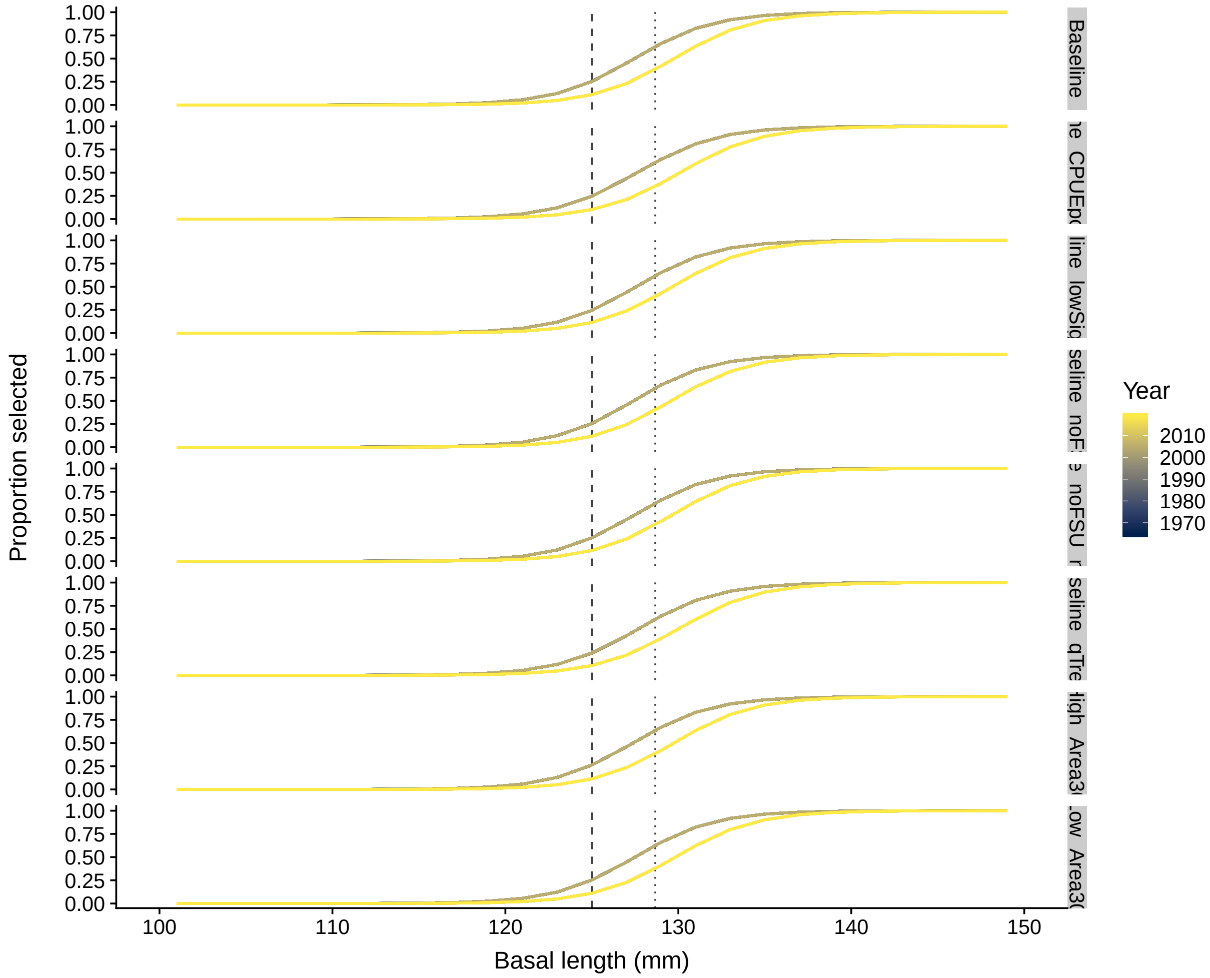

Figure A-5: Comparison of posterior mean selectivity-at-length in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

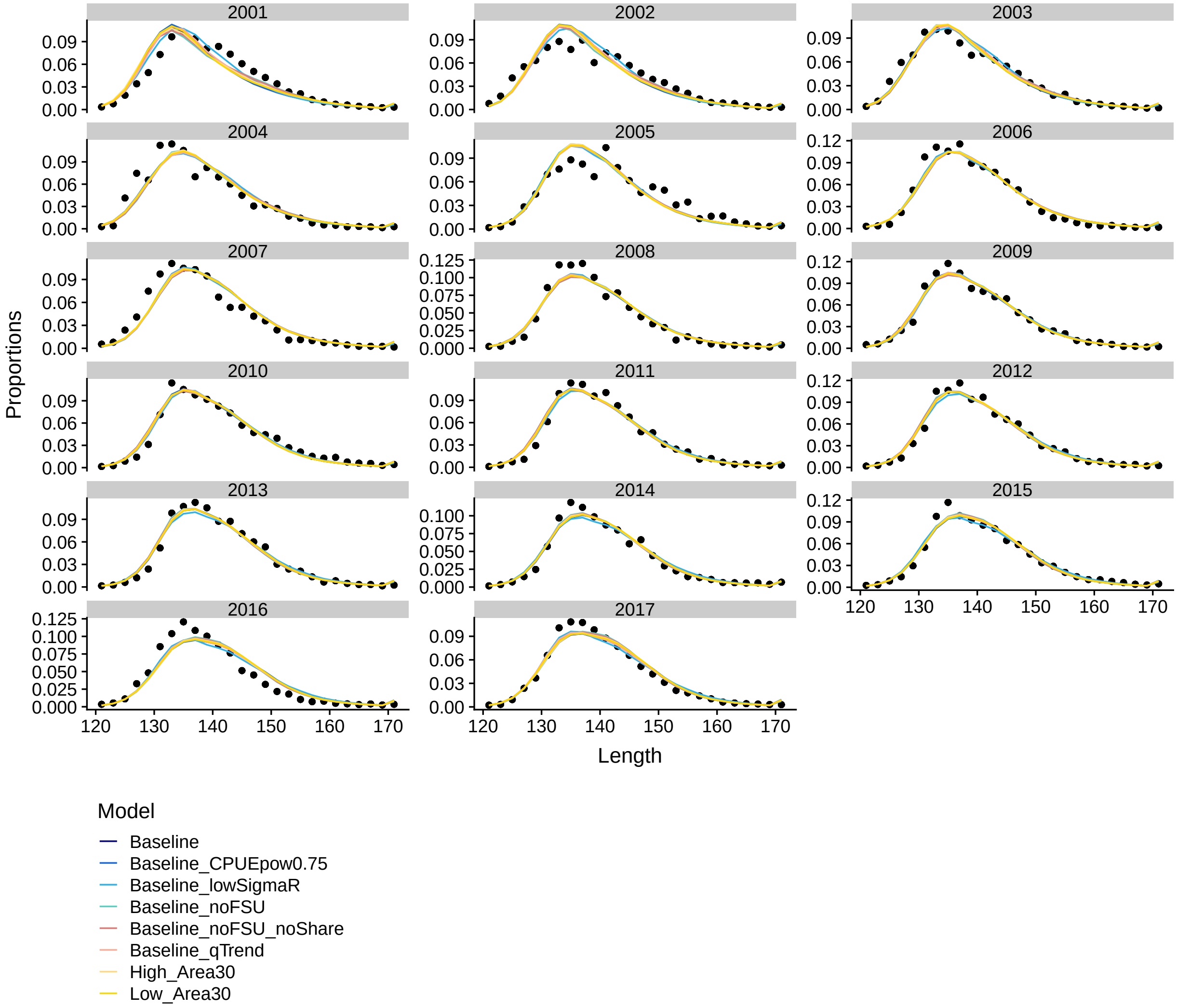

Figure A-6: Comparison of posterior mean predicted catch sampling length frequency (CSLF) with estimated CSLF proportions, in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R = 0.4).

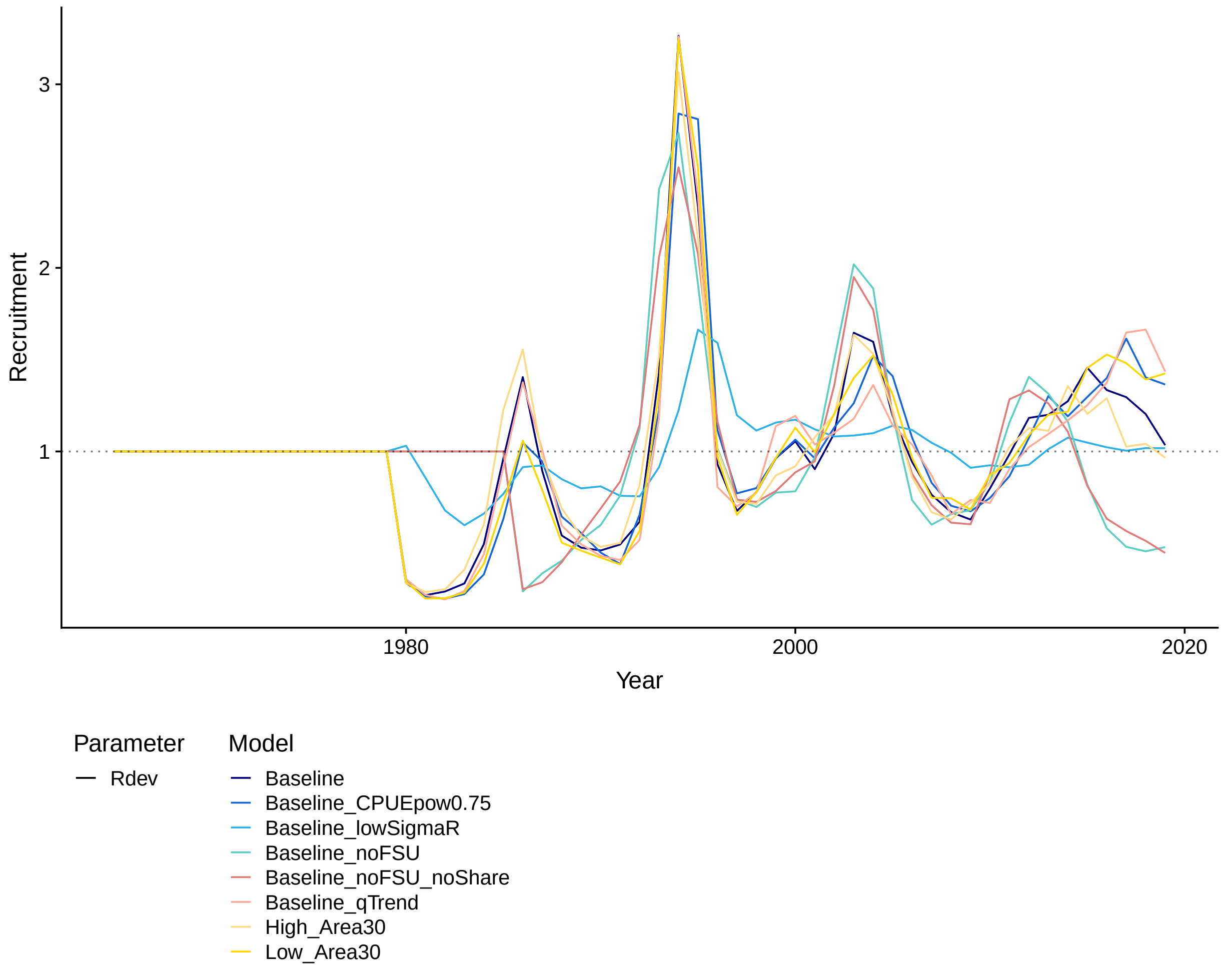

Figure A-7: Comparison of posterior mean recruitment deviations (R_{dev}) in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

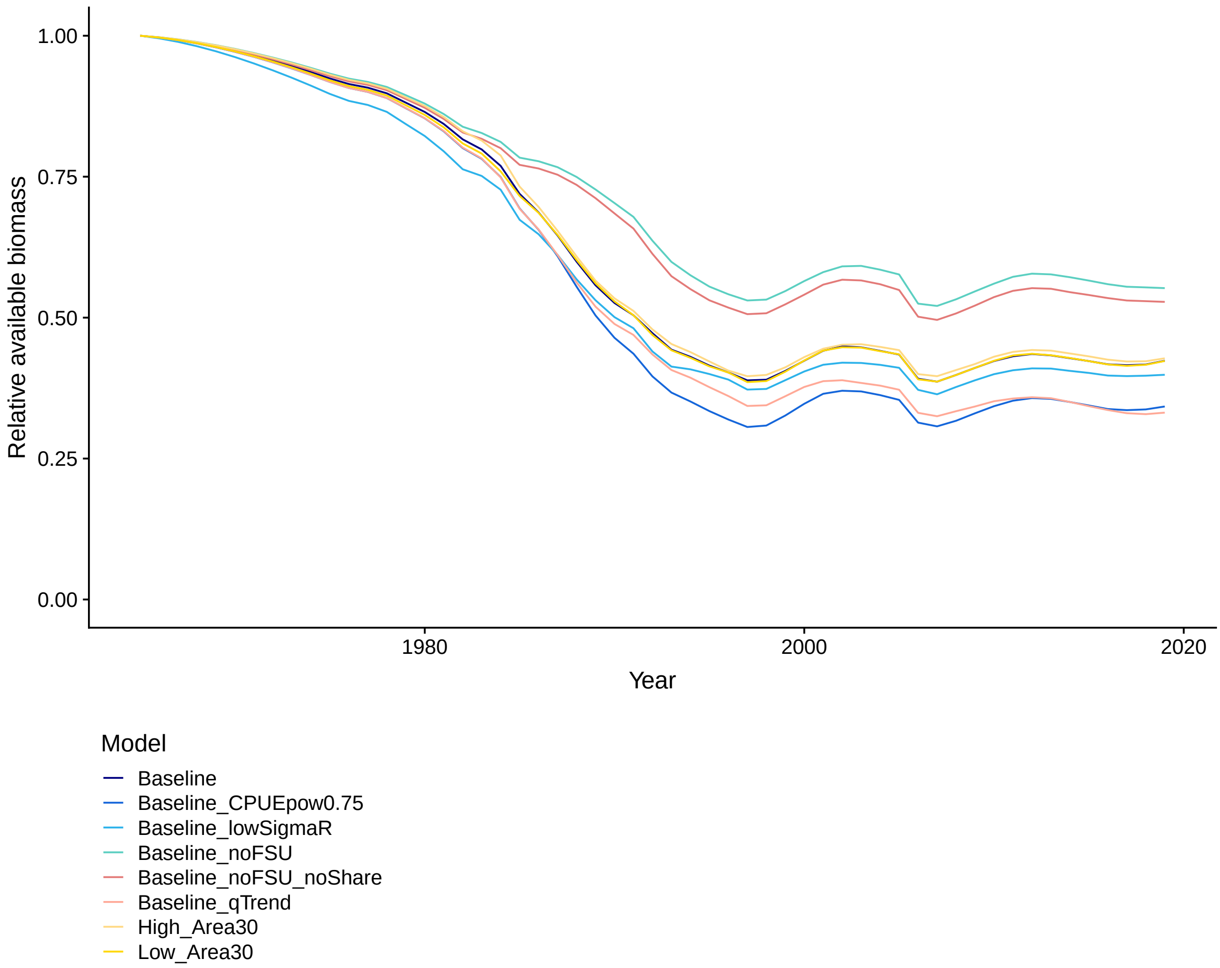

Figure A-8: Comparison of posterior median predicted relative available biomass trend in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

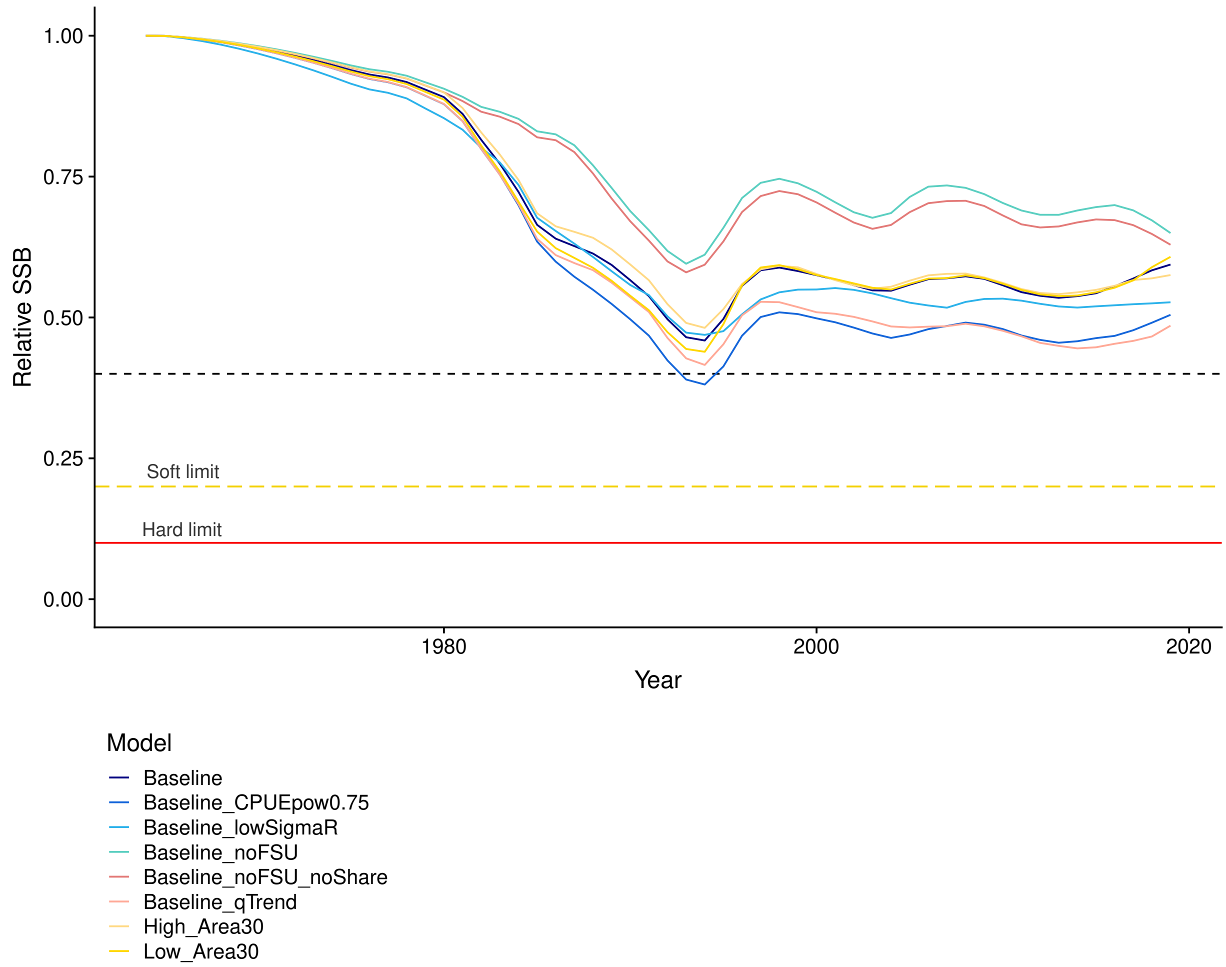

Figure A-9: Comparison of posterior median predicted relative spawning stock biomass trend in the stock assessment model using parameters for Set 1a. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

A.2 Model runs Set 1b—Spatial models

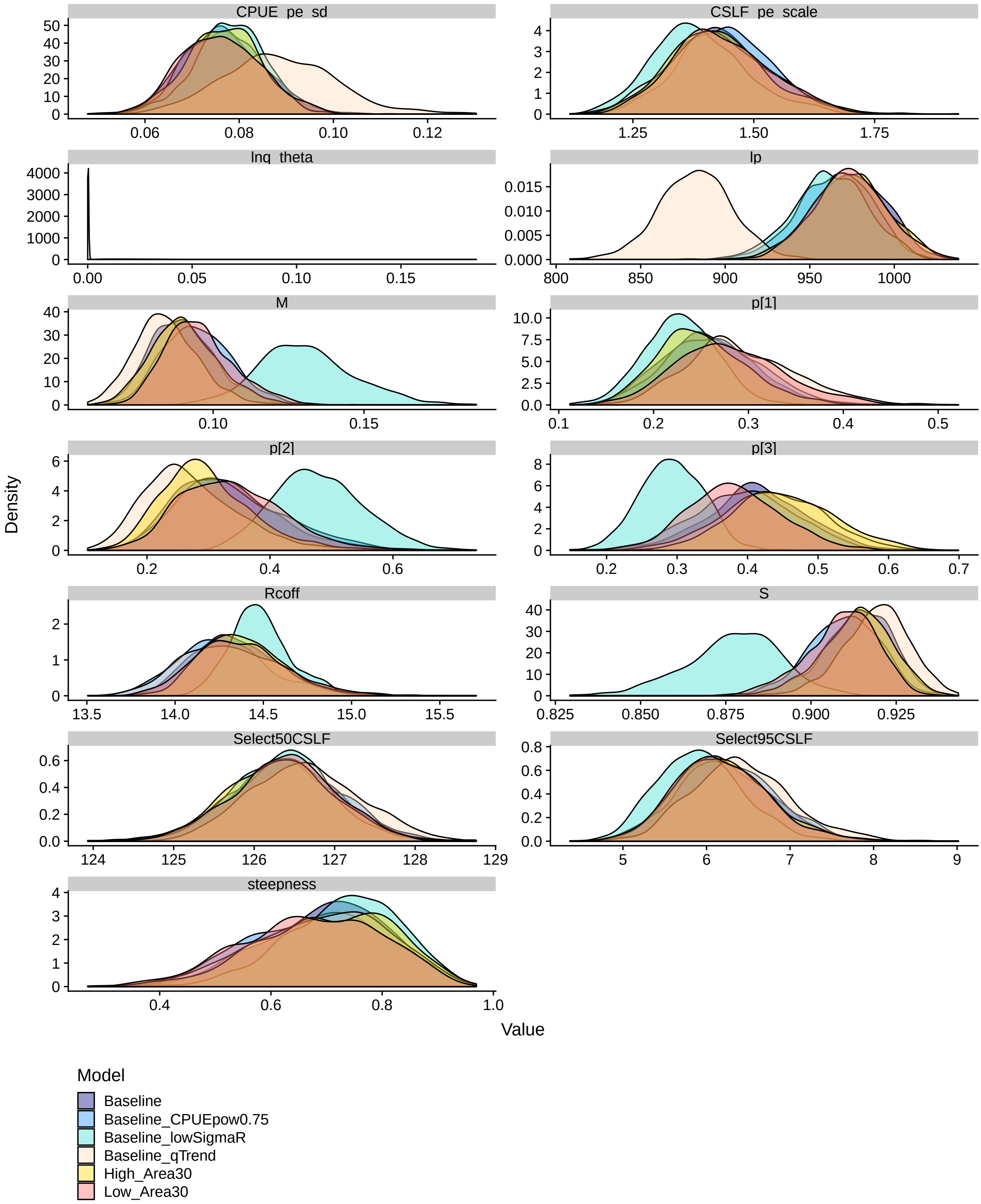

Figure A-10: Comparison of posterior densities for parameters in the spatial stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

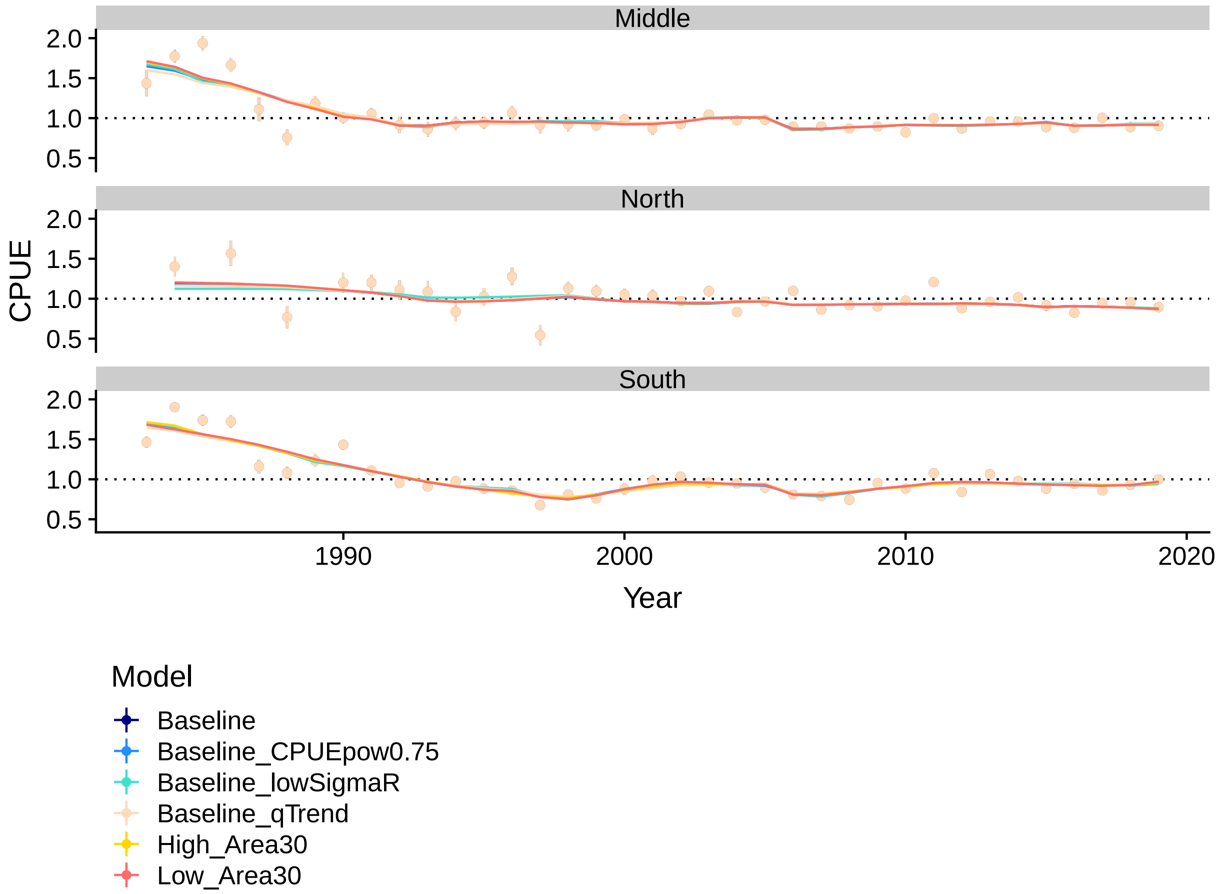

Figure A-11: Comparison of posterior median predicted catch-per-unit-effort (CPUE) in the stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

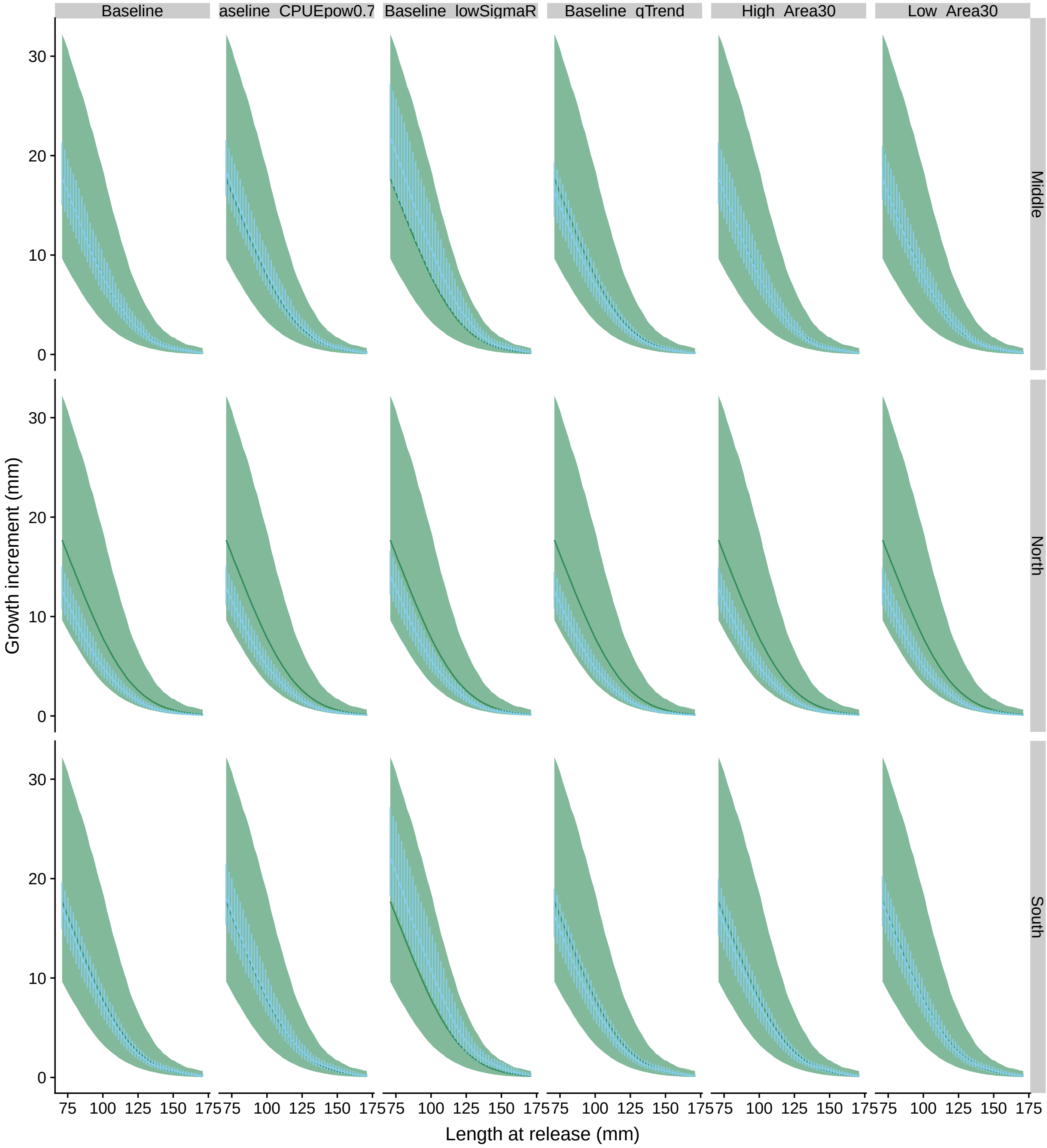

Figure A-12: Comparison of prior and posterior growth in the spatial stock assessment model using parameters for Set 1b. Prior for population mean growth (prior mean (green line) and 95% prior interval (green shading)), and posterior mean growth (light blue posterior median and 95% posterior interval). Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

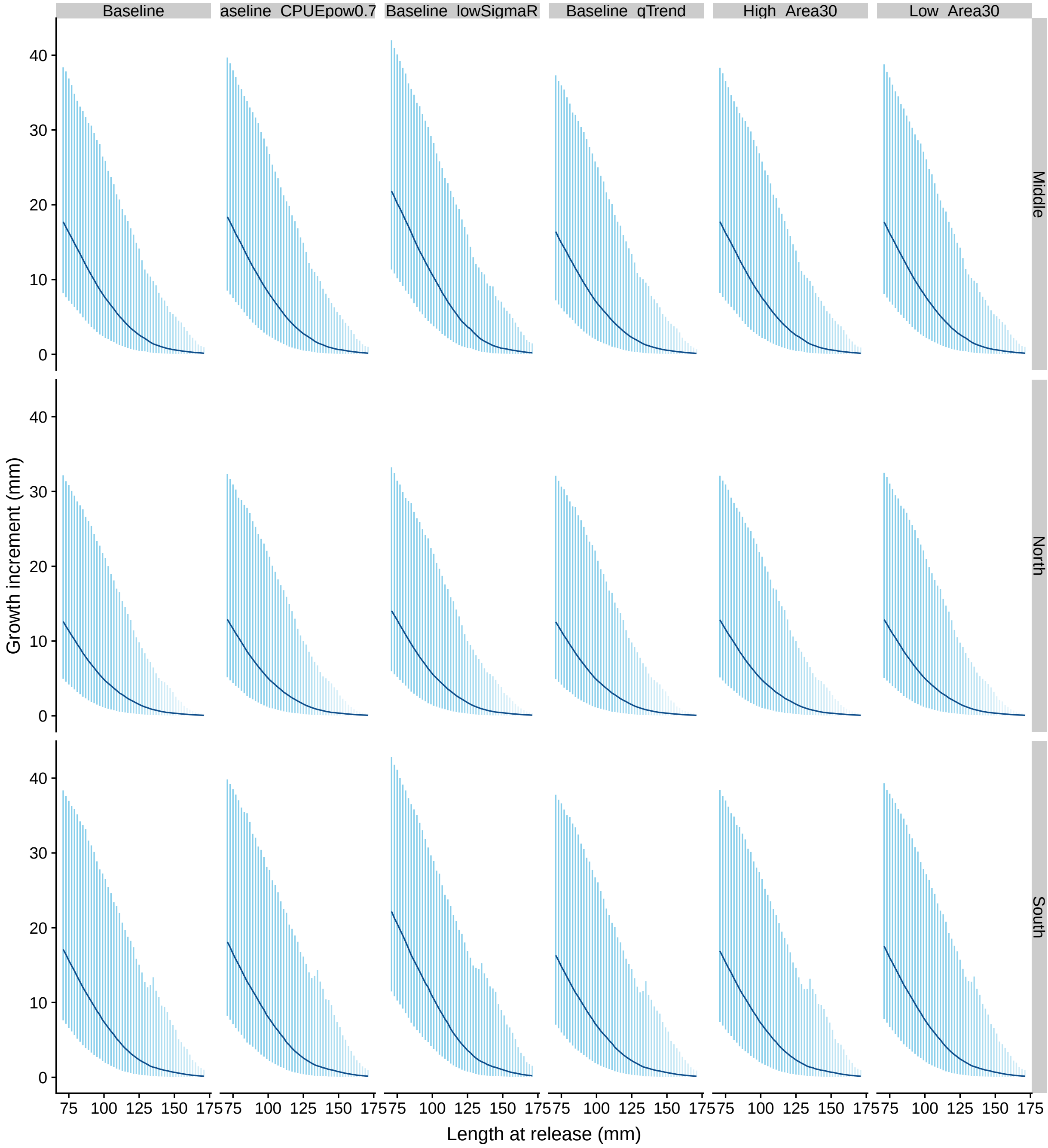

Figure A-13: Comparison of prior and posterior growth in the spatial stock assessment model using parameters for Set 1b. Median distribution of population somatic growth by size class with posterior mean (dark blue line) and 95% growth intervals. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

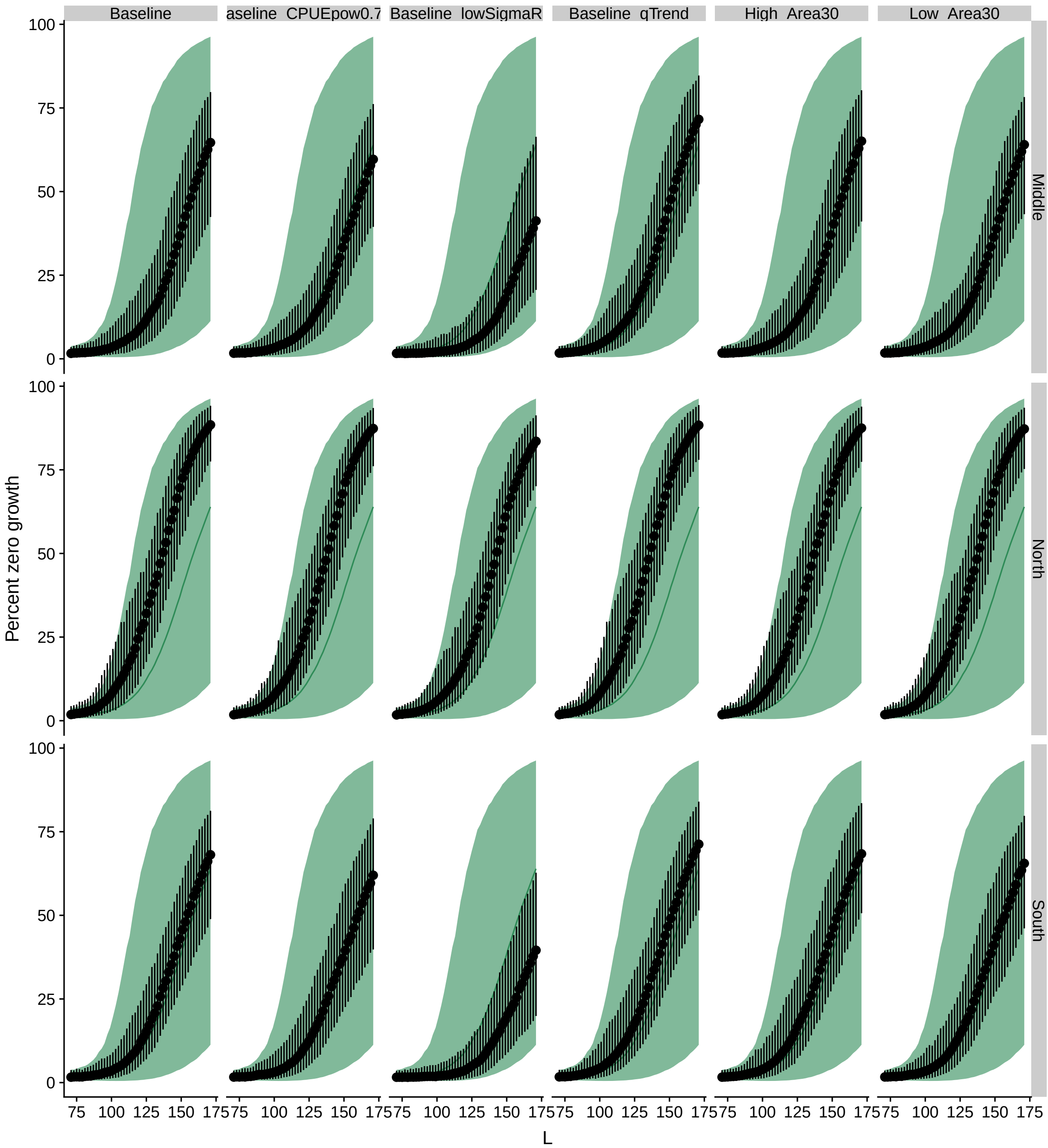

Figure A-14: Comparison of prior and posterior growth in the spatial stock assessment model using parameters for Set 1b. Prior for proportion of pāua not growing at each length class (prior mean (green line) and confidence interval (green shading)) and posterior distribution (black dots and 95% posterior confidence). Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

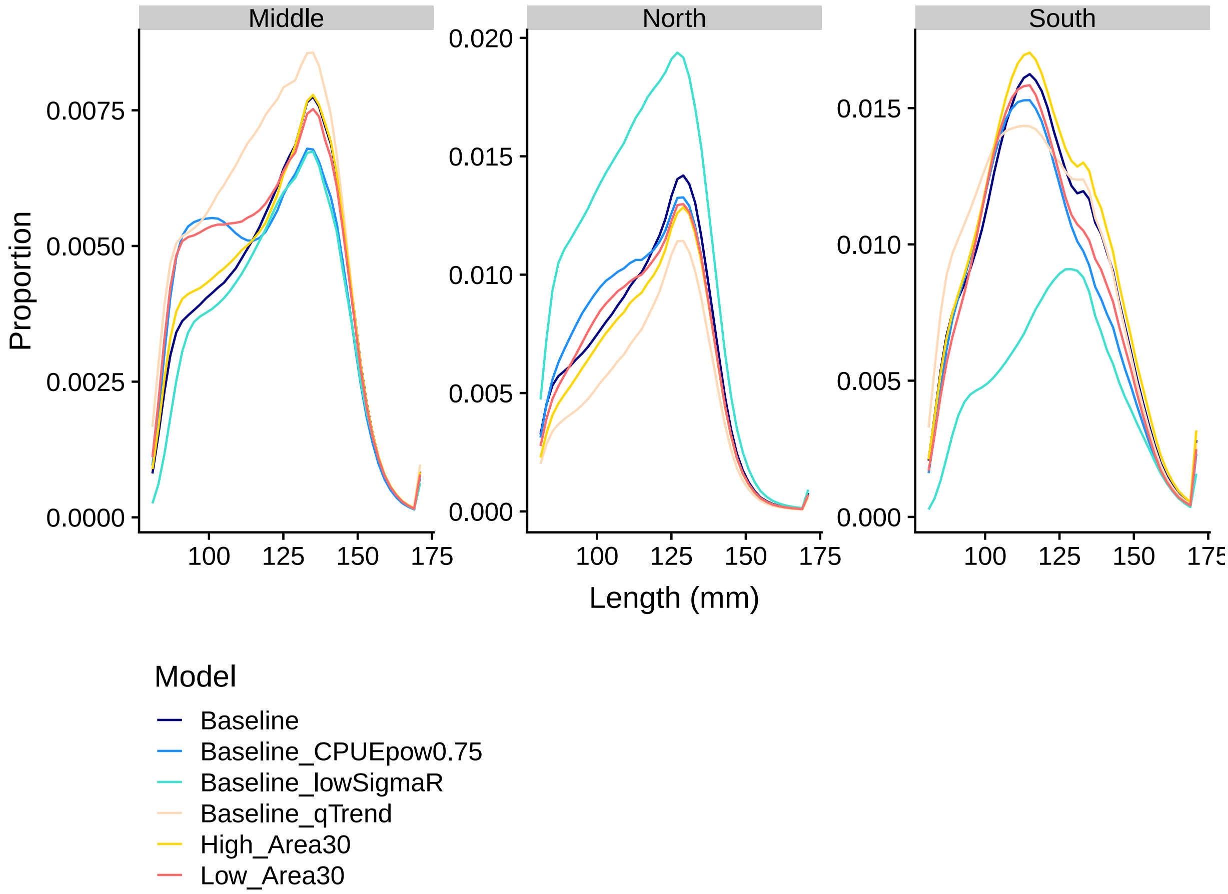

Figure A-15: Comparison of posterior mean proportions-at-length in the spatial stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

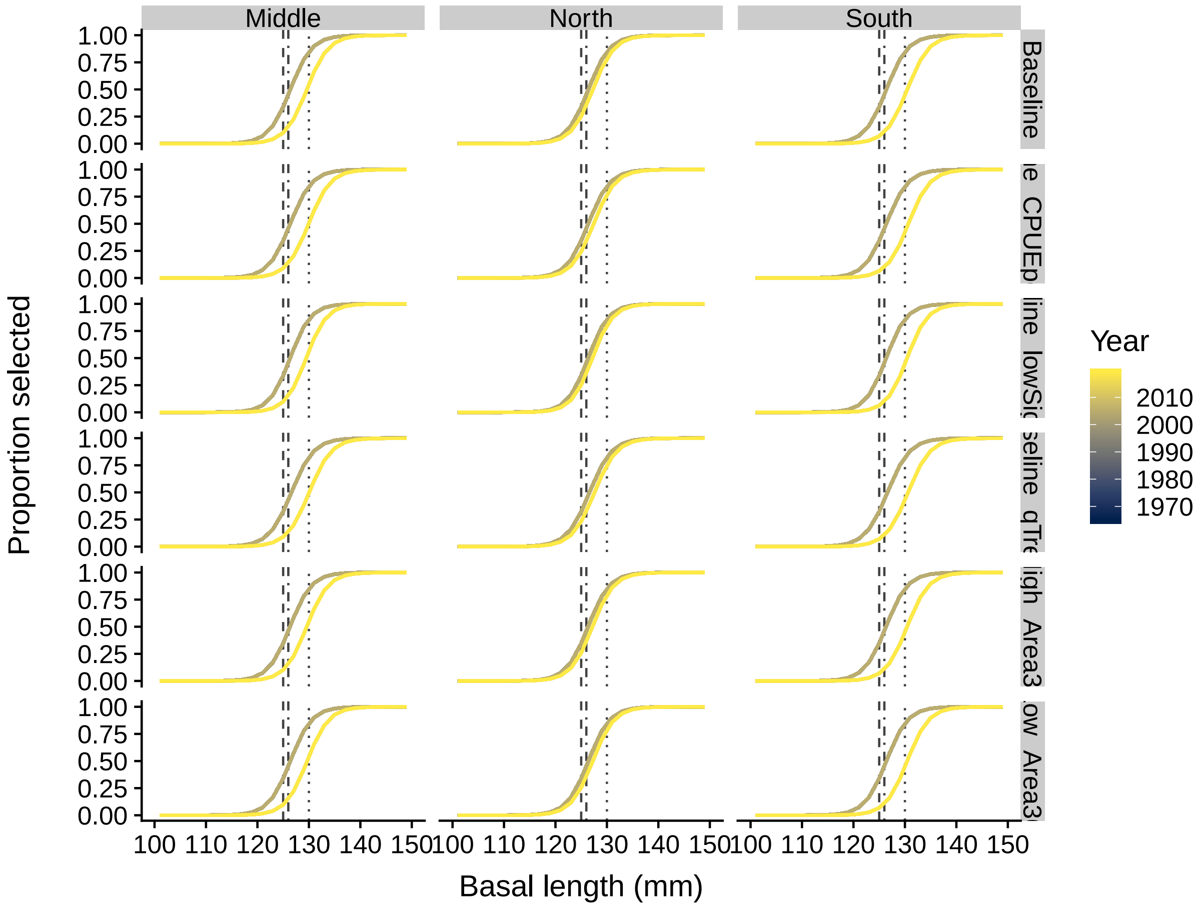

Figure A-16: Comparison of posterior mean selectivity-at-length in the spatial stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

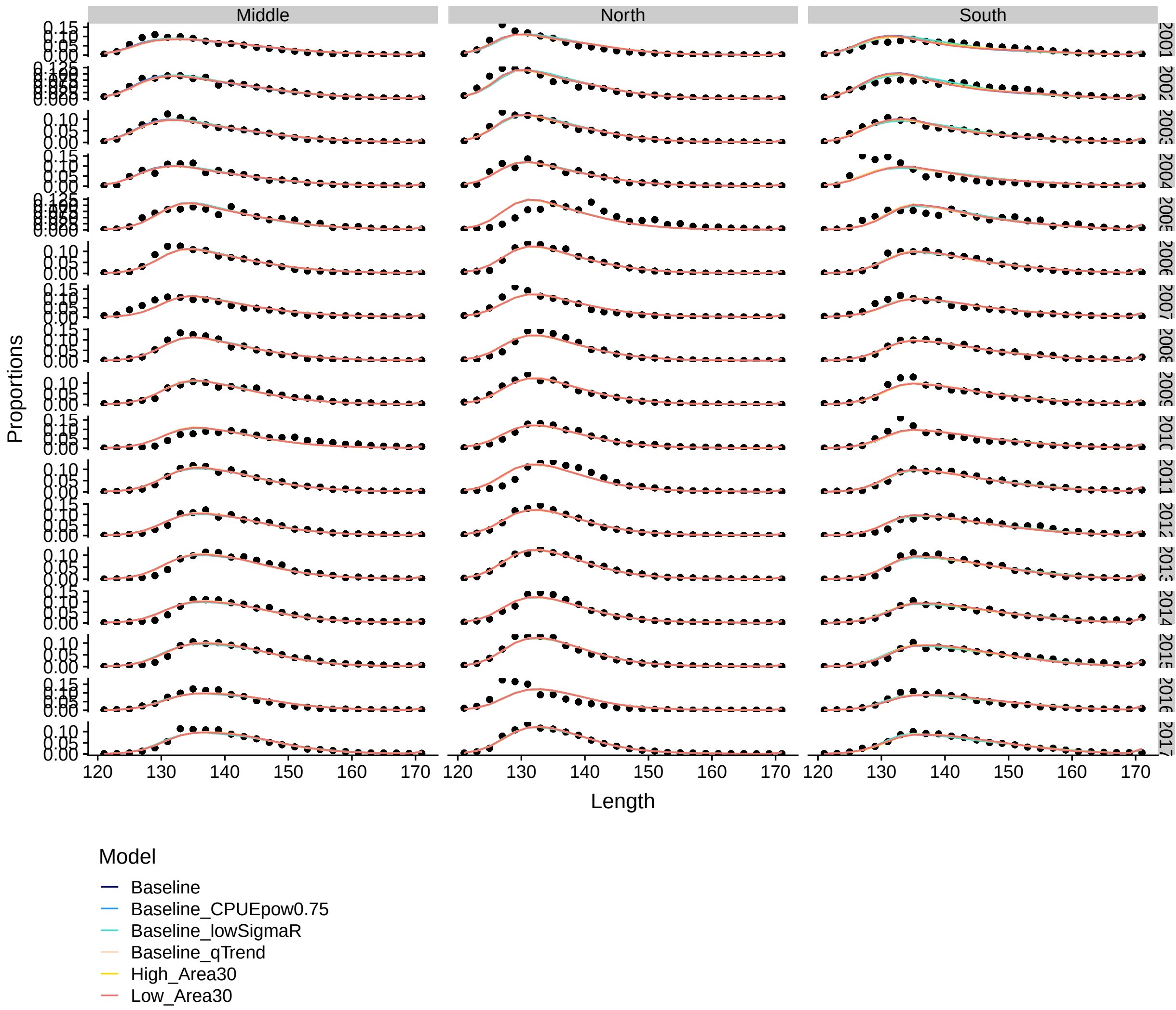

Figure A-17: Comparison of posterior mean predicted catch sampling length frequency (CSLF) with estimated CSLF proportions, in the spatial stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

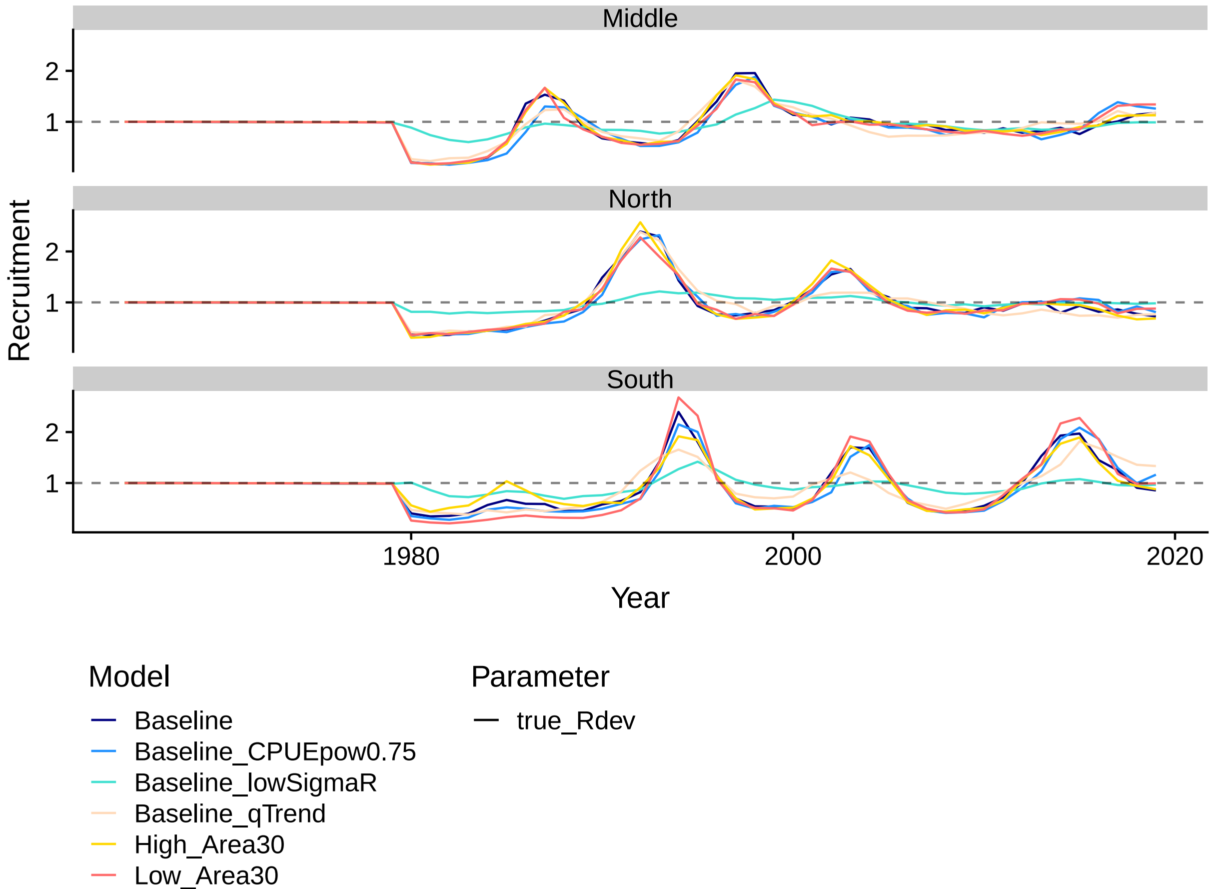

Figure A-18: Comparison of posterior mean recruitment in deviations (R_{dev}) the spatial stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

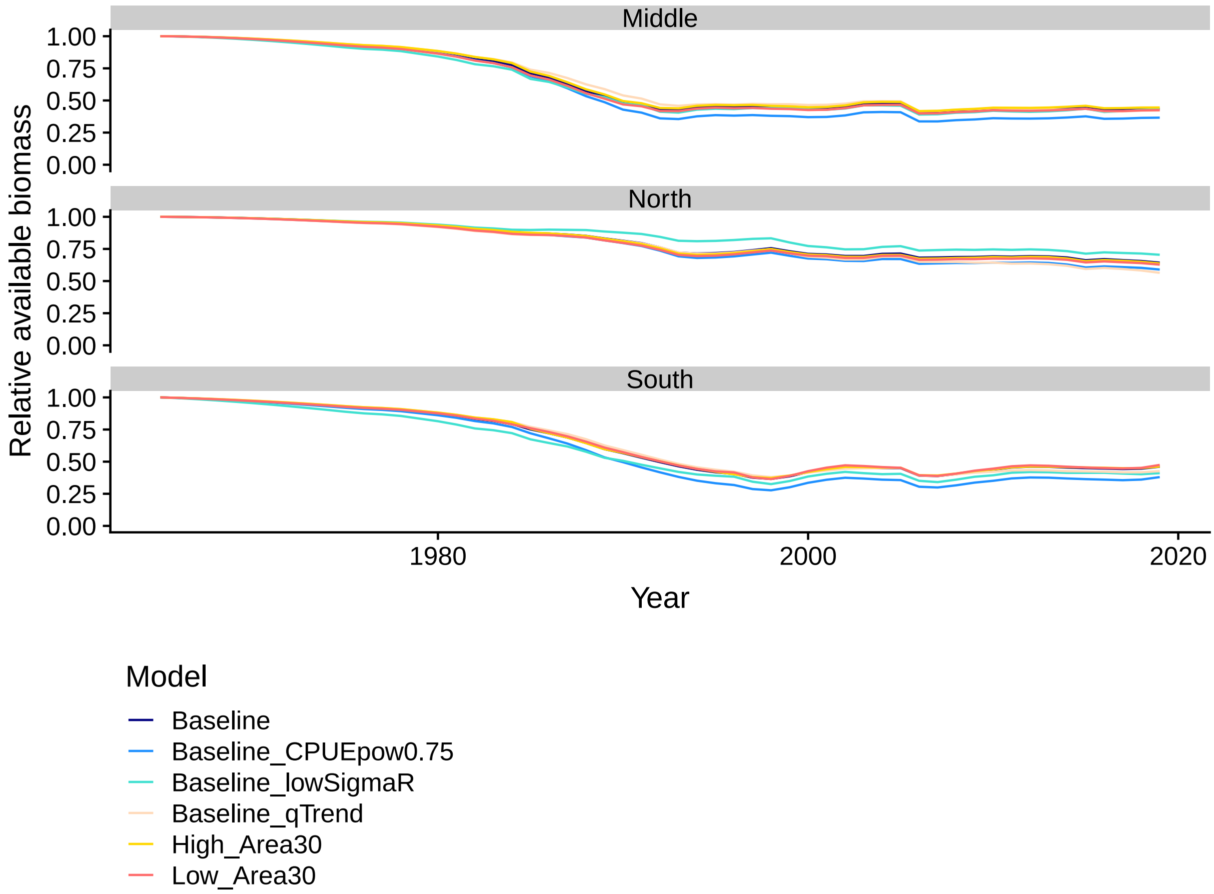

Figure A-19: Comparison of posterior median predicted relative available biomass trend in the spatial stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

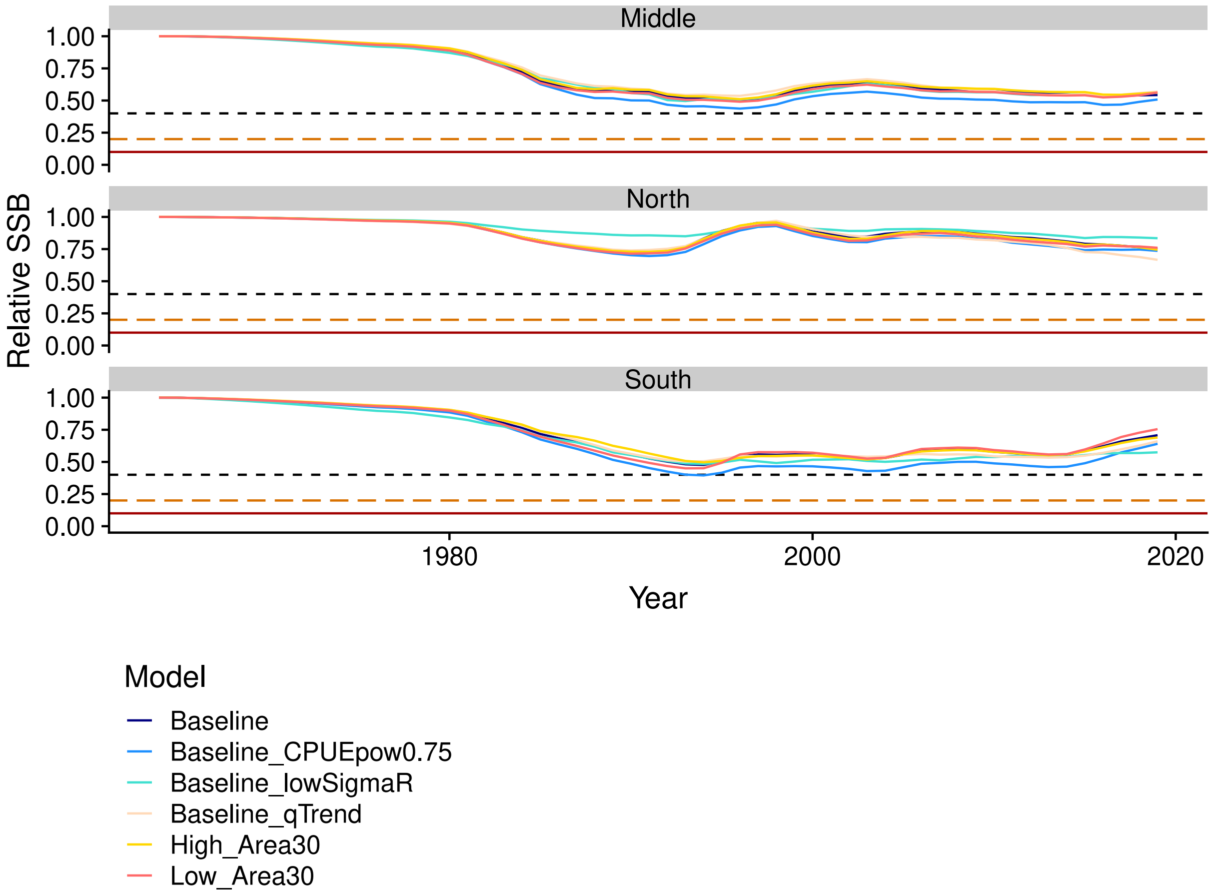

Figure A-20: Comparison of posterior median predicted relative spawning stock biomass trend in the spatial stock assessment model using parameters for Set 1b. Model scenario names show differences in catch (baseline, high or low catch in area 30). Catch-per-unit-effort (CPUE) with or without Fisheries Statistical Unit data (noFSU) and without data from area 30 for years when spatial CPUE was unclear (noShare). CPUE hyperstability (CPUEpow, fixed at 0.75) and trends in catchability (qTrend; estimated linear); low recruitment variation (σ_R=0.4).

A.3 Model runs: Set 2

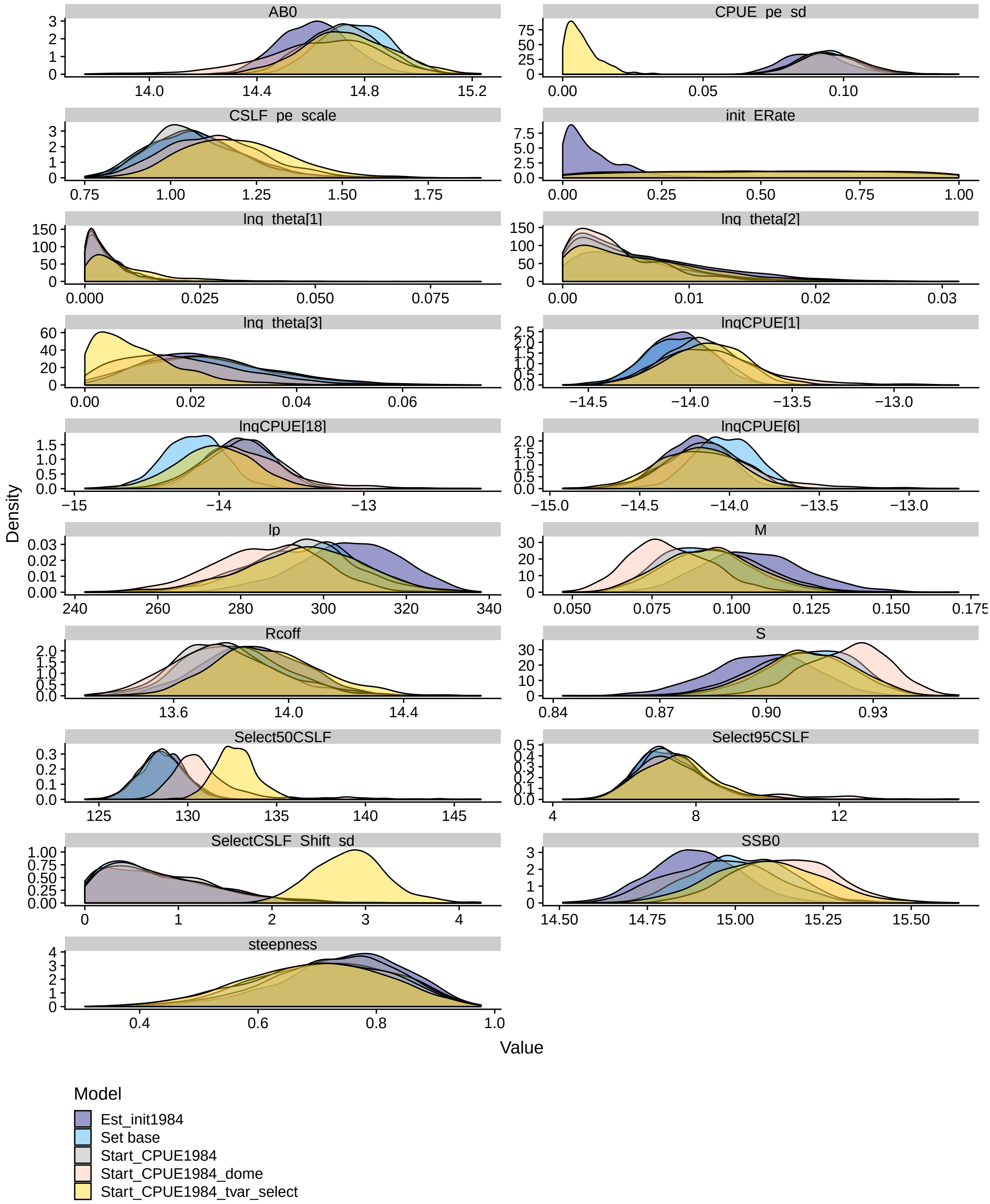

Figure A-21: Comparison of posterior densities for parameters in the stock assessment model using parameters for Set 2. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

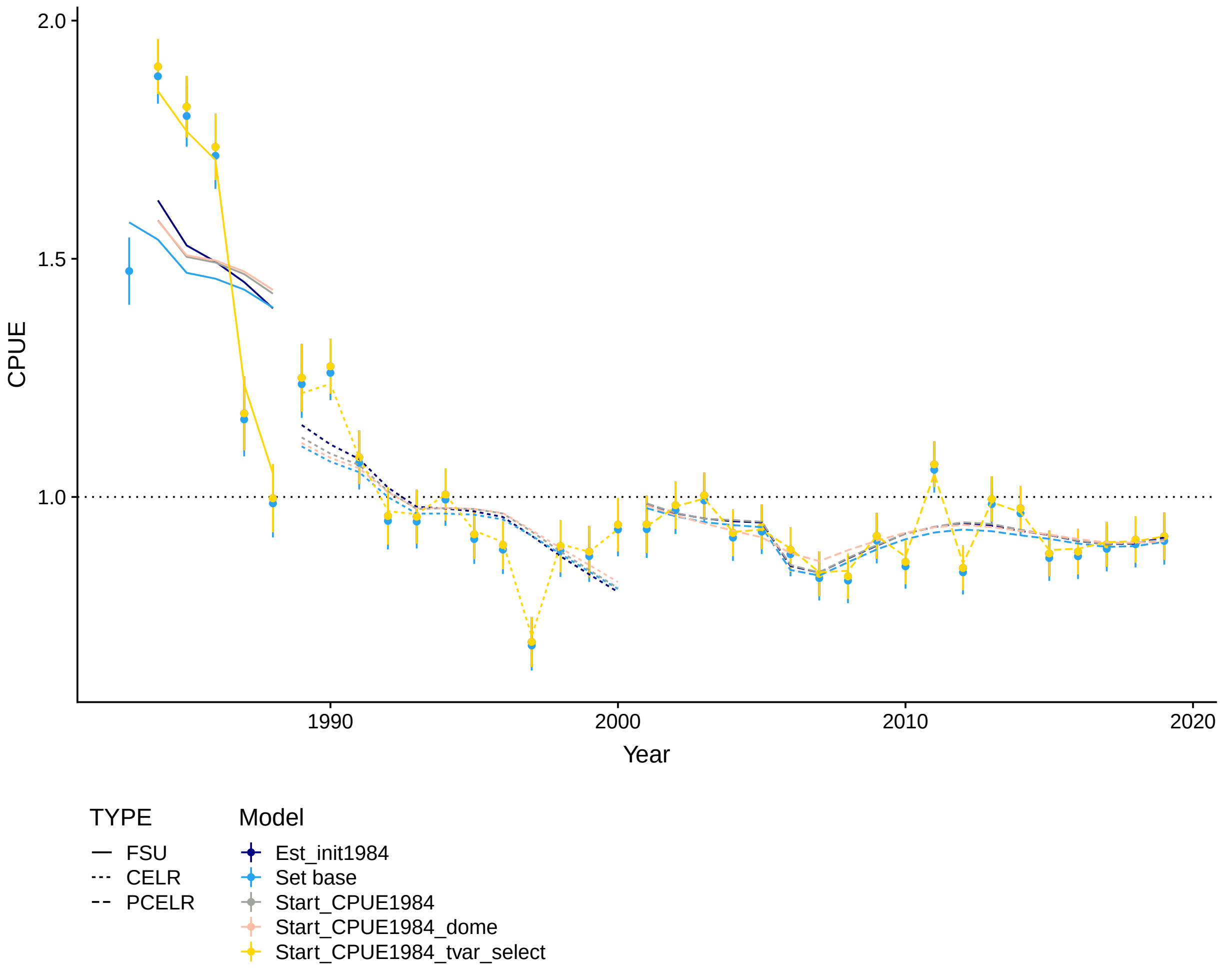

Figure A-22: Comparison of posterior median predicted catch-per-unit-effort (CPUE) in the stock assessment model using parameters for Set 2. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

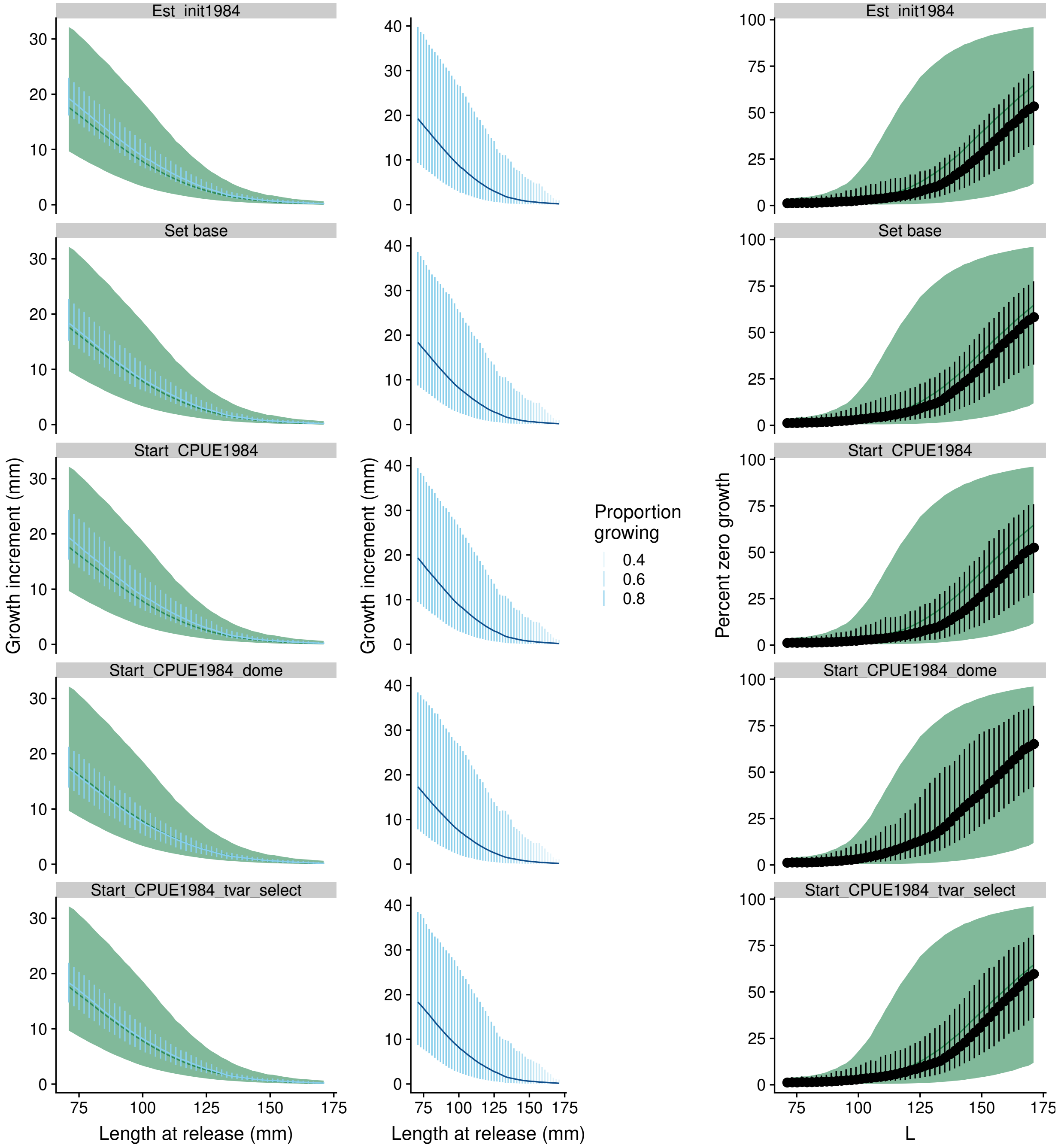

Figure A-23: Comparison of prior and posterior growth in the stock assessment model using parameters for Set 2. Left graphs: prior for population mean growth (prior mean (green line) and 95% prior interval (green shading)), and posterior mean growth (light blue posterior median and 95% posterior interval). Middle graphs: median distribution of population somatic growth by size class with posterior mean (dark blue line) and 95% growth intervals. Right graphs: prior for proportion of pāua not growing at each length class (prior mean (green line) and confidence interval (green shading)) and posterior distribution (black dots and 95% posterior confidence). Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

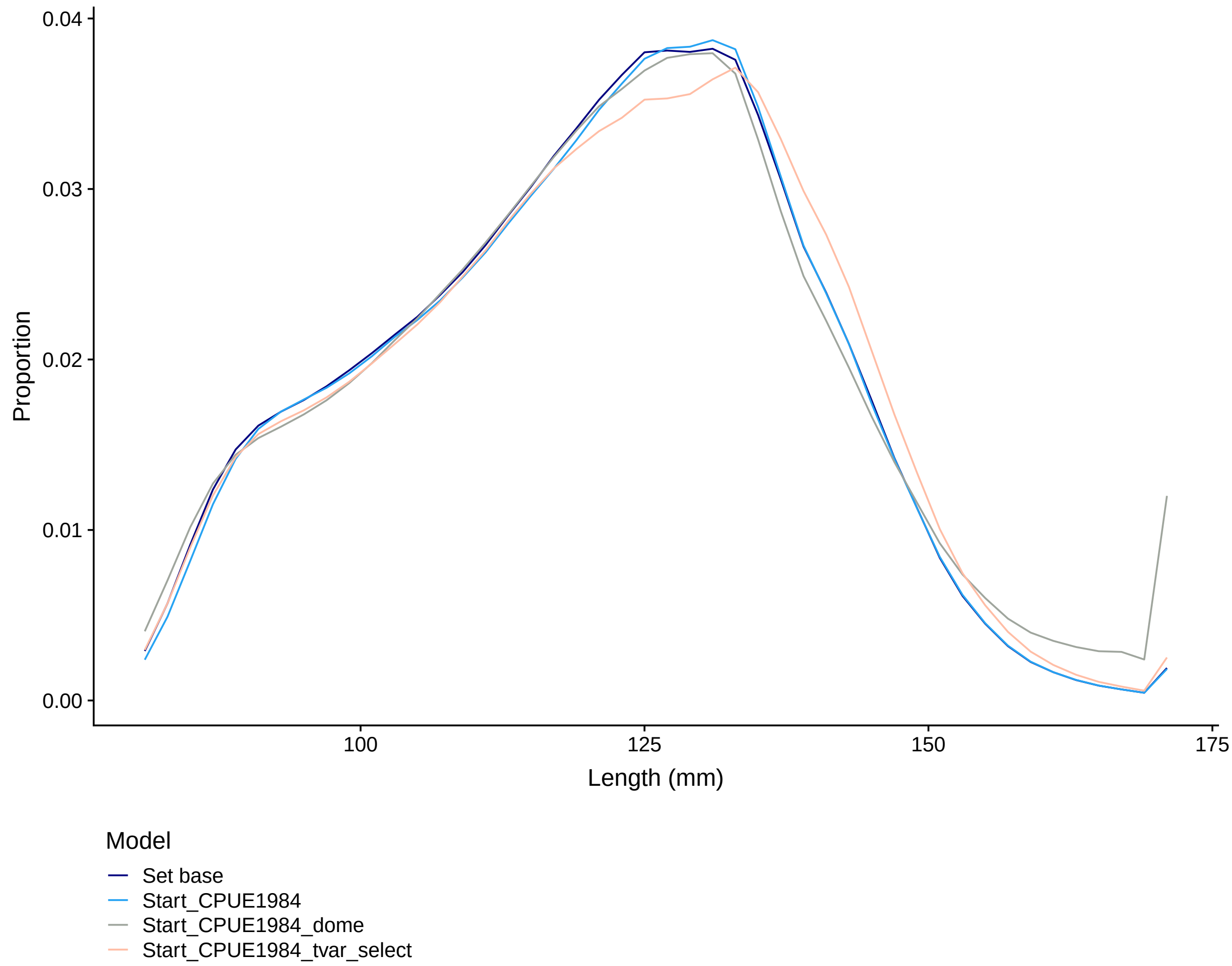

Figure A-24: Comparison of posterior mean proportions-at-length in the stock assessment model using parameters for Set 2. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

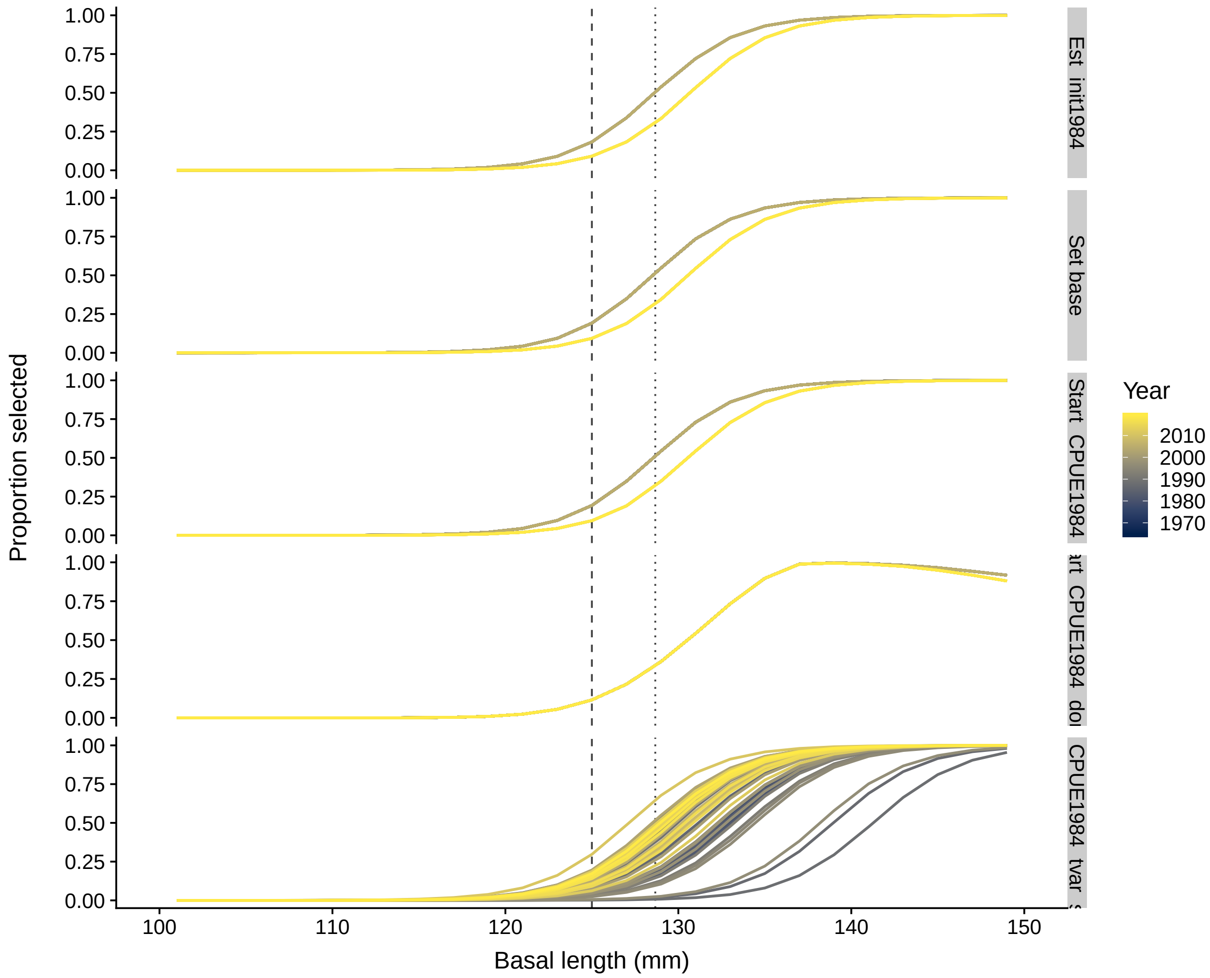

Figure A-25: Comparison of posterior mean selectivity-at-length in the stock assessment model using parameters for Set 2. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

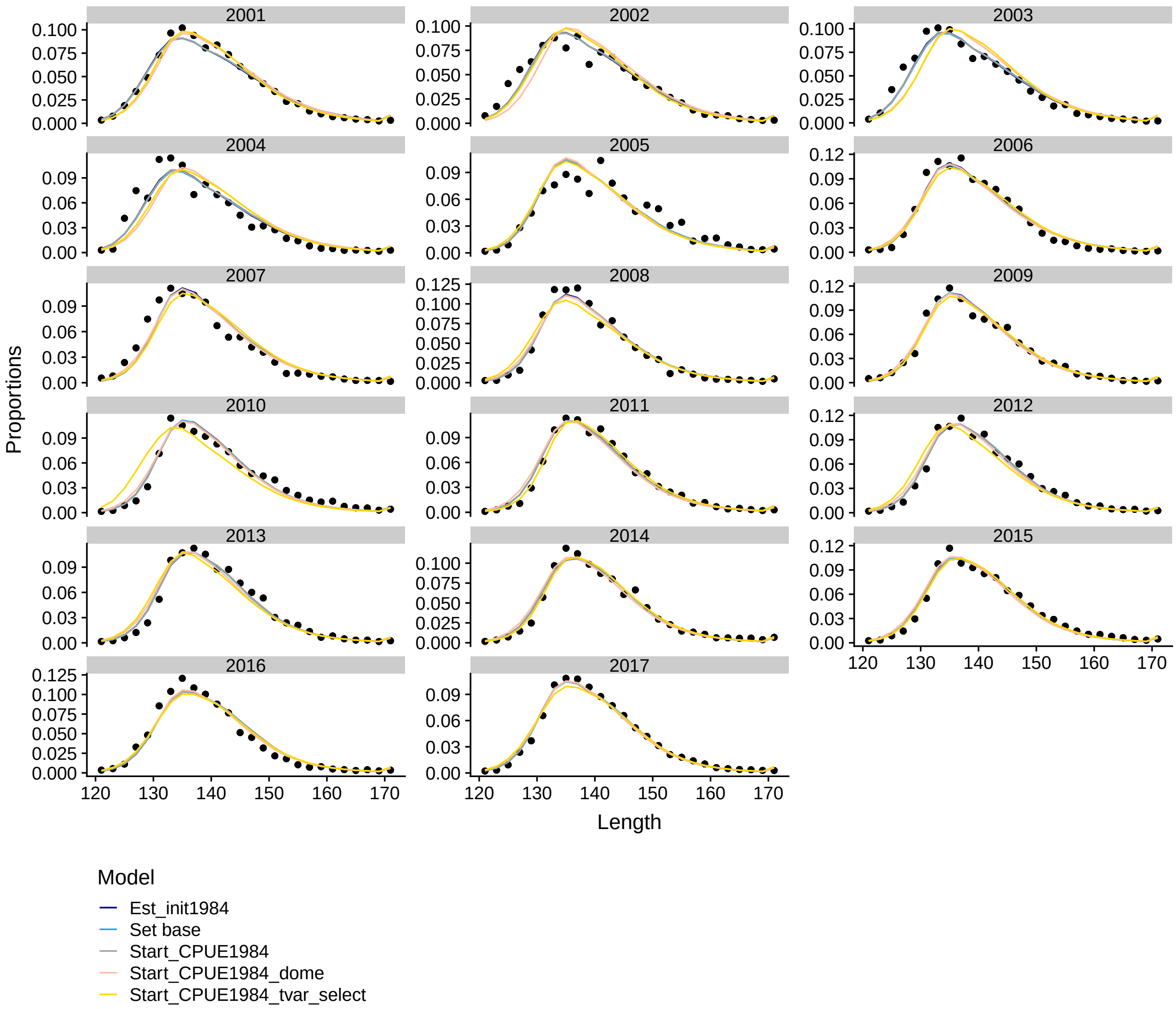

Figure A-26: Comparison of posterior mean predicted catch sampling length frequency (CSLF) with estimated CSLF proportions, in the stock assessment model using parameters for Set 2. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

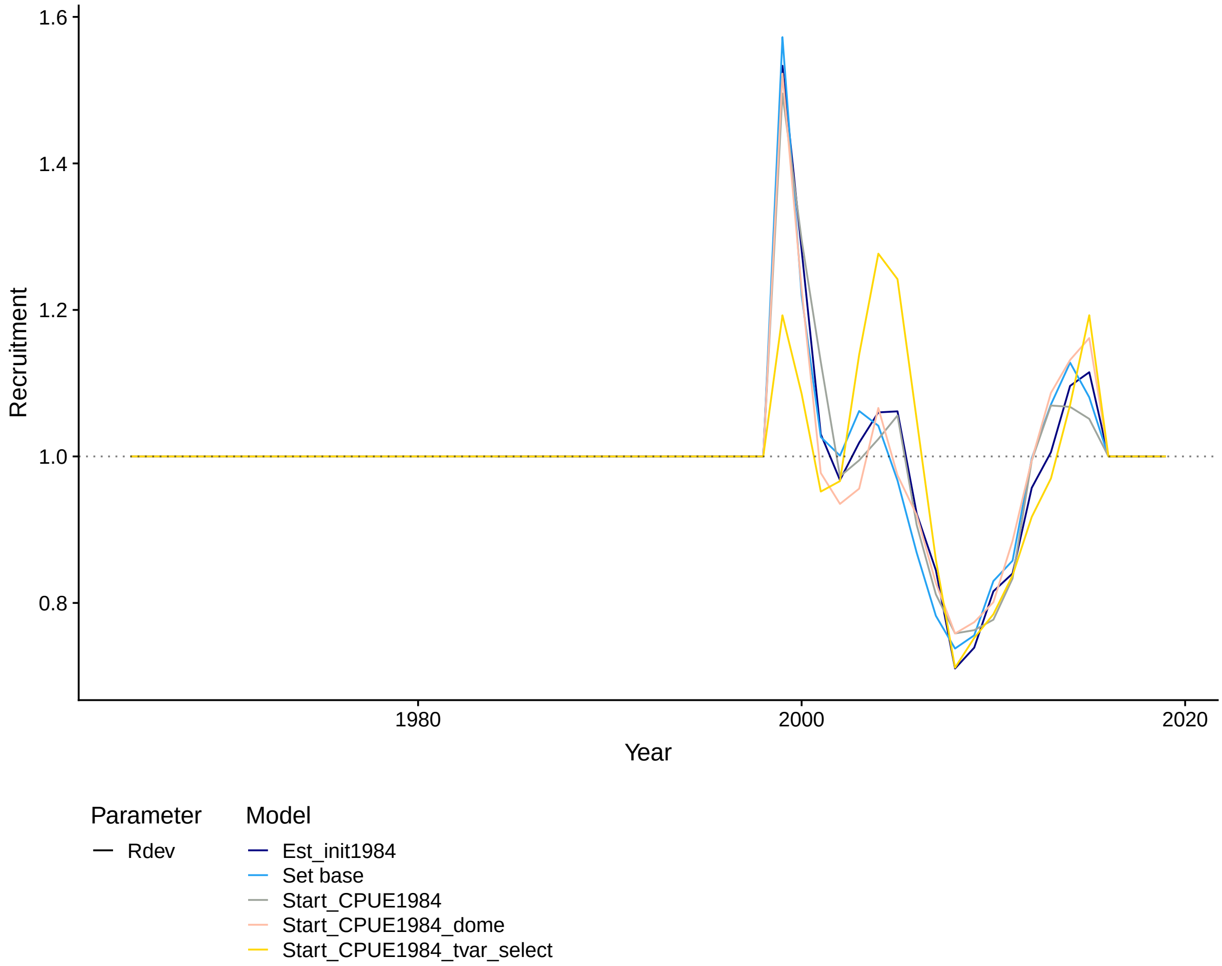

Figure A-27: Comparison of posterior mean recruitment deviations (R_{dev}) in the stock assessment model using parameters described in 2.3.3. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

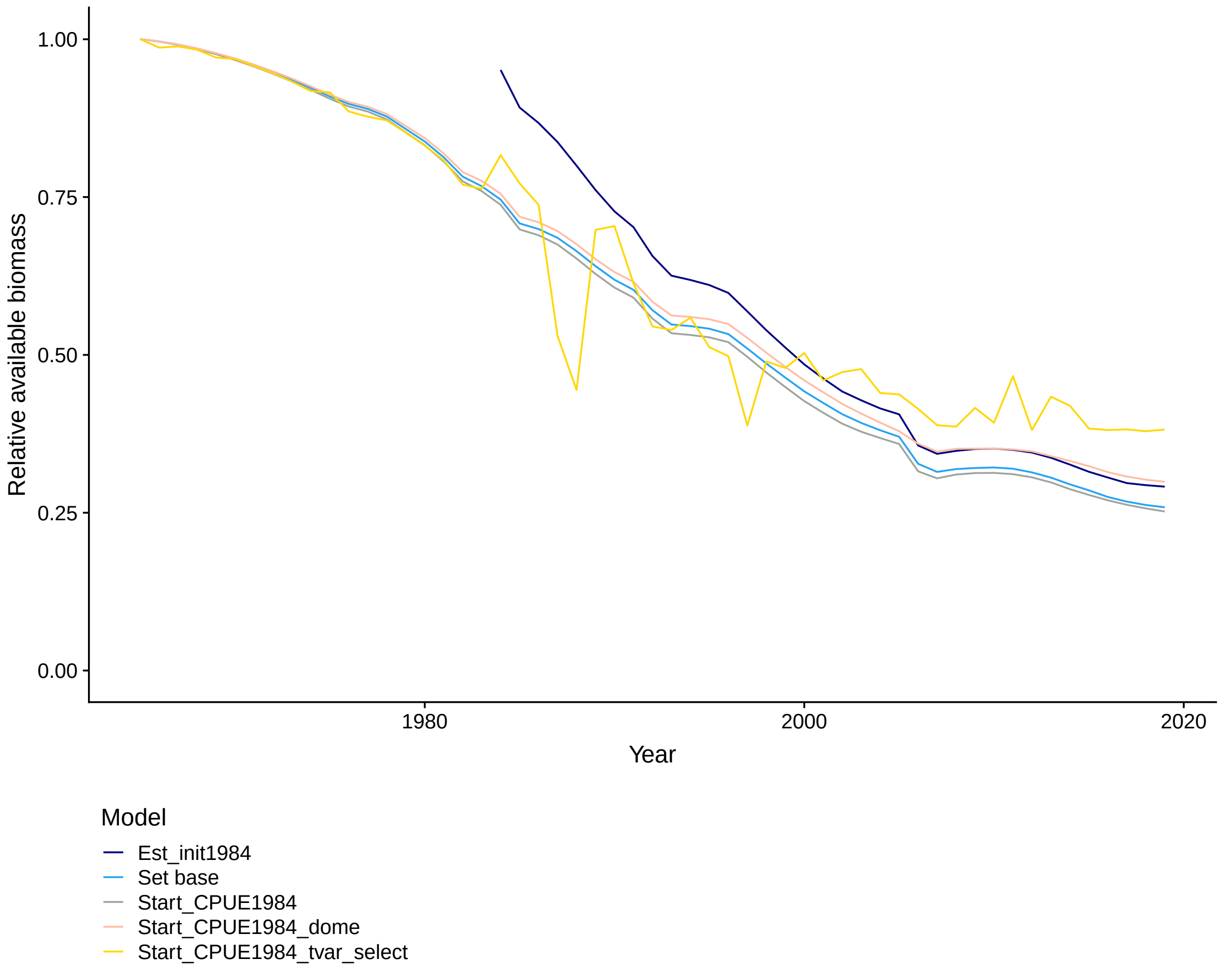

Figure A-28: Comparison of posterior median predicted relative available biomass trend in the stock assessment model using parameters for Set 2. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

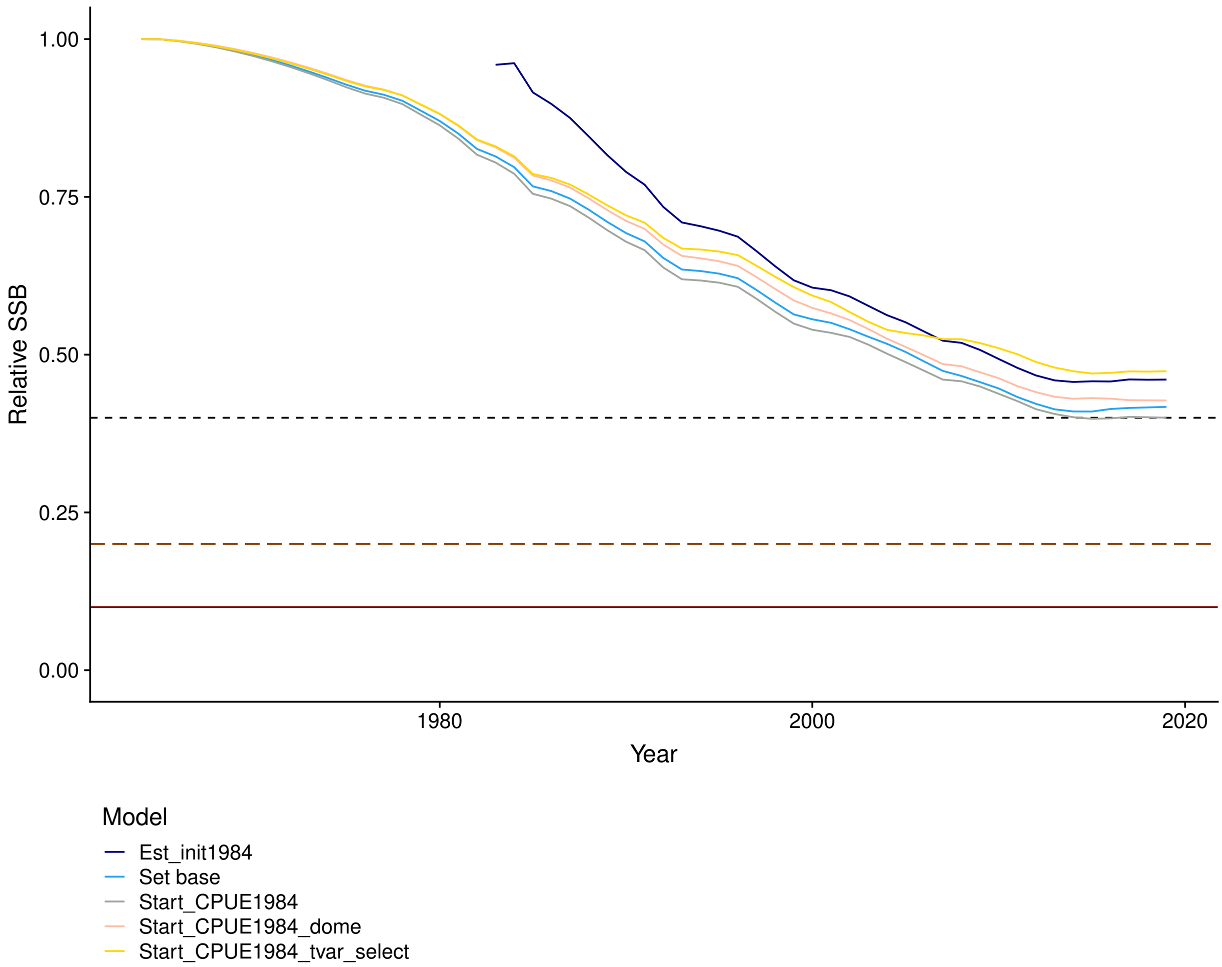

Figure A-29: Comparison of posterior median predicted relative spawning stock biomass trend in the stock assessment model using parameters for Set 2. Model scenario names show differences in initialisation (estimating initial depletion in 1984 (est init1984), or starting catch-per-unit-effort (CPUE) in 1984), selectivity (logistic, dome, or time-varying (tvar select) logistic). All models estimated three separate catchability parameters for reporting epochs, trends in catchability by epoch, and only estimated recruitment for years with catch sampling length frequency (CSLF) data.

A.4 Model runs: Set 3

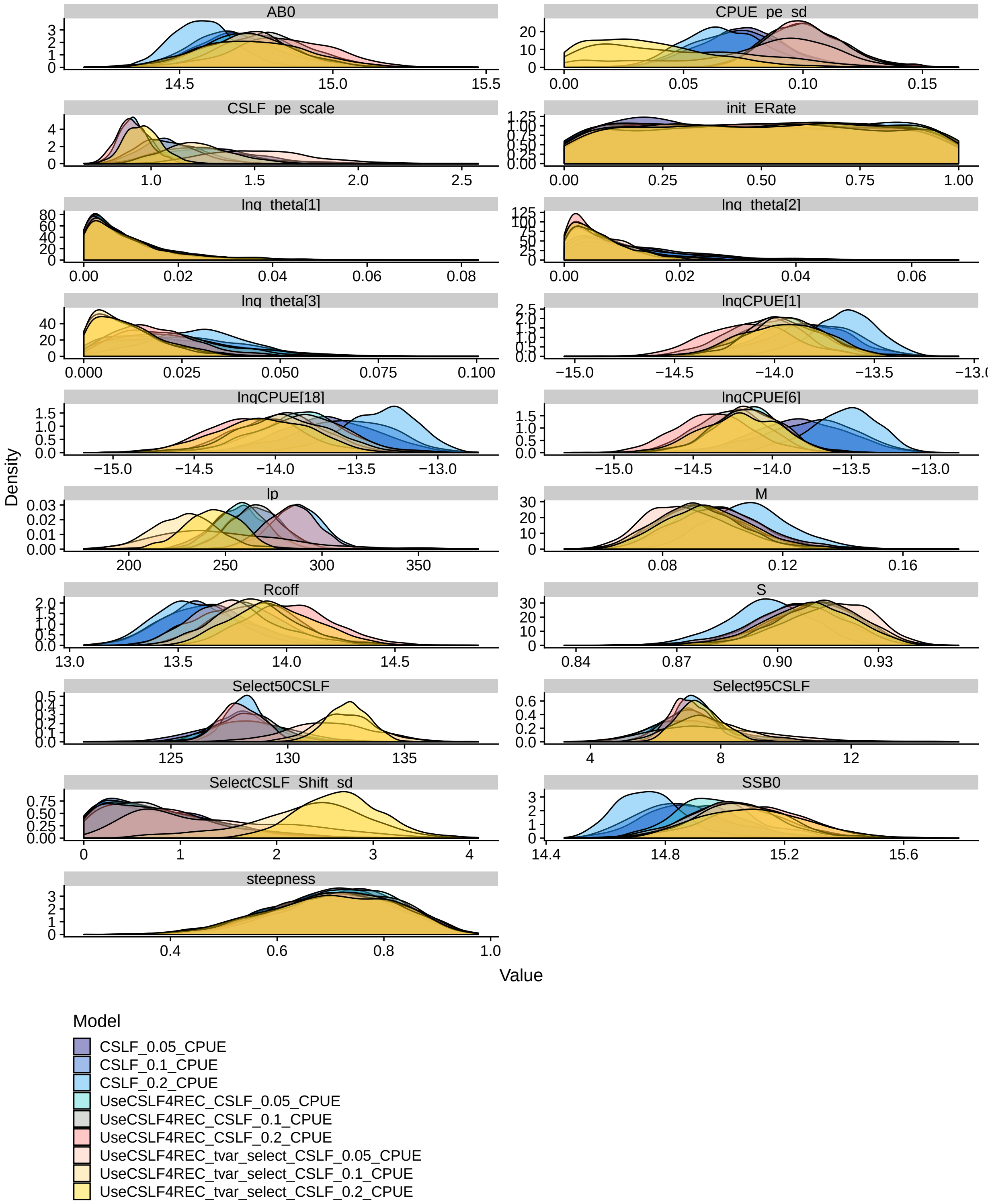

Figure A-30: Comparison of posterior densities for parameters in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for years with catch sampling length frequency (CSLF) data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

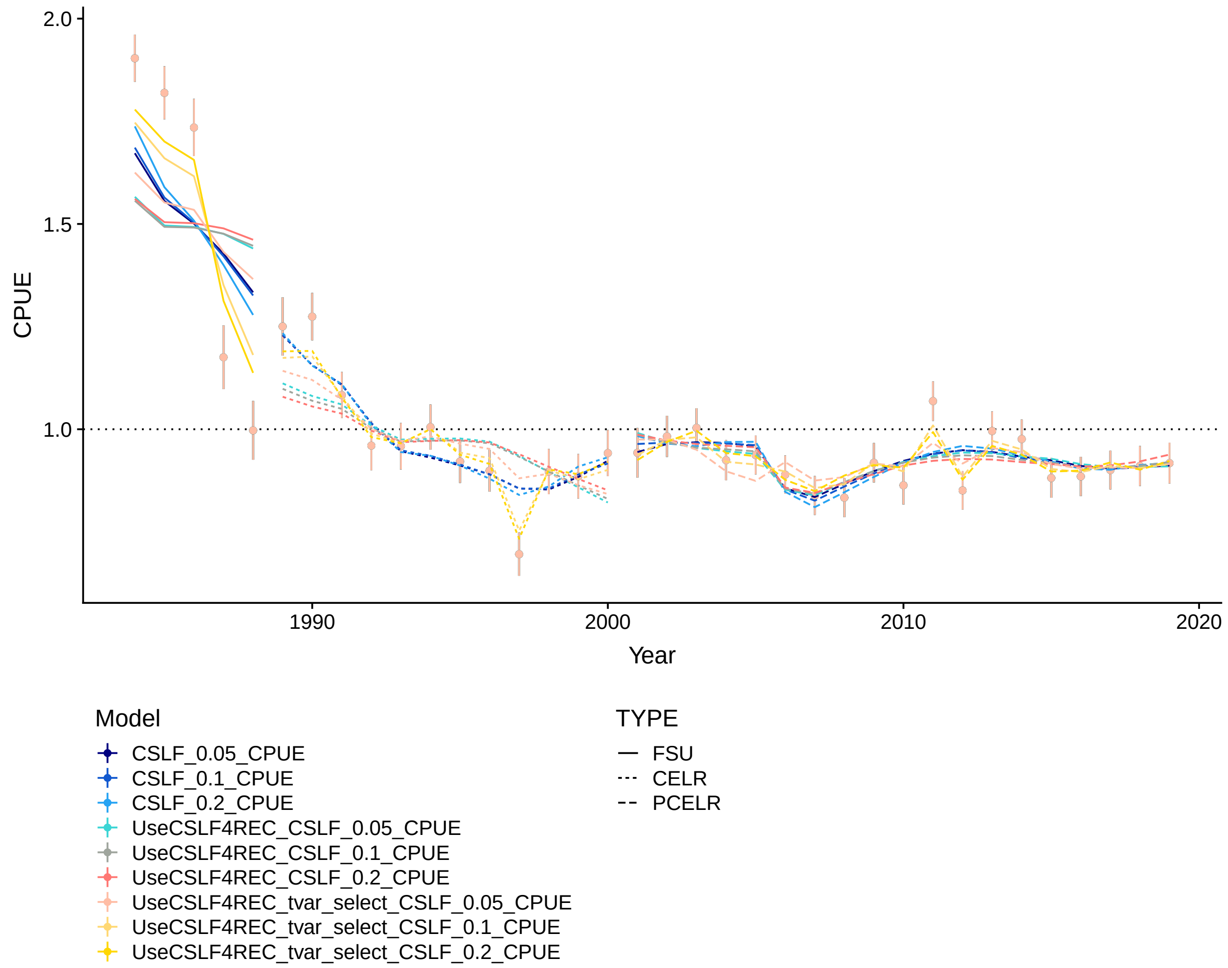

Figure A-31: Comparison of posterior median predicted catch-per-unit-effort (CPUE) in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for years with catch sampling length frequency (CSLF) data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

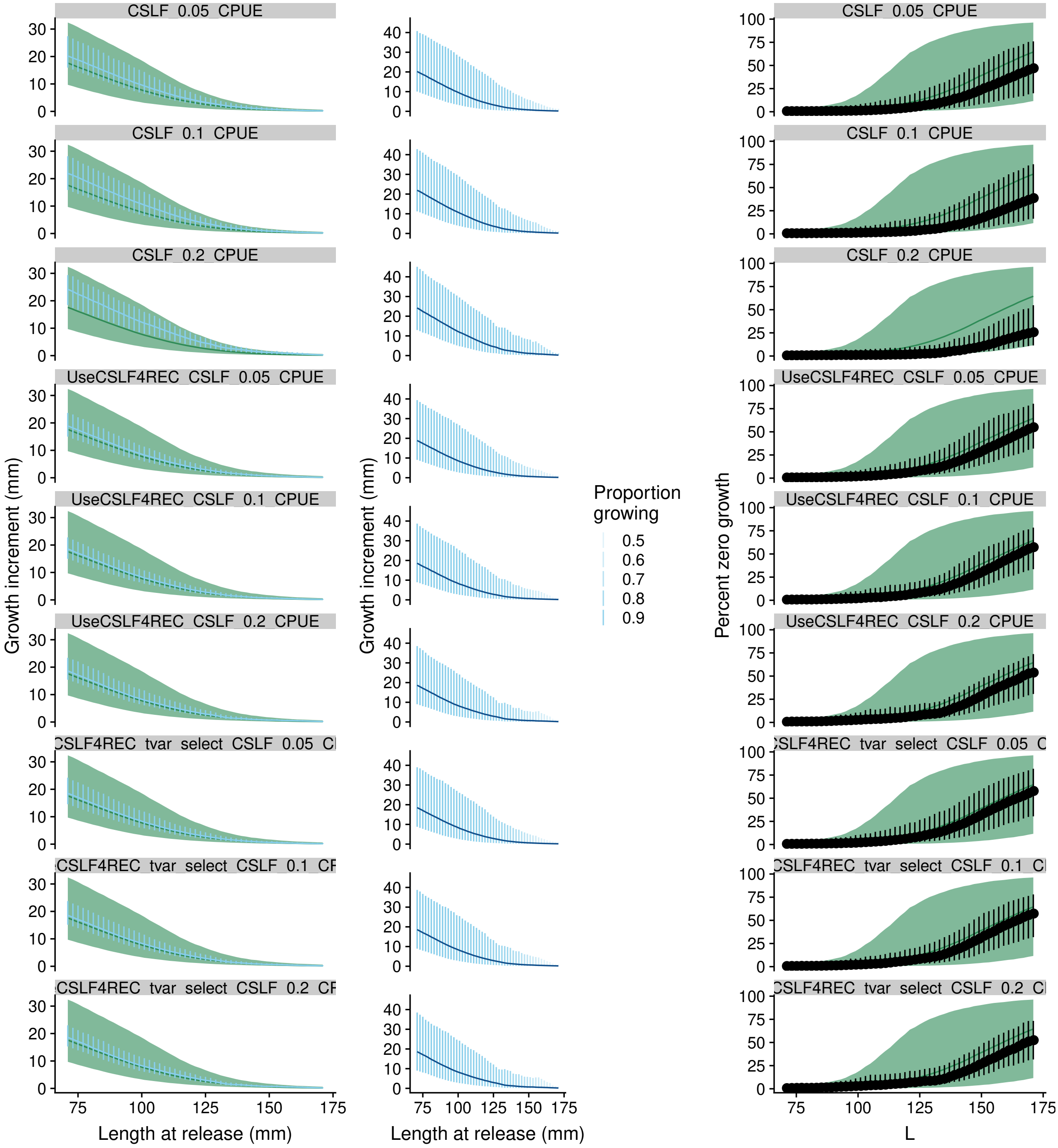

Figure A-32: Comparison of prior and posterior growth in the stock assessment model using parameters for Set 3. Left graphs: prior for population mean growth (prior mean (green line) and 95% prior interval (green shading)), and posterior mean growth (light blue posterior median and 95% posterior interval). Middle graphs: median distribution of population somatic growth by size class with posterior mean (dark blue line) and 95% growth intervals. Right graphs: prior for proportion of pāua not growing at each length class (prior mean (green line) and confidence interval (green shading)) and posterior distribution (black dots and 95% posterior confidence). Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for years with catch sampling length frequency (CSLF) data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

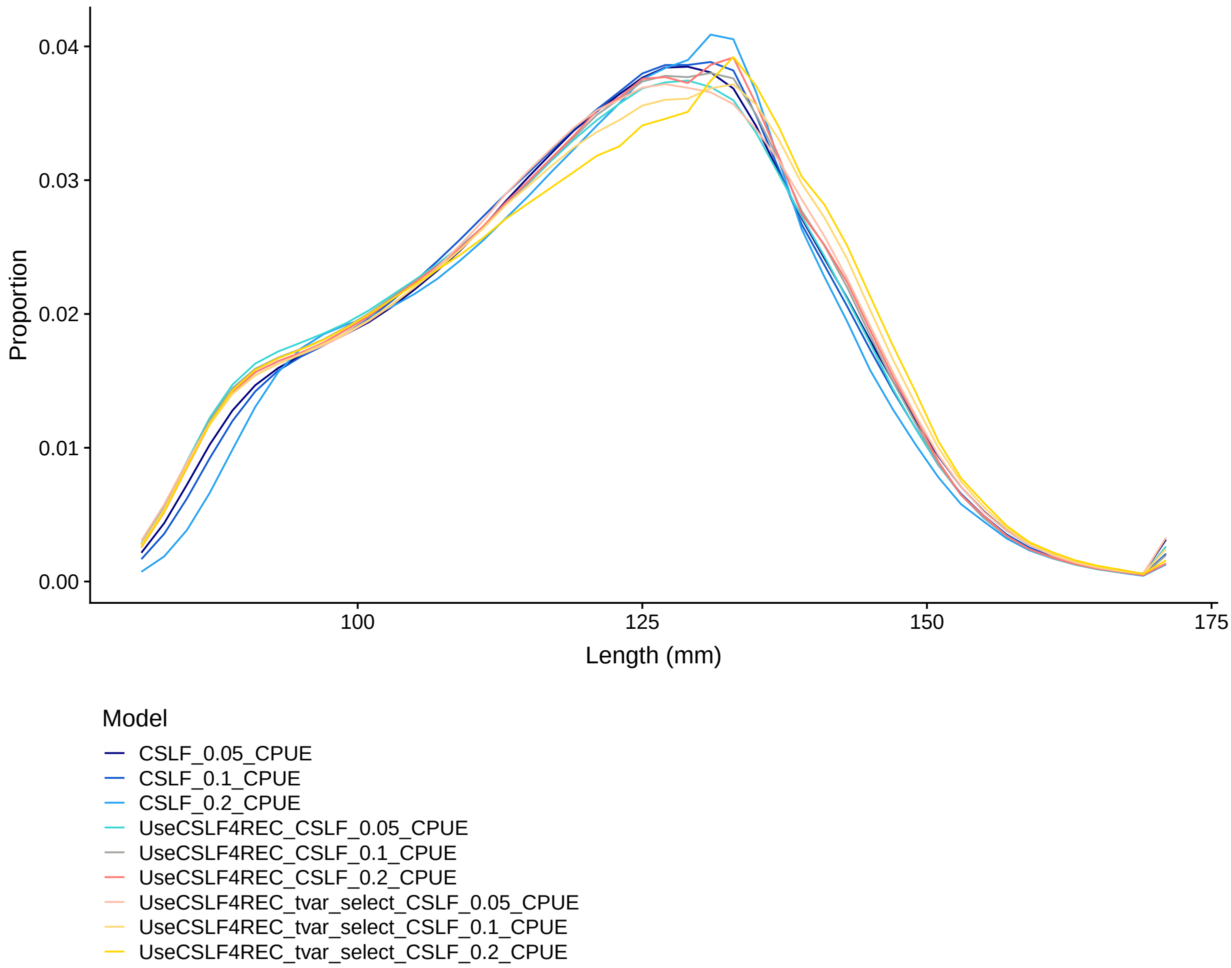

Figure A-33: Comparison of posterior mean proportions-at-length in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for years with catch sampling length frequency (CSLF) data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

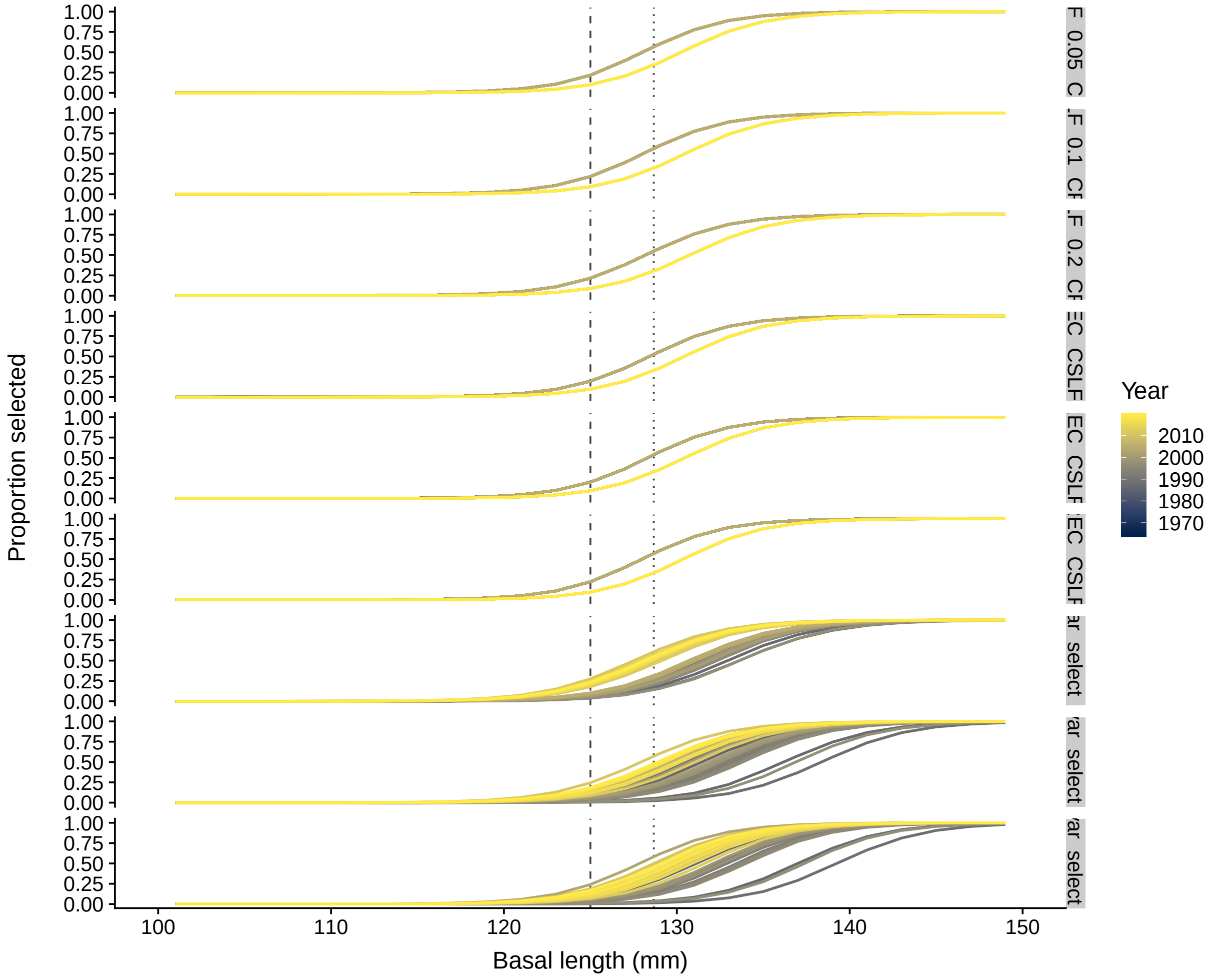

Figure A-34: Comparison of posterior mean selectivity-at-length in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for years with catch sampling length frequency (CSLF) data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

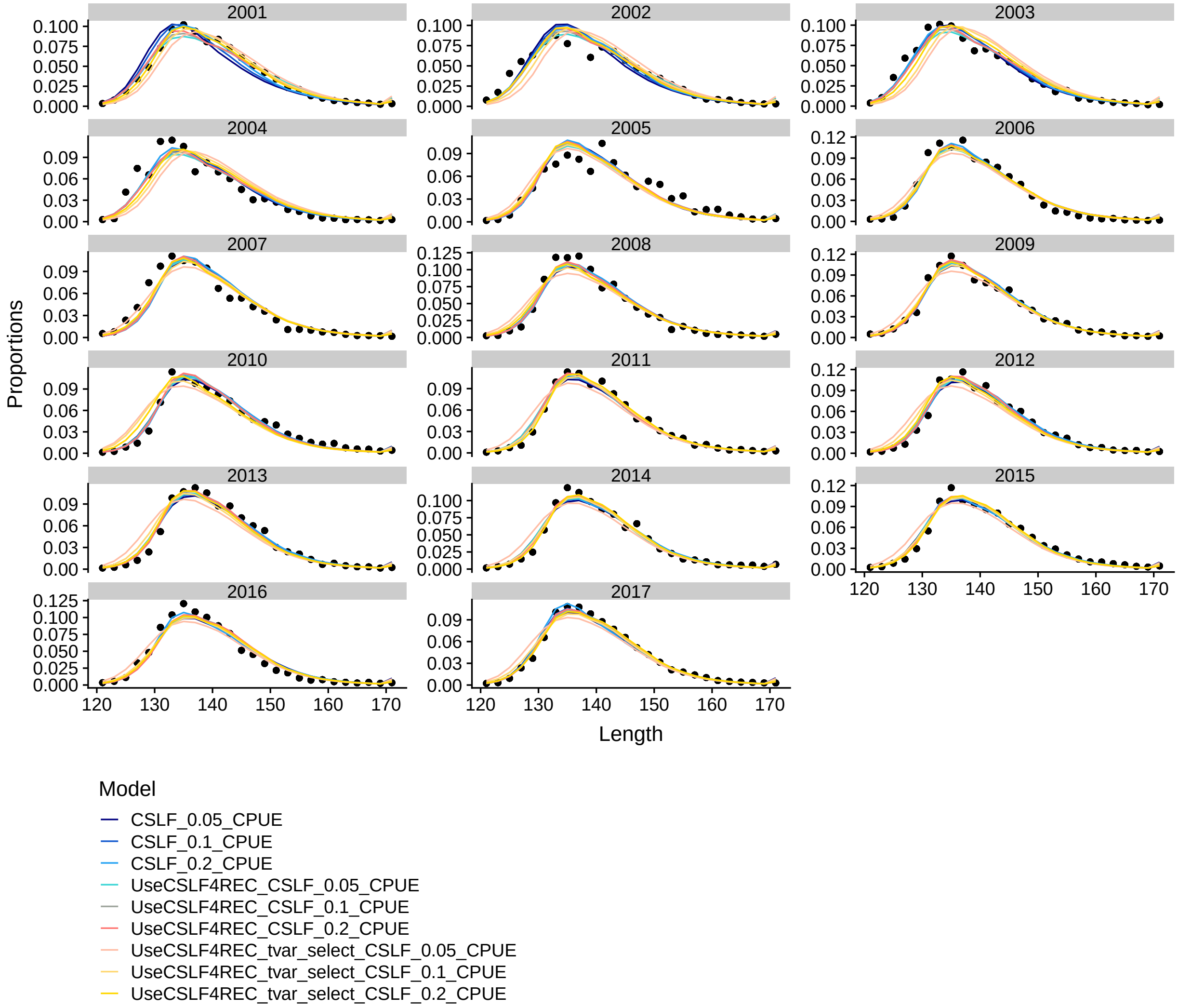

Figure A-35: Comparison of posterior mean predicted catch sampling length frequency (CSLF) with estimated CSLF proportions, in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for for years with CSLF data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

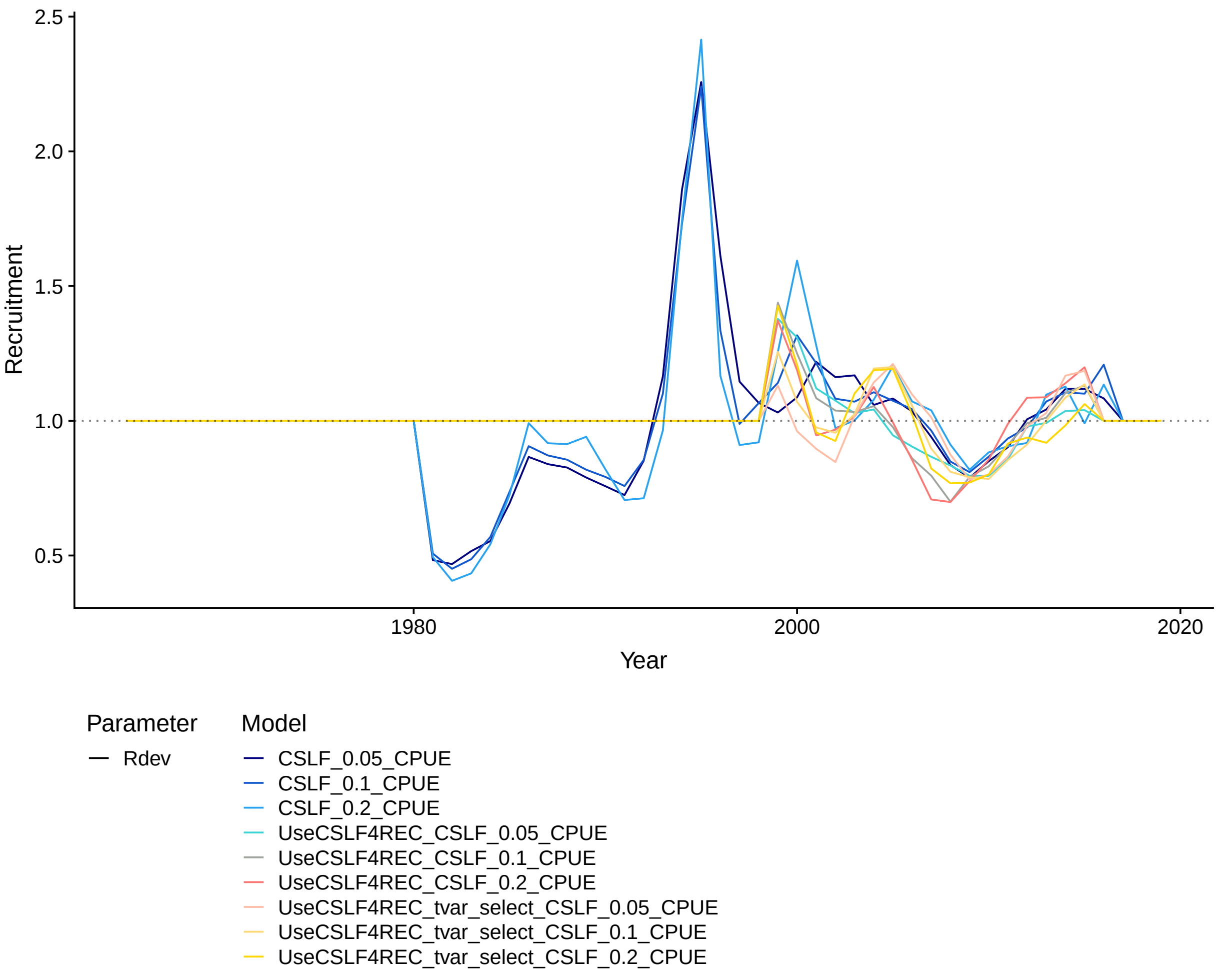

Figure A-36: Comparison of posterior mean recruitment deviations (R_{dev}) in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for years with catch sampling length frequency (CSLF) data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

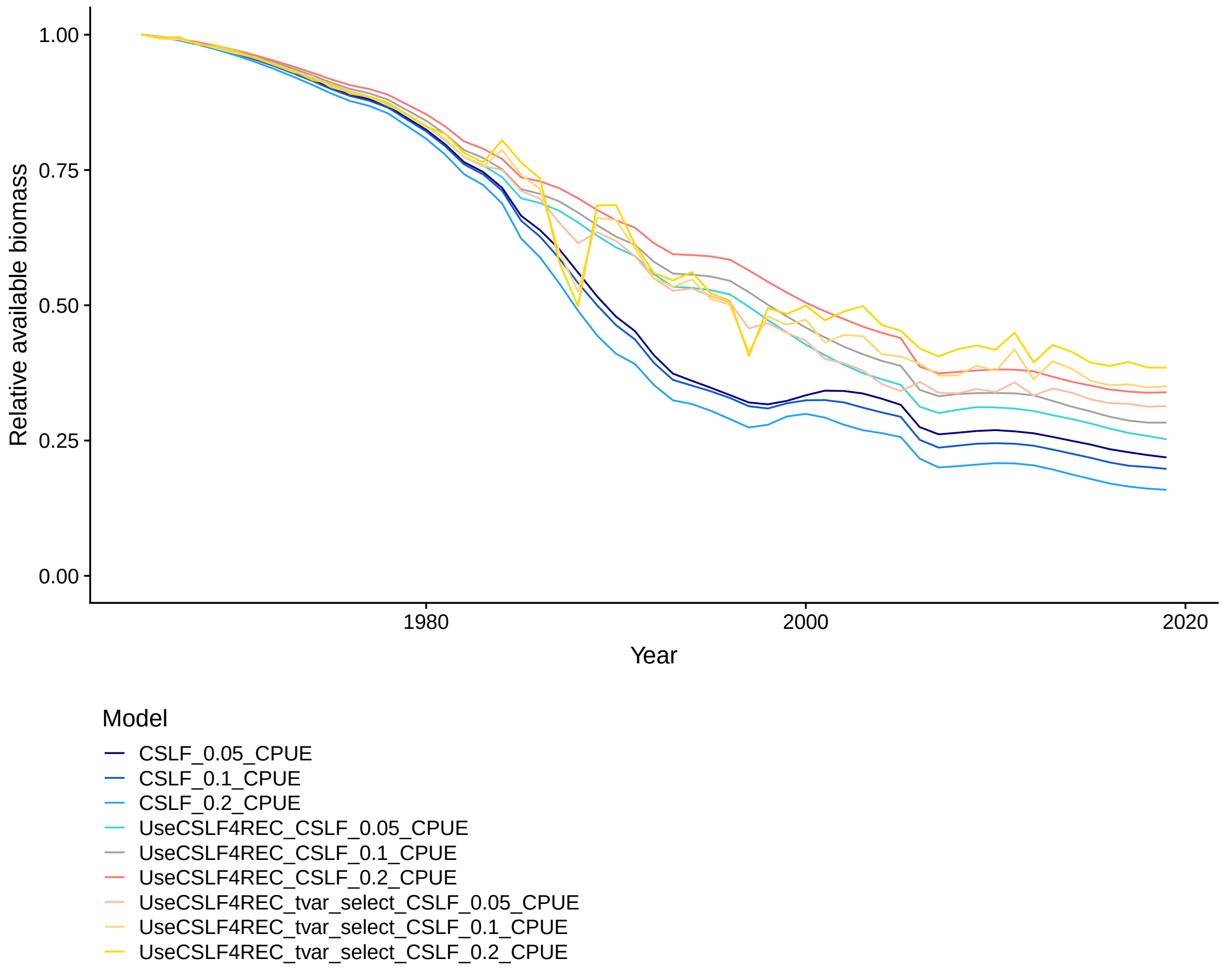

Figure A-37: Comparison of posterior median predicted relative available biomass trend in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for for years with catch sampling length frequency (CSLF) data). All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

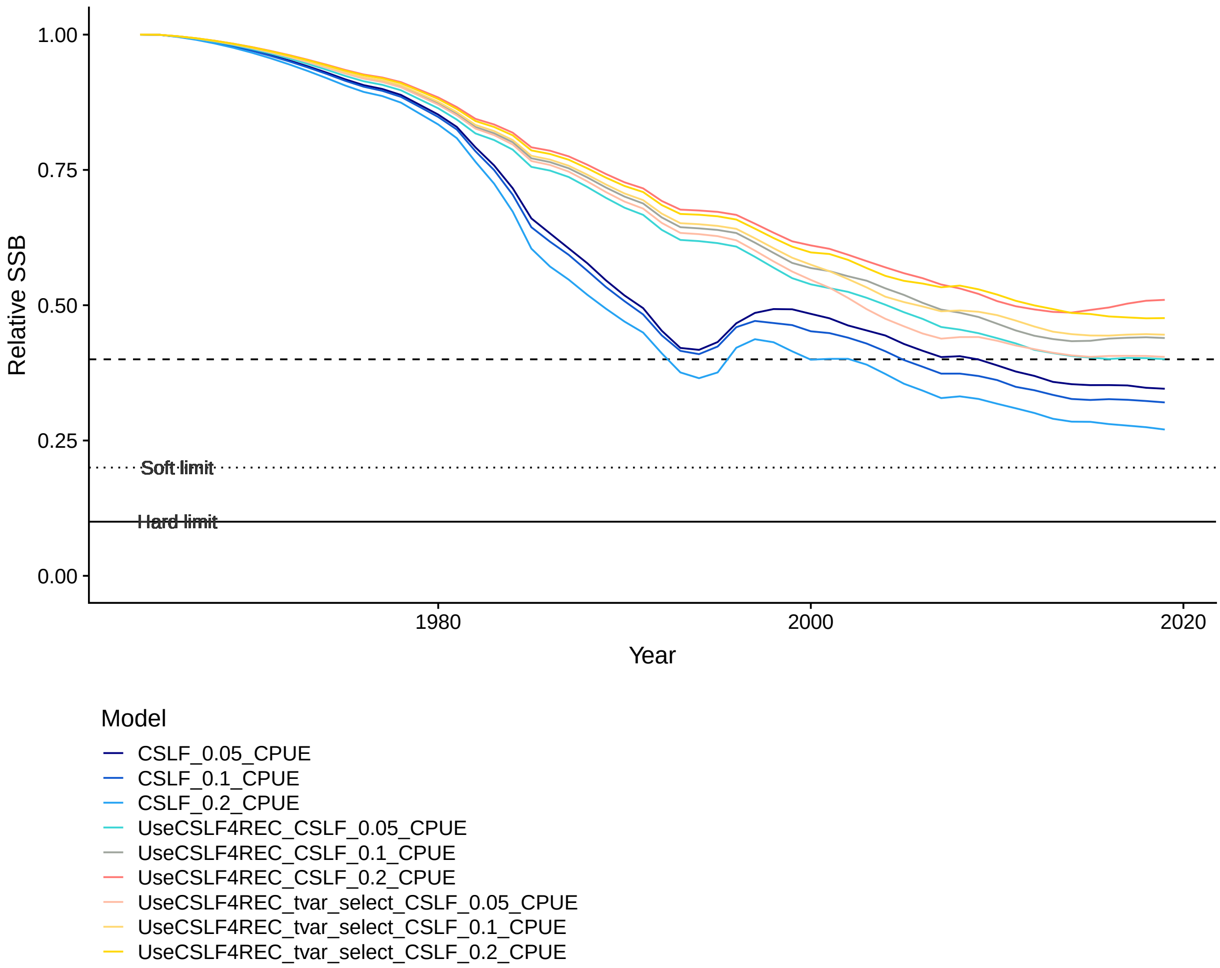

Figure A-38: Comparison of posterior median predicted relative spawning stock biomass trend in the stock assessment model using parameters for Set 3. Model scenario names show differences in selectivity (logistic or time-varying logistic (tvar select) and estimation of recruitment (useCSLF4REC, only estimate recruitment for for years with catch sampling length frequency (CSLF) data. All models estimated three separate catchability parameters for reporting epochs and trends in catchability by epoch. Values for CSLF indicate likelihood weights, catch-per-unit-effort (CPUE) weights were reduced by 50% relative to earlier runs (Sets 1 and 2).

APPENDIX B: INDIVIDUAL MODEL RUNS

B.1 Base case: Model Baseline sep q3 start CPUE1984 useCSLF4REC

B.1.1 Markov chain Monte Carlo and posteriors

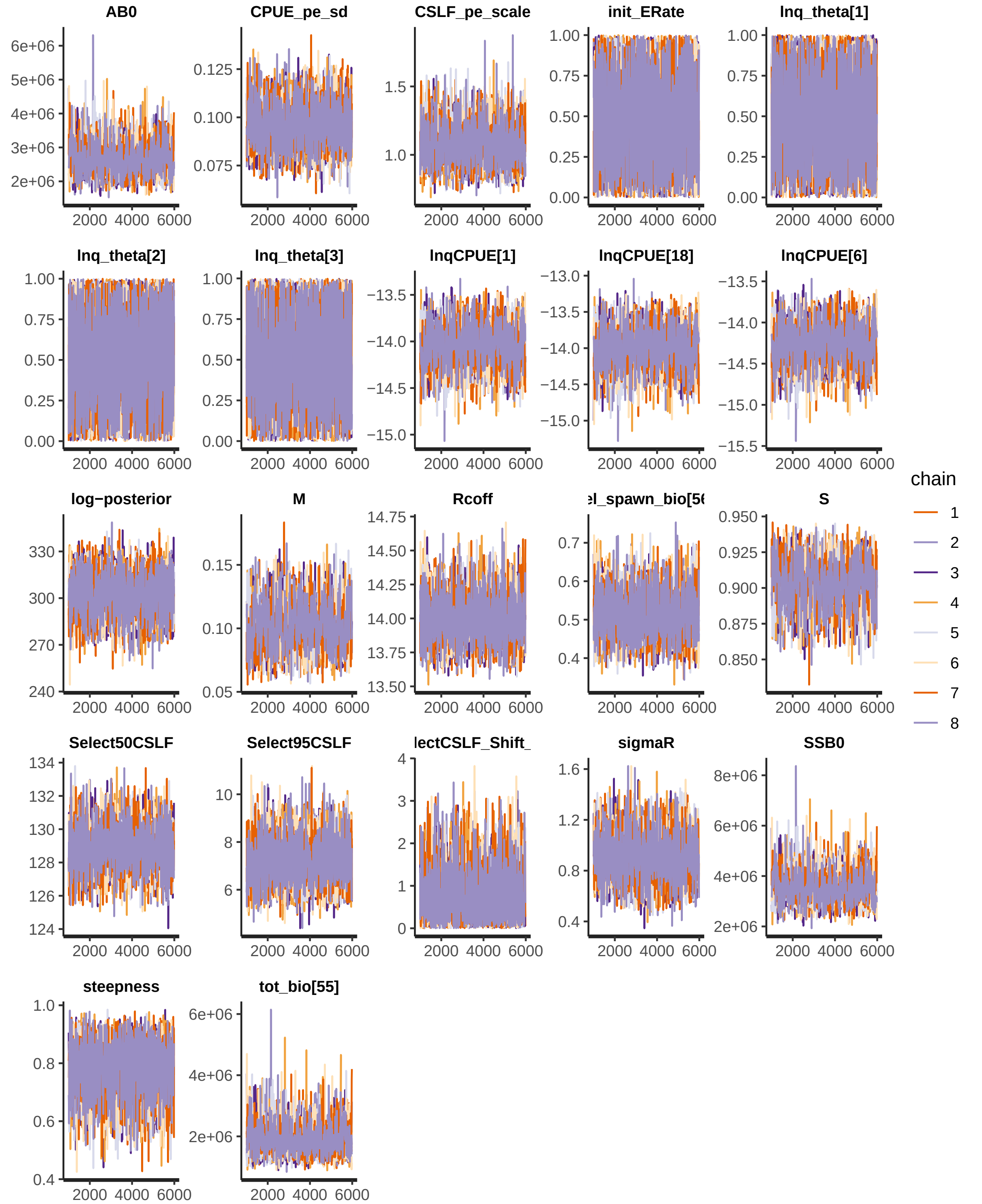

Figure B-1: Traces of Markov chain Monte Carlo estimation for the marginal posterior distribution of key model parameters for the base case stock assessment model of pāua for quota management area PAU 5A.

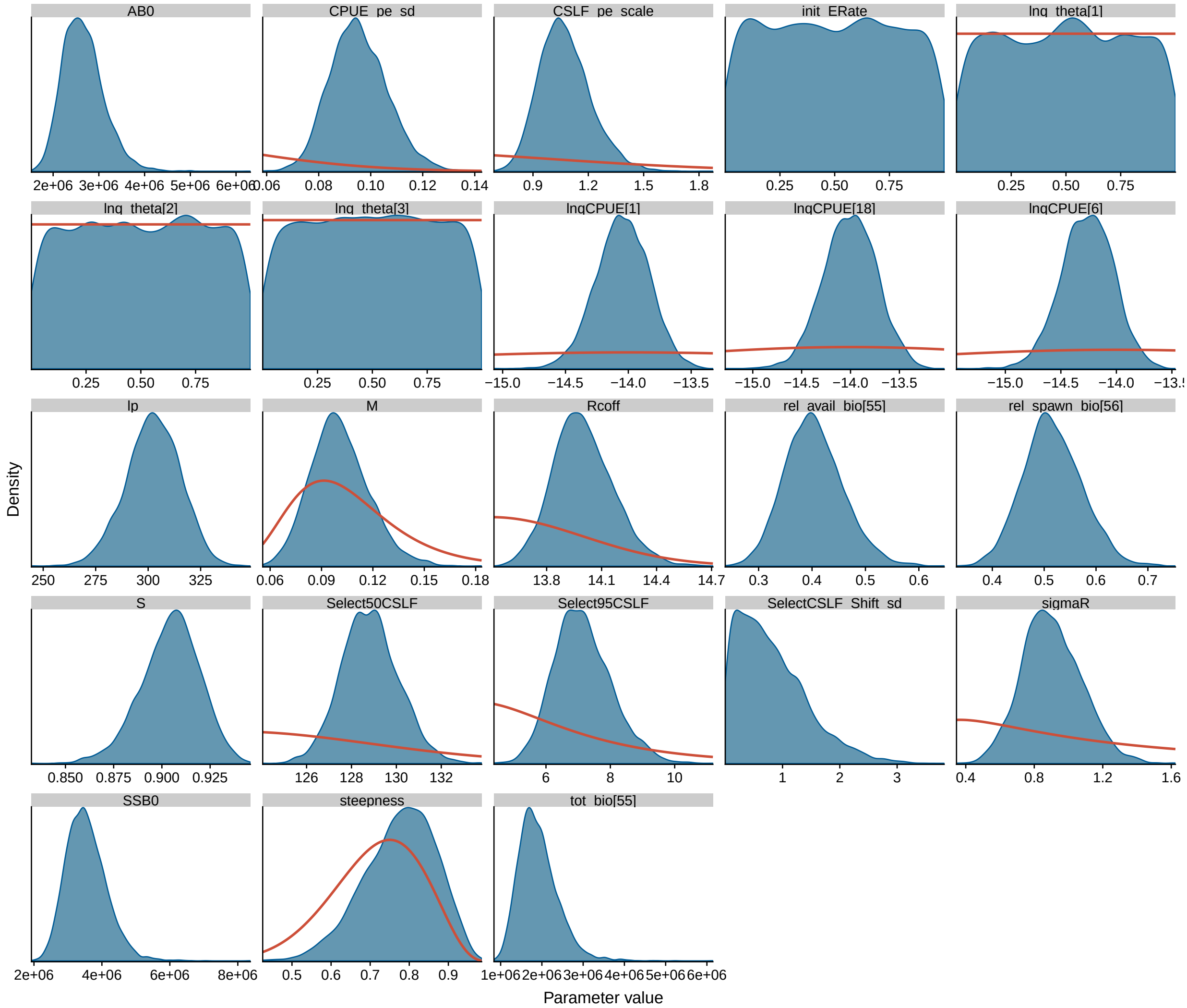

Figure B-2: Marginal posterior densities of key model parameters for the base case stock assessment model of pāua for quota management area PAU 5A, with prior densities indicated in red.

Table B-1: Posterior quantities for key parameters in the base case pāua stock assessment model for quota management area PAU 5A. Process error, PE; catchability slope (trend) and intercept, q; natural mortality, M; size at which 50% of individuals are selected, D_{50}; size at which 95% of individuals are selected, D_{95}; shift in selectivity curve between periods, D_a; baseline recruitment, R_0, the Bayes log posterior; relative available biomass, B^{avail}; stock status (relative spawning stock biomass (SSB)); the exploitation rate ($U_{40\%\text{SSB}_0}$) leading to 40% of unfished spawning stock biomass (SSB_0); steepness. PCELR and CELR, (Paua) Catch Effort Landing Return; FSU, Fisheries Statistical Unit.

Parameter	Posterior percentile				
	2.5%	25%	50%	75%	97.5%
$\log(q_{\text{CELR}})$	-14.73	-14.42	-14.26	-14.10	-13.81
$\log(q_{\text{FSU}})$	-14.48	-14.19	-14.05	-13.90	-13.64
$\log(q_{\text{PCELR}})$	-14.54	-14.18	-14.00	-13.82	-13.48
$\log(R_0)$	13.70	13.89	13.99	14.10	14.35
σ_R	0.59	0.78	0.89	1.02	1.26
D_{50}	126.40	127.96	128.79	129.66	131.46
D_{95}	5.57	6.52	7.07	7.71	9.08
D_a	0.04	0.33	0.69	1.18	2.29
M	0.07	0.09	0.10	0.11	0.14
q_{CELR} trend (linear)	0.02	0.25	0.50	0.75	0.97
q_{FSU} trend (linear)	0.03	0.25	0.51	0.75	0.98
q_{PCELR} trend (linear)	0.02	0.26	0.50	0.75	0.97
$U_{40\%\text{SSB}_0}$	0.07	0.13	0.19	0.27	0.57
log posterior	275.85	293.95	302.64	311.34	326.59
PE_{CPUE}	0.08	0.09	0.09	0.10	0.12
PE_{CSLF}	0.84	0.98	1.06	1.16	1.38
relative B^{avail}	0.30	0.37	0.40	0.44	0.52
relative SSB_{2019}	0.41	0.48	0.51	0.55	0.63
steepness	0.58	0.72	0.78	0.84	0.93

B.1.2 Growth

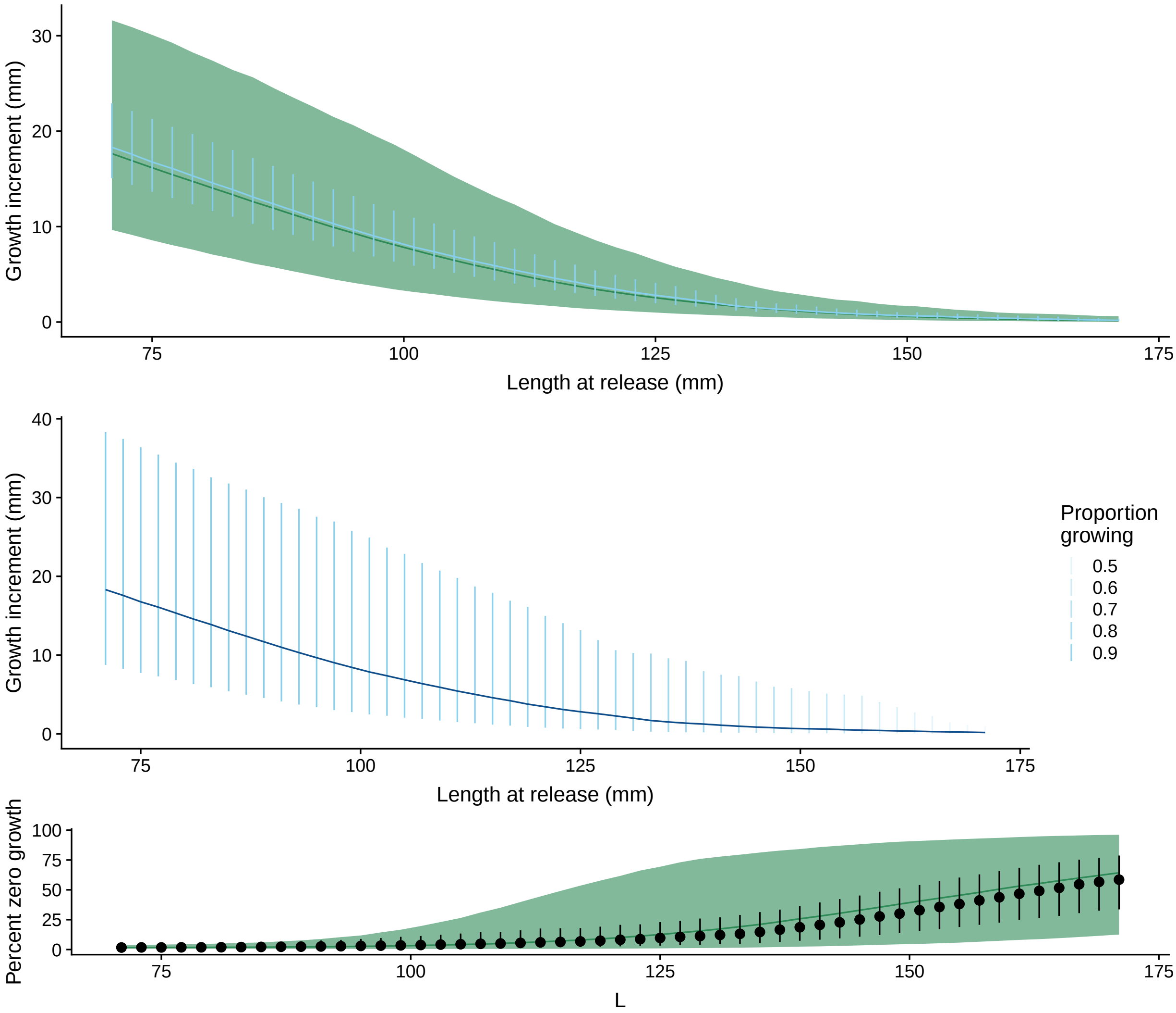

Figure B-3: Top: Posterior mean growth (population mean (dark blue line) and standard deviation of the estimate (light blue ribbon)), relative to the prior (dark green), middle: estimated population standard deviation (posterior median; light blue) relative to estimated population mean (blue line), bottom panel: estimated proportion of pāua stock not growing at each length relative to the prior (green) for the base case stock assessment model of pāua for quota management area PAU 5A.

B.1.3 Kullback-Leibler divergence

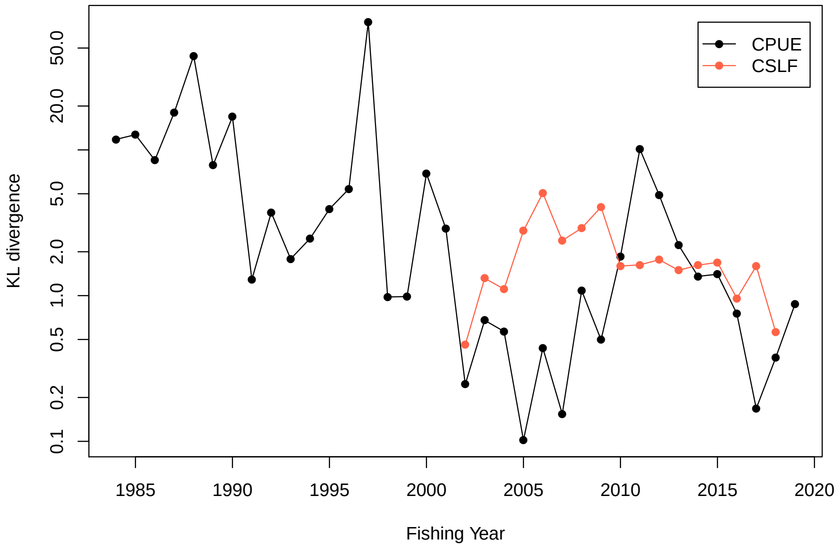

Figure B-4: Comparison of scaled Kullback-Leibler divergence (KLD) between posterior distributions for catch-per-unit-effort (CPUE) and catch sampling length frequency (CSLF) data (assumed Gaussian after log and centred-log-ratio transformation, respectively) for the base case stock assessment model of pāua for quota management area PAU 5A.

B.1.4 Catch-per-unit-effort fits

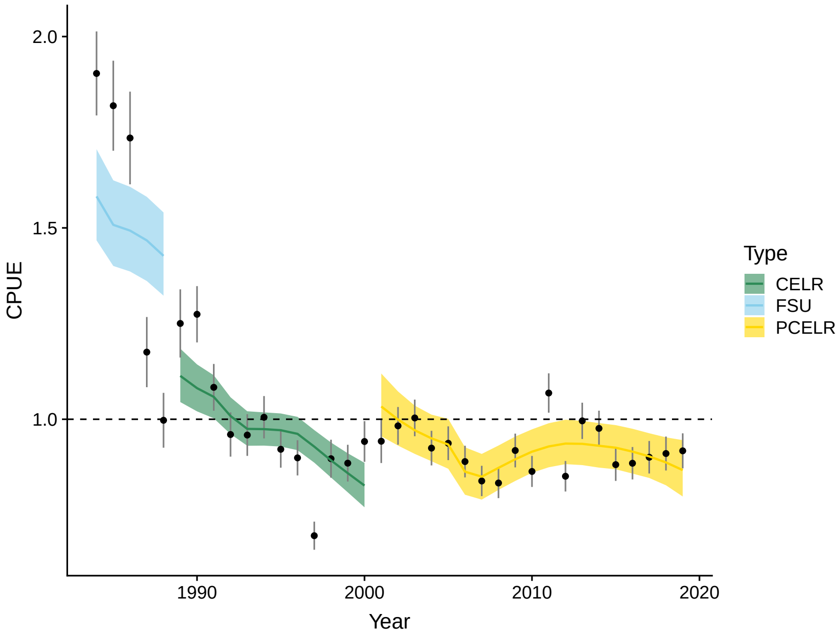

Figure B-5: Comparison of posterior median predicted catch-per-unit-effort (CPUE) with estimated CPUE index and observation error for the base case stock assessment model of pāua for quota management area PAU 5A (black points and error bars; CELR, data from Catch Effort Landing Return forms).

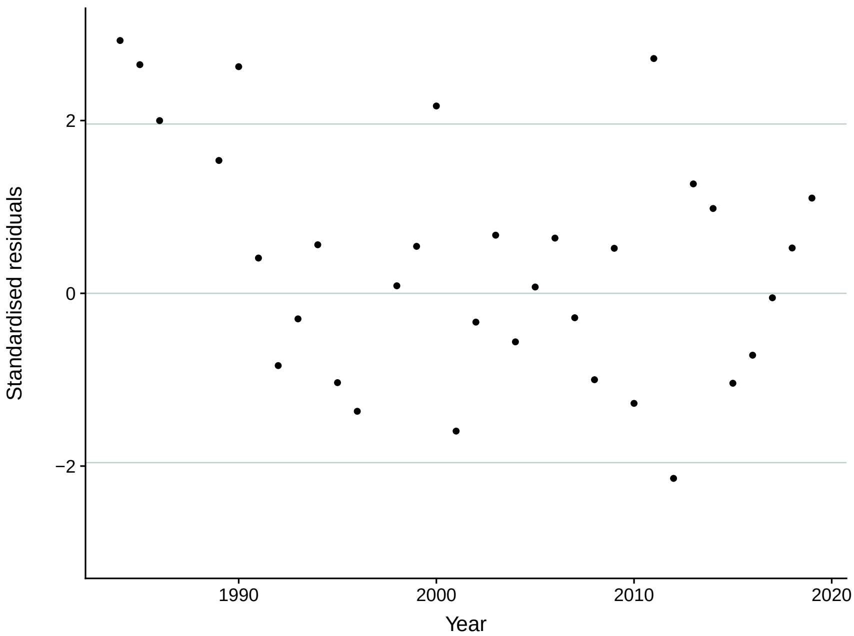

Figure B-6: Standardised residuals at the posterior median of predicted catch-per-unit-effort for the base case stock assessment model of pāua for quota management area PAU 5A.

B.1.5 Catch sampling length frequency fits

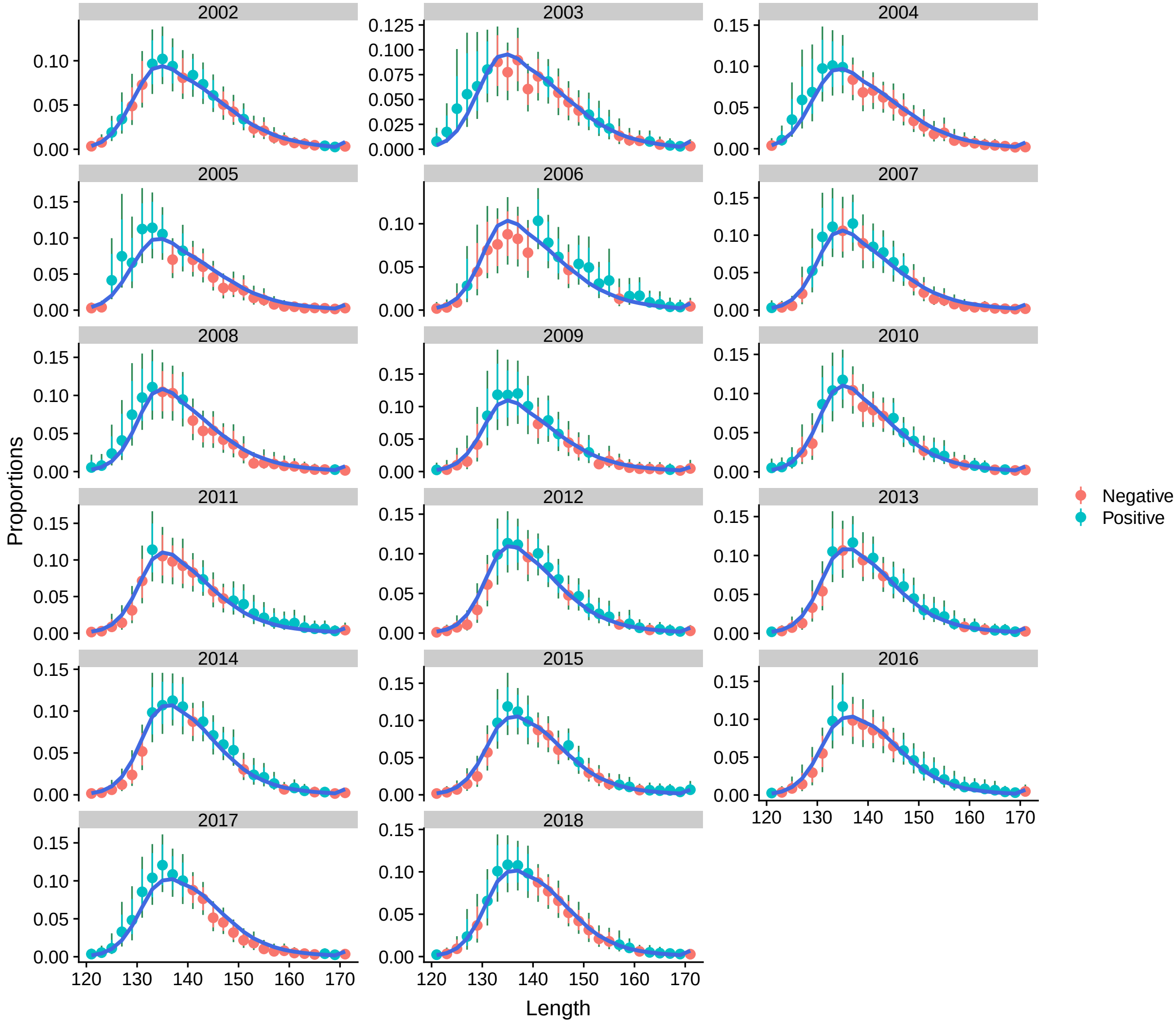

Figure B-7: Comparison of posterior mean predicted catch sampling length frequency (CSLF) with estimated CSLF proportions and observation error for the base case stock assessment model of pāua for quota management area PAU 5A. Length classes with positive residuals in blue, with negative residuals in red.

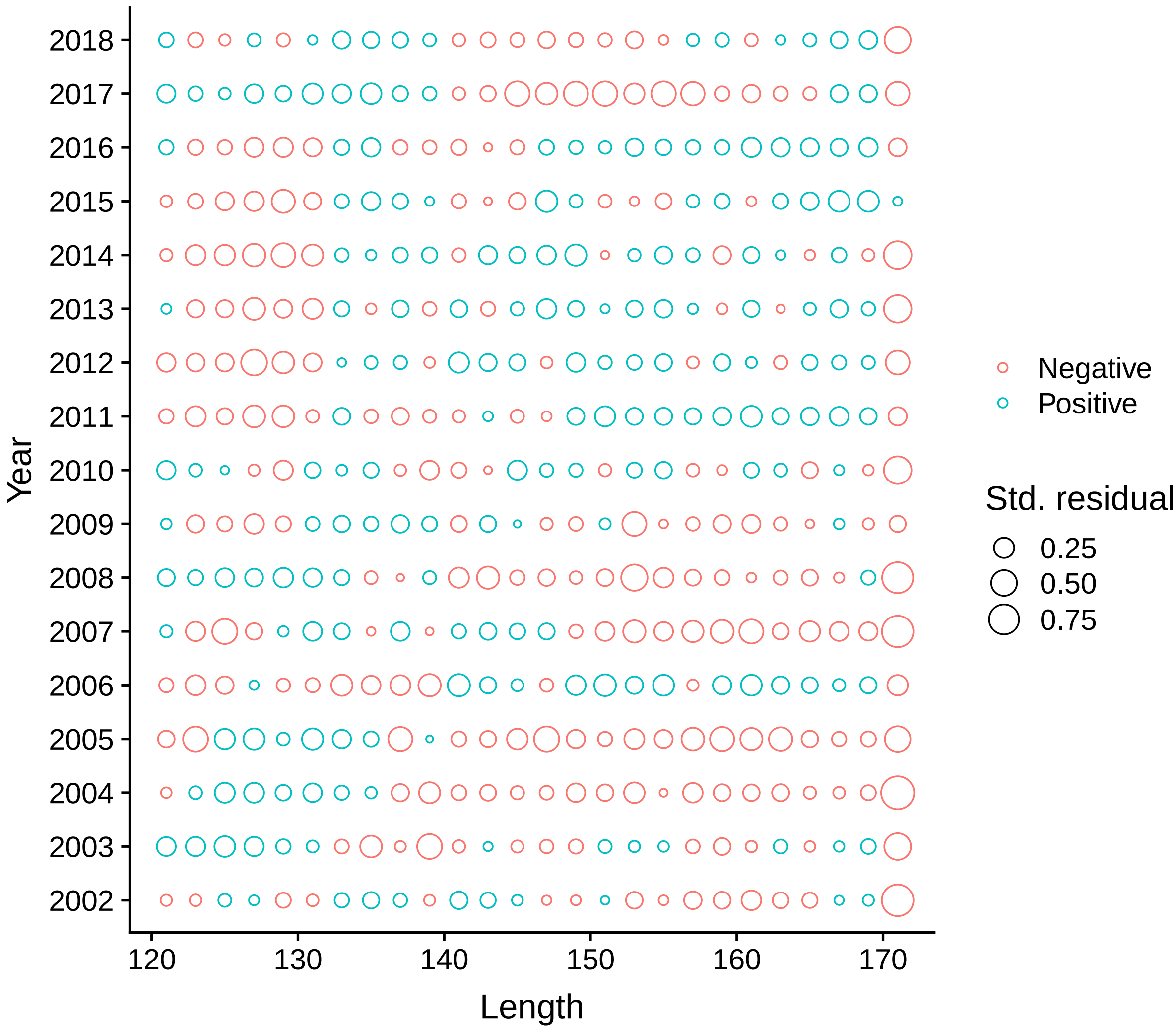

Figure B-8: Catch sampling length frequency model residuals for the base case stock assessment model of pāua for quota management area PAU 5A. Length classes with positive residuals in blue, with negative residuals in red.

B.1.6 Selectivity

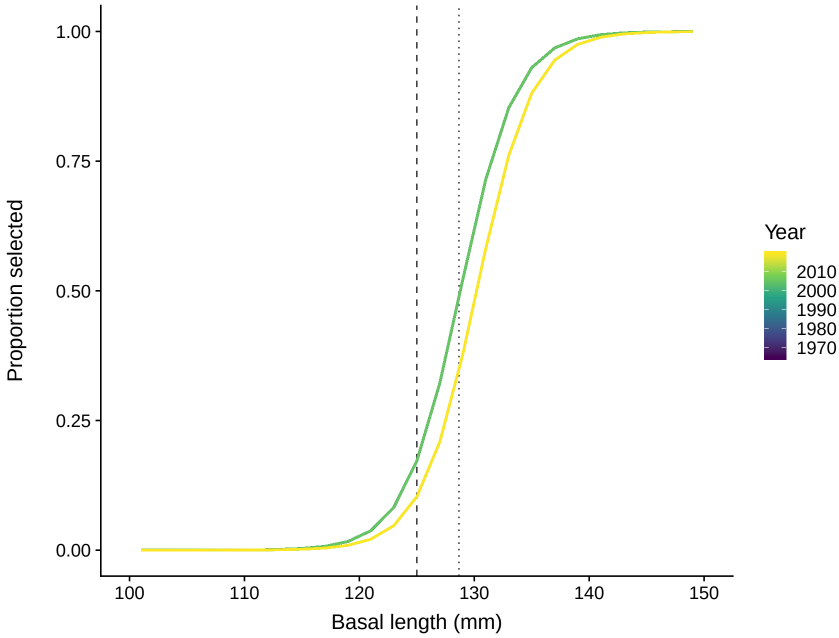

Figure B-9: Estimated selectivity (posterior mean) for periods of varying minimum harvest size of pāua for the base case stock assessment model for quota management area PAU 5A.

B.1.7 Recruitment and biomass trends

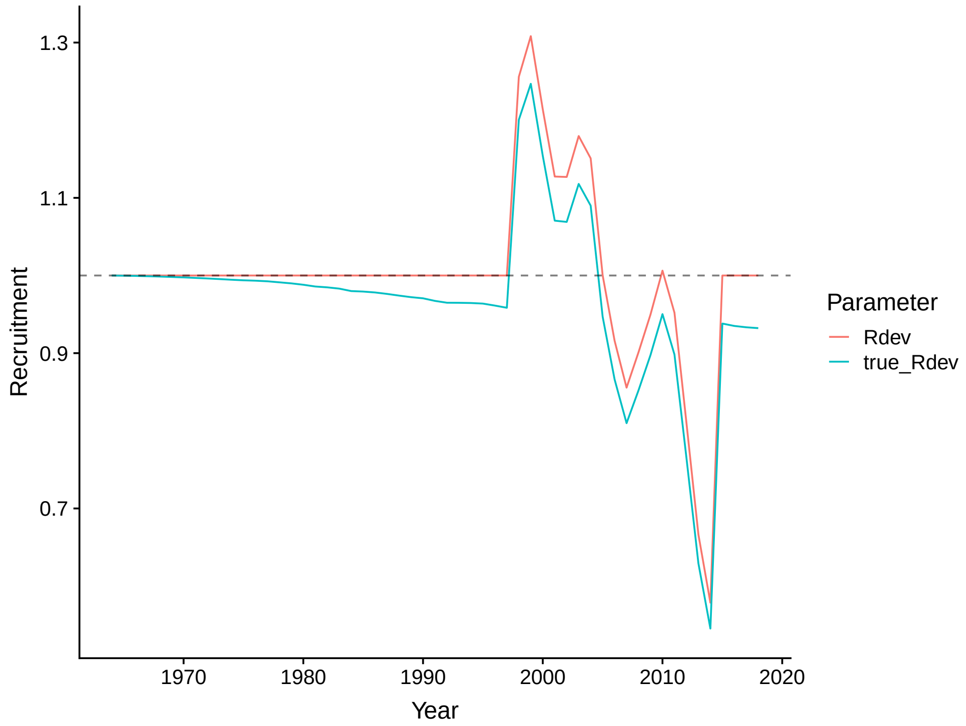

Figure B-10: Posterior mean recruitment for the base case stock assessment model of pāua for quota management area PAU 5A (R_{dev}, recruitment deviation).

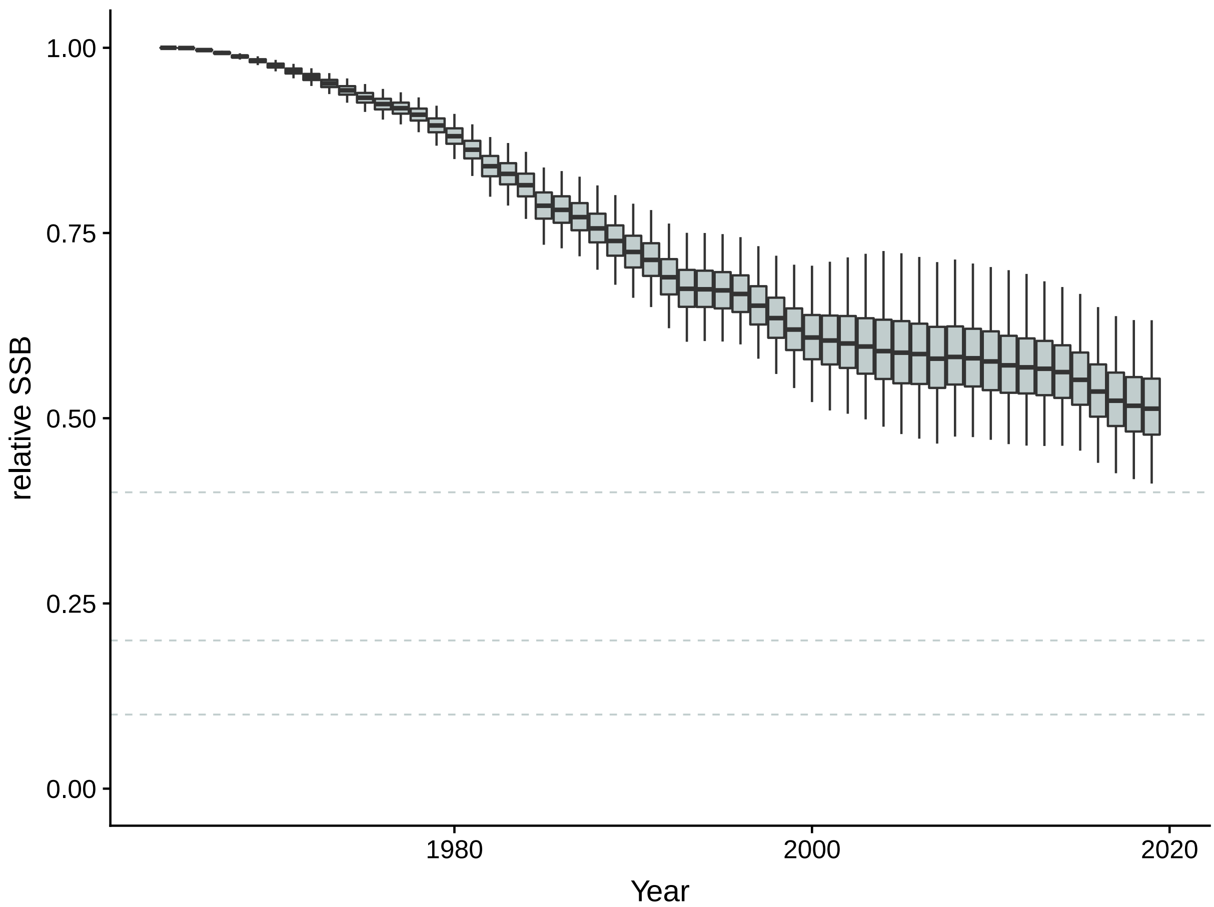

Figure B-11: Predicted relative spawning stock biomass (SSB) trend for pāua for the base case stock assessment model for quota management area PAU 5A (black line and 95% confidence interval).

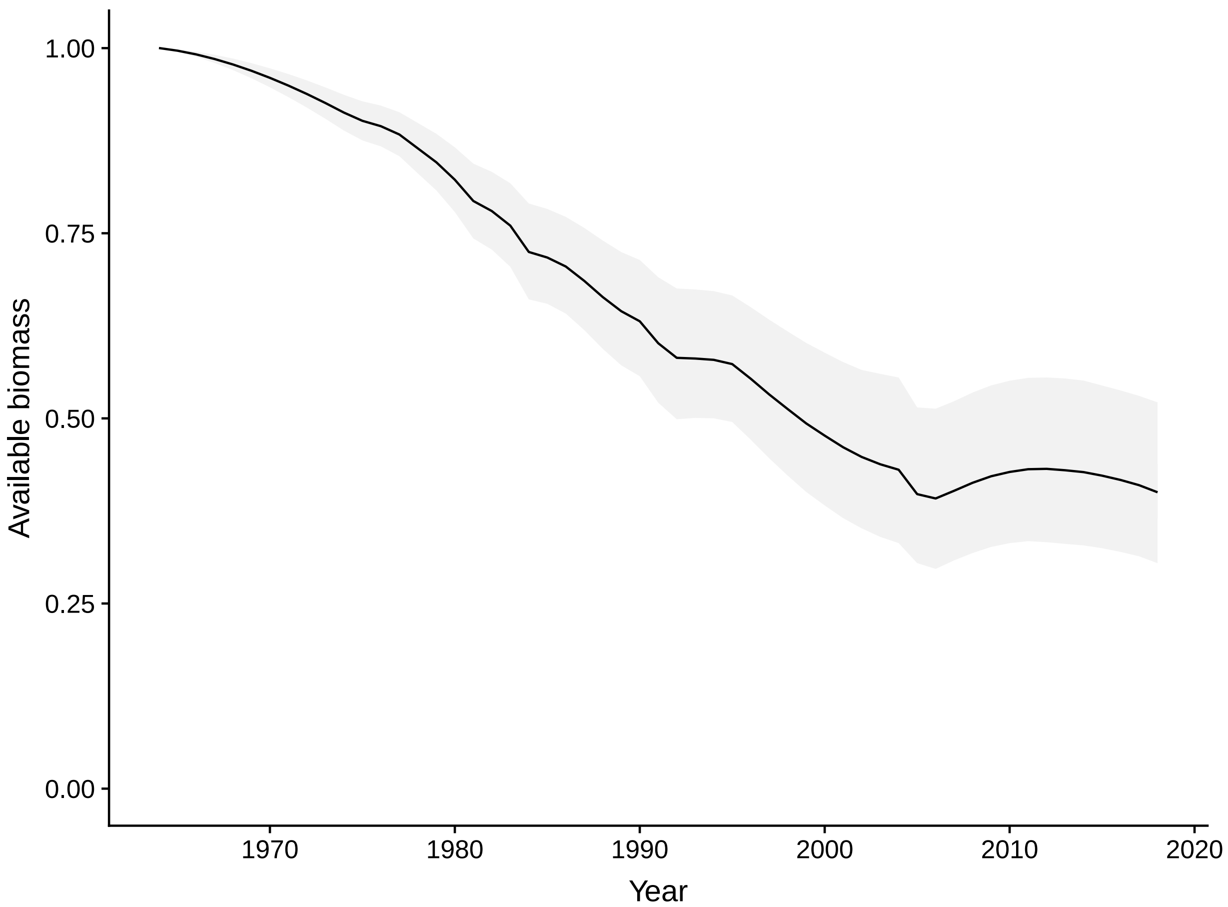

Figure B-12: Predicted relative available biomass trend for pāua for the base case stock assessment model for quota management area PAU 5A (black line and 95% confidence interval).

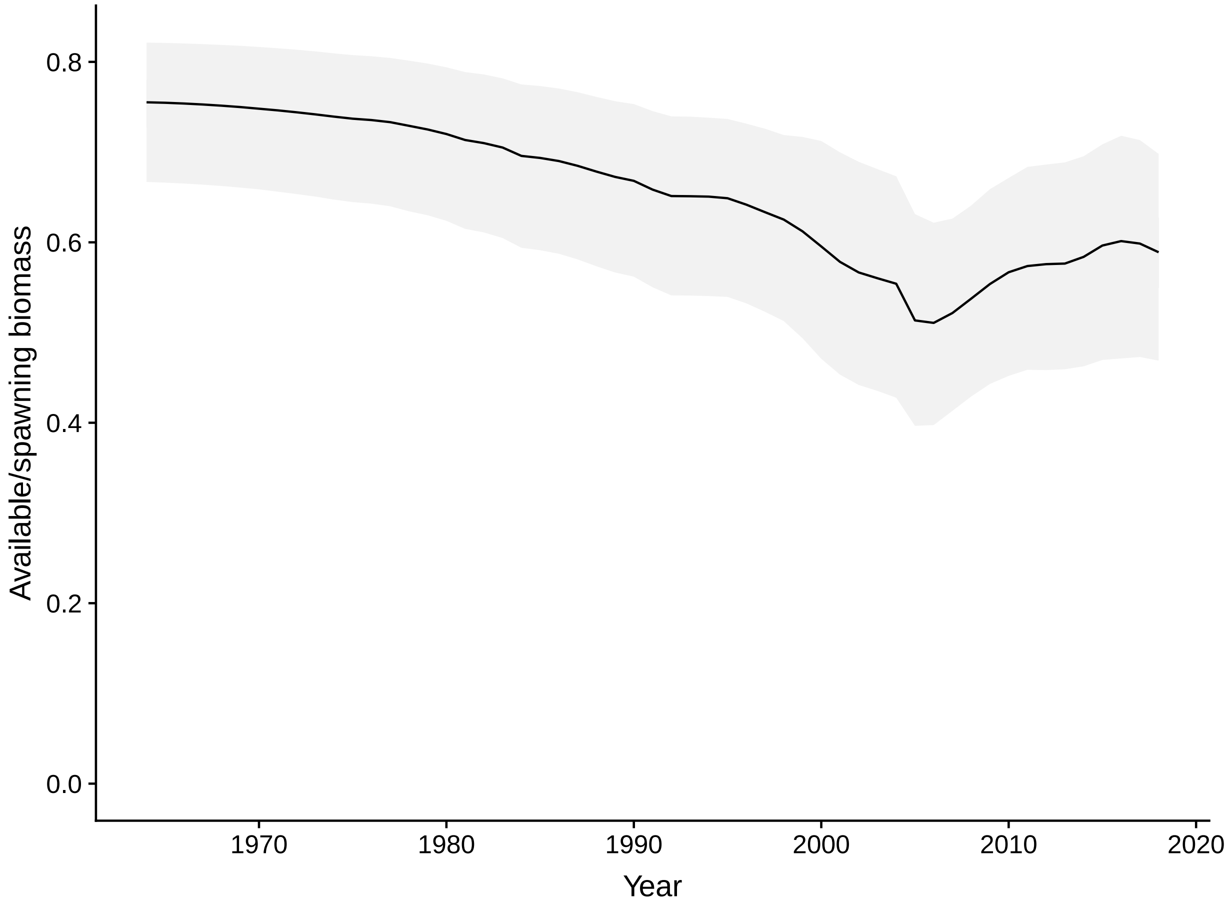

Figure B-13: Predicted relative available pāua biomass (relative to spawning stock) for the base case stock assessment model for quota management area PAU 5A (black line and 95% confidence interval).

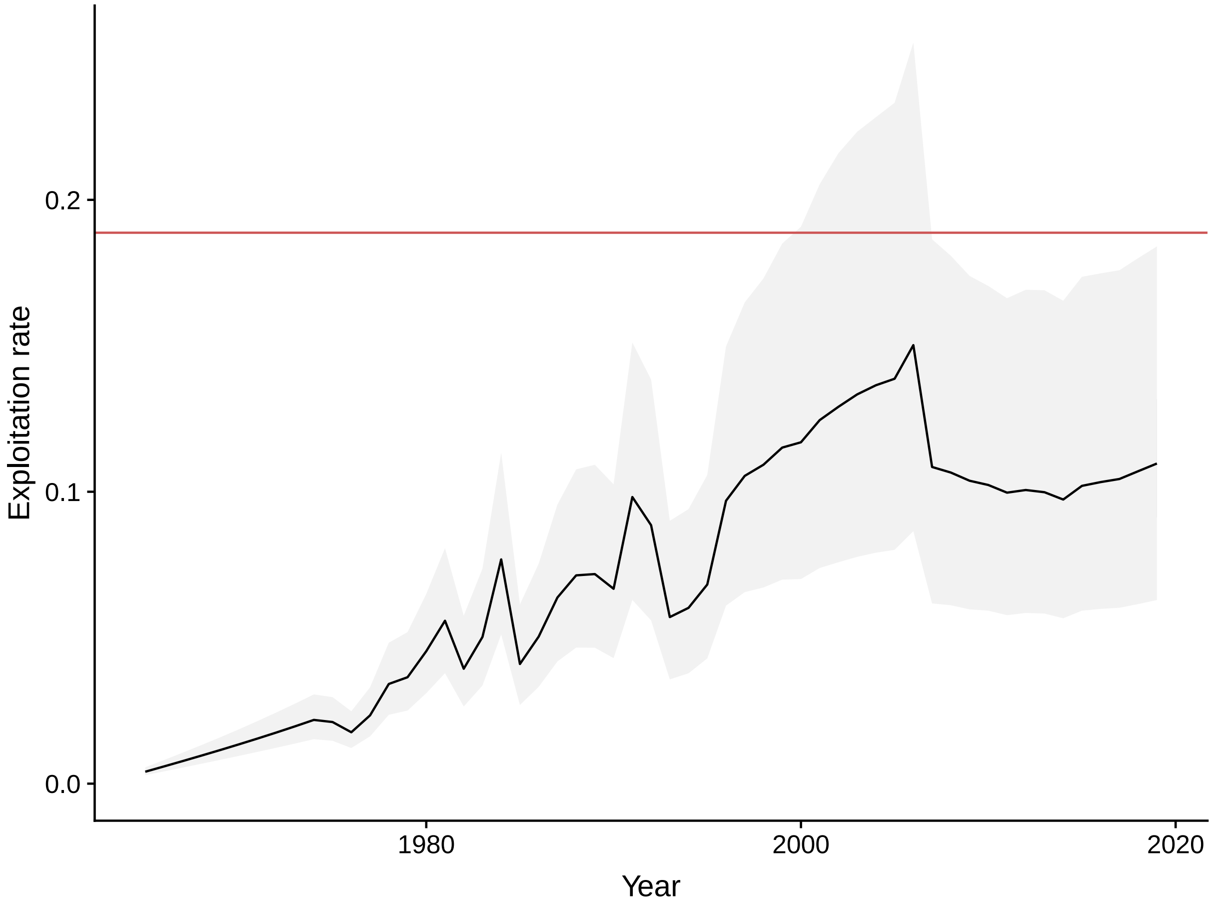

Figure B-14: Predicted exploitation rate (black line and 95% confidence interval) for the base case relative to the posterior median estimate of the explotiation rate (U) leading to 40% SSB $U_{40\%\mathrm{SSB}_0}$ (red line) of pāua for quota management area PAU 5A.

B.1.8 Status and projections

Table B-2: Stock status and fishery indicators for the last fishing year considered in this assessment and projections for key fishery indicators from the base case stock assessment model of pāua for quota management area PAU 5A for three years, for current catch (indicated by the asterisk), and 20% and 50% increases and reductions from current catch. Results at equilibrium (Eq.) are also given (assumed to be reached after 50 years). Columns are: probabilities of being above 40% (P(SSB>0.4SSB$_0$)) and 20% (P(SSB>0.2SSB$_0$)) of unfished spawning stock biomass (SSB), the probability that SSB in the projection year is above current SSB, the posterior median relative SSB, the posterior median relative available biomass (B^{avail}), the posterior median relative available spawning biomass (B^{avail}), the probability that B^{avail} in the projection year is above current B^{avail}, and the probability that the exploitation rate (U) is greater than the exploitation rate leading to 40% SSB (TCC, total commercial catch).

TCC (t)	Year	Fishery indicator							
		P(SSB>0.4SSB$_0$)	P(SSB>0.2SSB$_0$)	P(SSB>SSB$_{\text{current}}$)	Median rel. SSB	Median rel. B^{avail}	Median rel. SSB$^{\text{avail}}$	P($B^{\text{avail}} > B^{\text{avail}}_{\text{current}}$)	P($U > U_{40\%\text{SSB}_0}$)
52.14	2019	0.99	1.00	0.00	0.52	0.41	0.60	0.01	0.13
	2020	0.98	1.00	0.12	0.52	0.40	0.59	0.01	0.01
	2021	0.99	1.00	0.64	0.53	0.41	0.59	0.01	0.00
	2022	0.99	1.00	0.69	0.54	0.42	0.59	0.02	0.00
	Eq.	0.97	1.00	0.86	0.71	0.62	0.66	0.53	0.01
83.43	2019	0.99	1.00	0.00	0.52	0.41	0.60	0.01	0.13
	2020	0.98	1.00	0.12	0.52	0.40	0.59	0.01	0.06
	2021	0.98	1.00	0.39	0.52	0.40	0.58	0.01	0.07
	2022	0.98	1.00	0.46	0.52	0.40	0.57	0.01	0.07
	Eq.	0.85	0.99	0.63	0.59	0.46	0.59	0.23	0.12
104.29*	2019	0.99	1.00	0.00	0.52	0.41	0.60	0.01	0.13
	2020	0.98	1.00	0.12	0.52	0.40	0.59	0.01	0.13
	2021	0.98	1.00	0.27	0.51	0.39	0.58	0.00	0.14
	2022	0.96	1.00	0.34	0.51	0.39	0.57	0.01	0.16
	Eq.	0.68	0.95	0.43	0.50	0.36	0.51	0.11	0.31
125.14	2019	0.99	1.00	0.00	0.52	0.41	0.60	0.01	0.13
	2020	0.98	1.00	0.12	0.52	0.40	0.59	0.01	0.22
	2021	0.97	1.00	0.19	0.51	0.39	0.57	0.00	0.24
	2022	0.95	1.00	0.25	0.50	0.37	0.56	0.00	0.27
	Eq.	0.48	0.87	0.24	0.41	0.25	0.42	0.05	0.56
156.43	2019	0.99	1.00	0.00	0.52	0.41	0.60	0.01	0.13
	2020	0.98	1.00	0.12	0.52	0.40	0.59	0.01	0.35
	2021	0.96	1.00	0.11	0.50	0.38	0.57	0.00	0.40
	2022	0.91	1.00	0.14	0.49	0.35	0.54	0.00	0.45
	Eq.	0.24	0.73	0.08	0.31	0.14	0.29	0.01	0.86

B.2 Sensitivity run 1: Model Baseline sep q3 qTrend start CPUE1984 useCSLF4REC

B.2.1 Markov chain Monte Carlo and posteriors

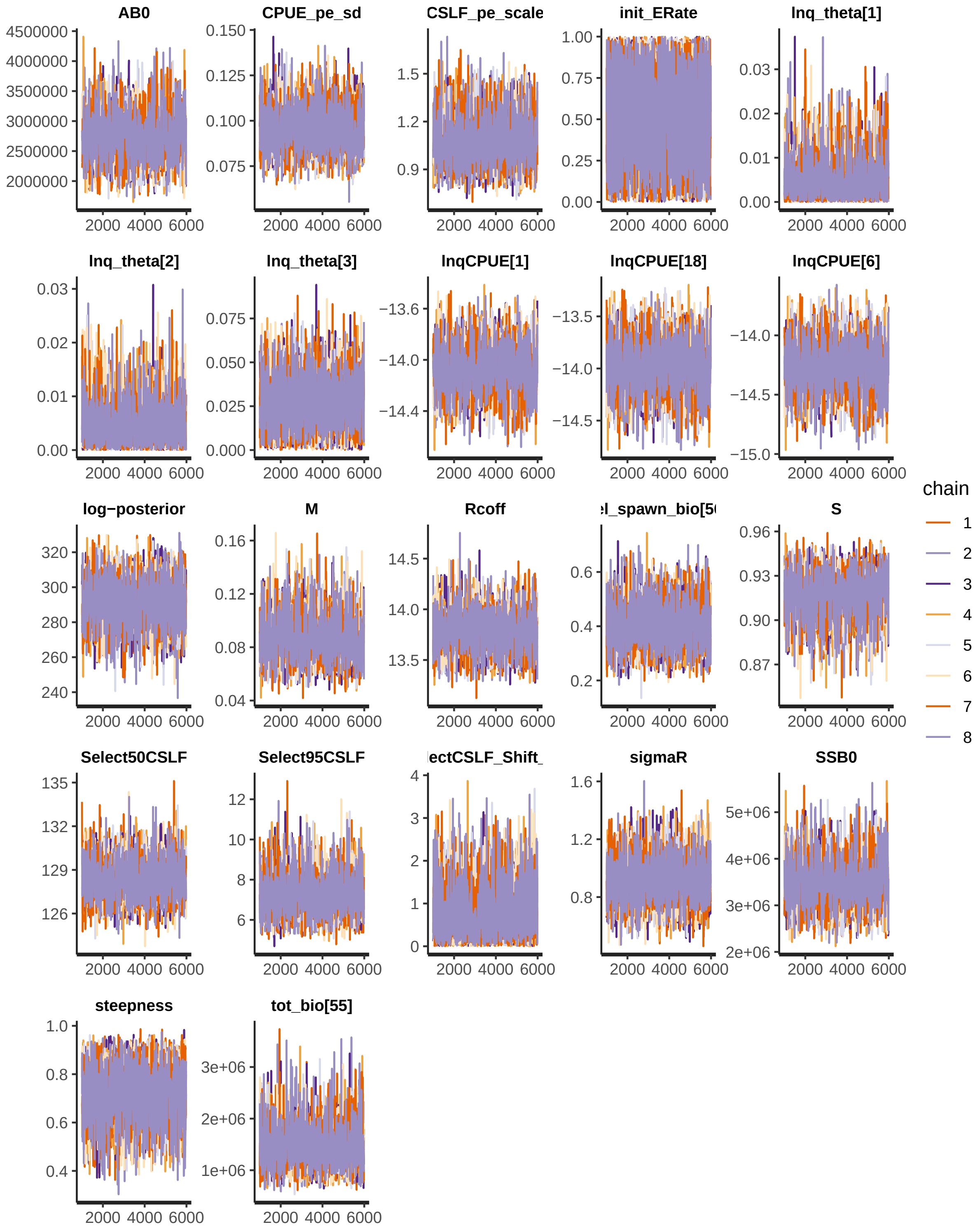

Figure B-15: Traces of Markov chain Monte Carlo estimation for the marginal posterior distribution of key model parameters for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A.

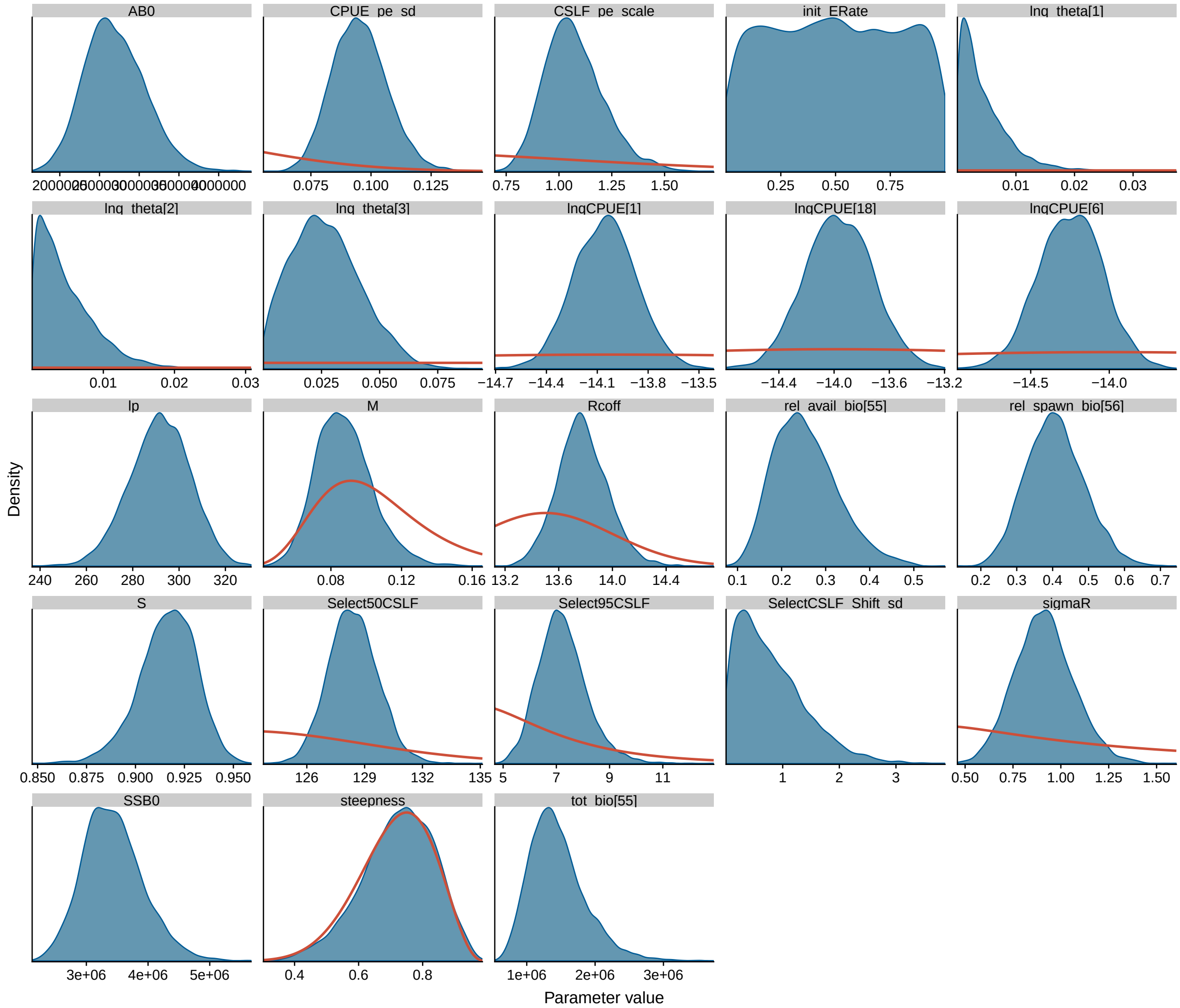

Figure B-16: Marginal posterior densities of key model parameters for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A, with prior densities indicated in red.

Table B-3: Posterior quantities for key parameters in the main sensitivity run 1 of the pāua stock assessment model for quota management area PAU 5A. Process error, PE; catchability slope (trend) and intercept, q; natural mortality, M; size at which 50% of individuals are selected, D_{50}; size at which 95% of individuals are selected, D_{95}; shift in selectivity curve between periods, D_a; baseline recruitment, R_0, the Bayes log posterior; relative available biomass, B^{avail}; stock status (relative spawning stock biomass (SSB)); the exploitation rate ($U_{40\%\text{SSB}_0}$) leading to 40% of unfished spawning stock biomass (SSB_0); steepness. PCELR and CELR, (Paua) Catch Effort Landing Return; FSU, Fisheries Statistical Unit.

Parameter	Posterior percentile				
	2.5%	25%	50%	75%	97.5%
$\log(q_{\text{CELR}})$	-14.65	-14.39	-14.24	-14.11	-13.85
$\log(q_{\text{FSU}})$	-14.41	-14.18	-14.05	-13.93	-13.69
$\log(q_{\text{PCELR}})$	-14.45	-14.13	-13.97	-13.80	-13.49
$\log(R_0)$	13.42	13.65	13.77	13.90	14.17
σ_R	0.63	0.81	0.91	1.01	1.23
D_{50}	126.01	127.54	128.35	129.24	131.01
D_{95}	5.66	6.62	7.17	7.78	9.31
D_a	0.03	0.32	0.67	1.14	2.26
M	0.06	0.08	0.09	0.10	0.12
q_{CELR} trend (linear)	0.00	0.00	0.00	0.01	0.02
q_{FSU} trend (linear)	0.00	0.00	0.00	0.01	0.02
q_{PCELR} trend (linear)	0.00	0.02	0.03	0.04	0.06
$U_{40\%\text{SSB}_0}$	0.07	0.13	0.18	0.26	0.53
log posterior	264.79	283.13	291.96	300.64	315.93
PE_{CPUE}	0.07	0.09	0.09	0.10	0.12
PE_{CSLF}	0.83	0.97	1.06	1.16	1.40
relative B^{avail}	0.14	0.20	0.25	0.30	0.42
relative SSB_{2019}	0.26	0.35	0.40	0.46	0.57
steepness	0.48	0.65	0.73	0.81	0.92

B.2.2 Growth

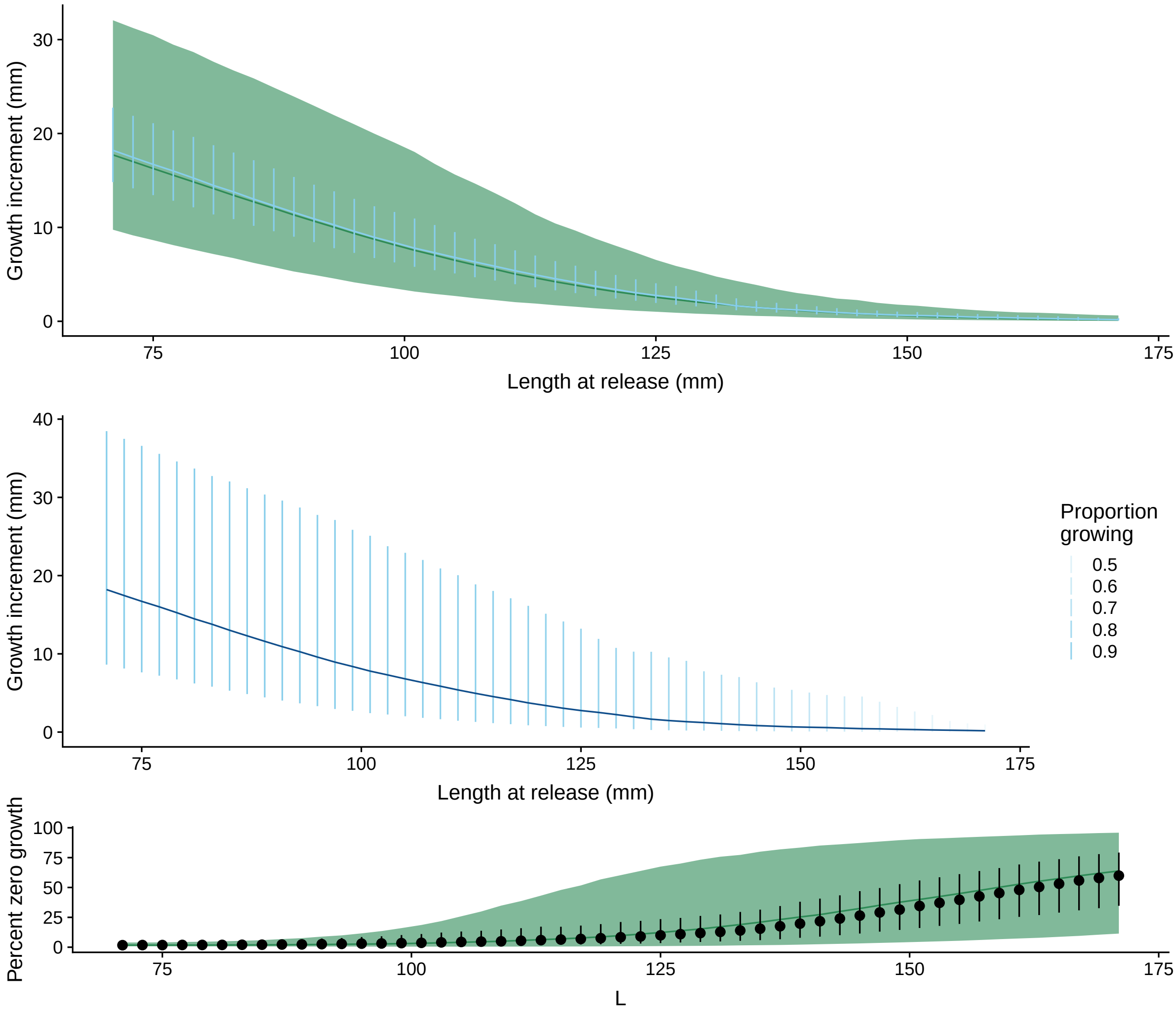

Figure B-17: Top: Posterior mean growth (population mean (dark blue line) and standard deviation of the estimate (light blue ribbon)), relative to the prior (dark green), middle: estimated population standard deviation (posterior median; light blue) relative to estimated population mean (blue line), bottom panel: estimated proportion of pāua stock not growing at each length relative to the prior (green) for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A.

B.2.3 Kullback-Leibler divergence

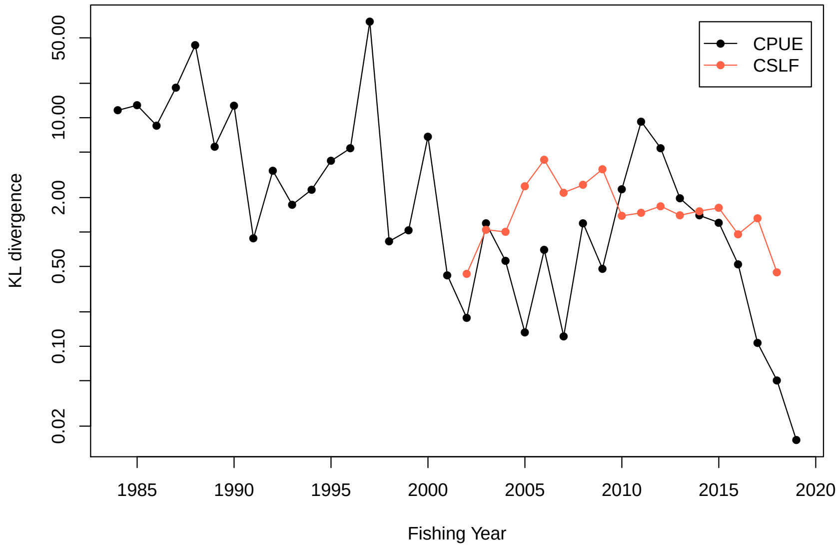

Figure B-18: Comparison of scaled Kullback-Leibler divergence (KLD) between posterior distributions for catch-per-unit-effort (CPUE) and catch sampling length frequency (CSLF) data (assumed Gaussian after log and centred-log-ratio transformation, respectively) for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A.

B.2.4 Catch-per-unit-effort fits

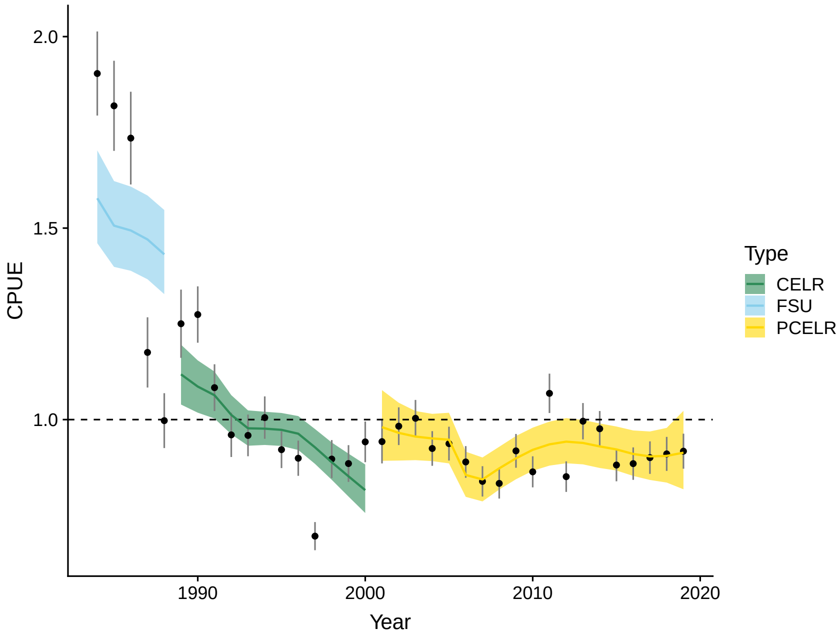

Figure B-19: Comparison of posterior median predicted catch-per-unit-effort (CPUE) with estimated CPUE index and observation error for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A (black points and error bars; CELR, data from Catch Effort Landing Return forms).

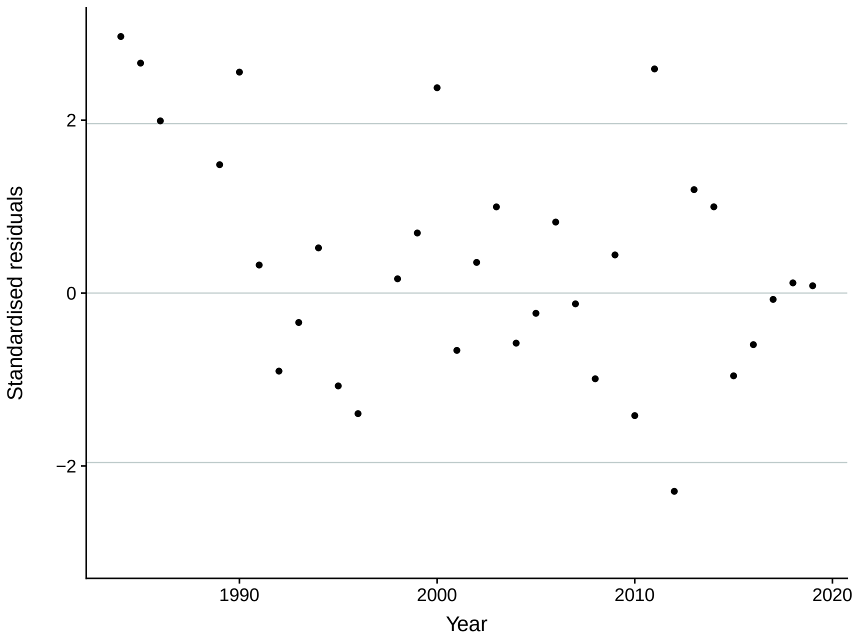

Figure B-20: Standardised residuals at the posterior median of predicted catch-per-unit-effort for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A.

B.2.5 Catch sampling length frequency fits

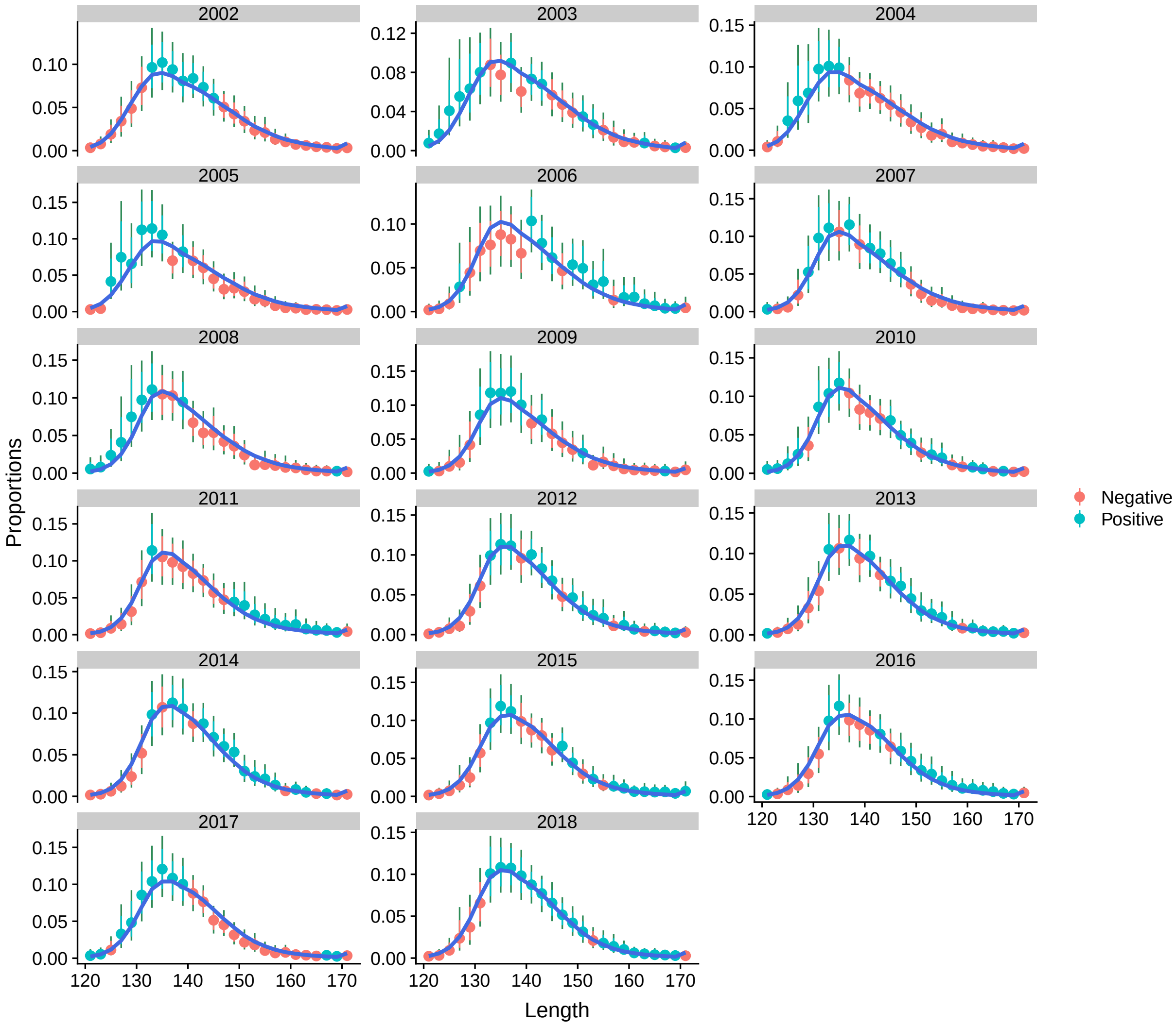

Figure B-21: Comparison of posterior mean predicted catch sampling length frequency (CSLF) with estimated CSLF proportions and observation error for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A. Length classes with positive residuals in blue, with negative residuals in red.

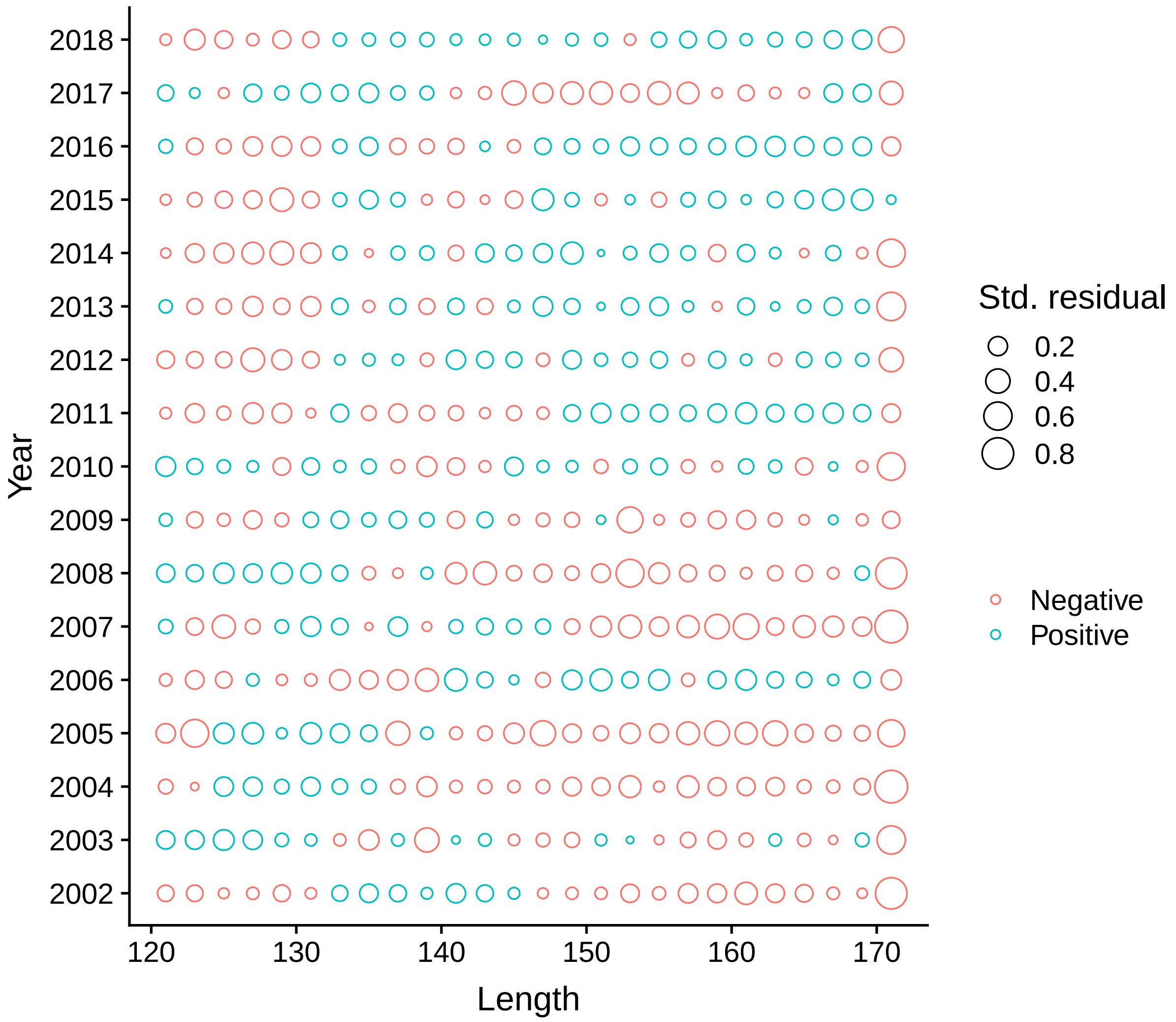

Figure B-22: Catch sampling length frequency model residuals for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A. Length classes with positive residuals in blue, with negative residuals in red.

B.2.6 Selectivity

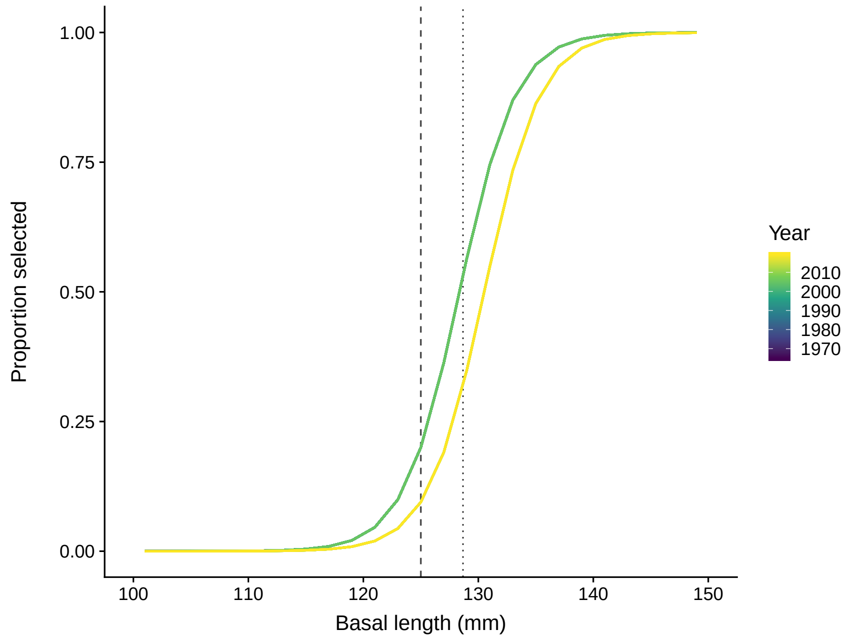

Figure B-23: Estimated selectivity (posterior mean) for periods of varying minimum harvest size of pāua for the main sensitivity run 1 of the stock assessment model for quota management area PAU 5A.

B.2.7 Recruitment and biomass trends

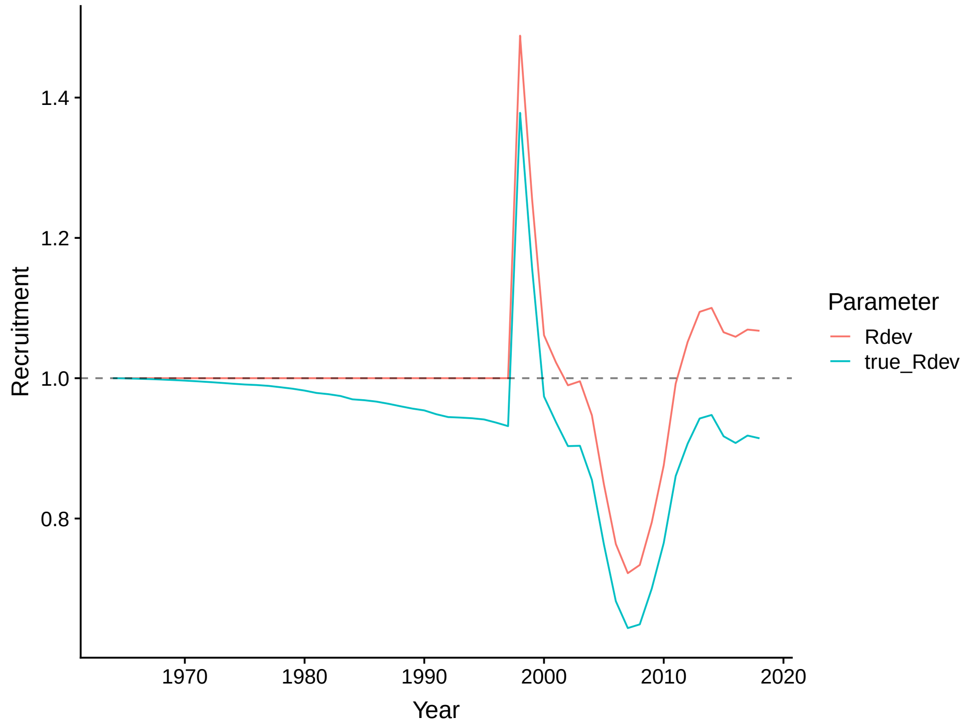

Figure B-24: Posterior mean recruitment for the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A (R_{dev}, recruitment deviation).

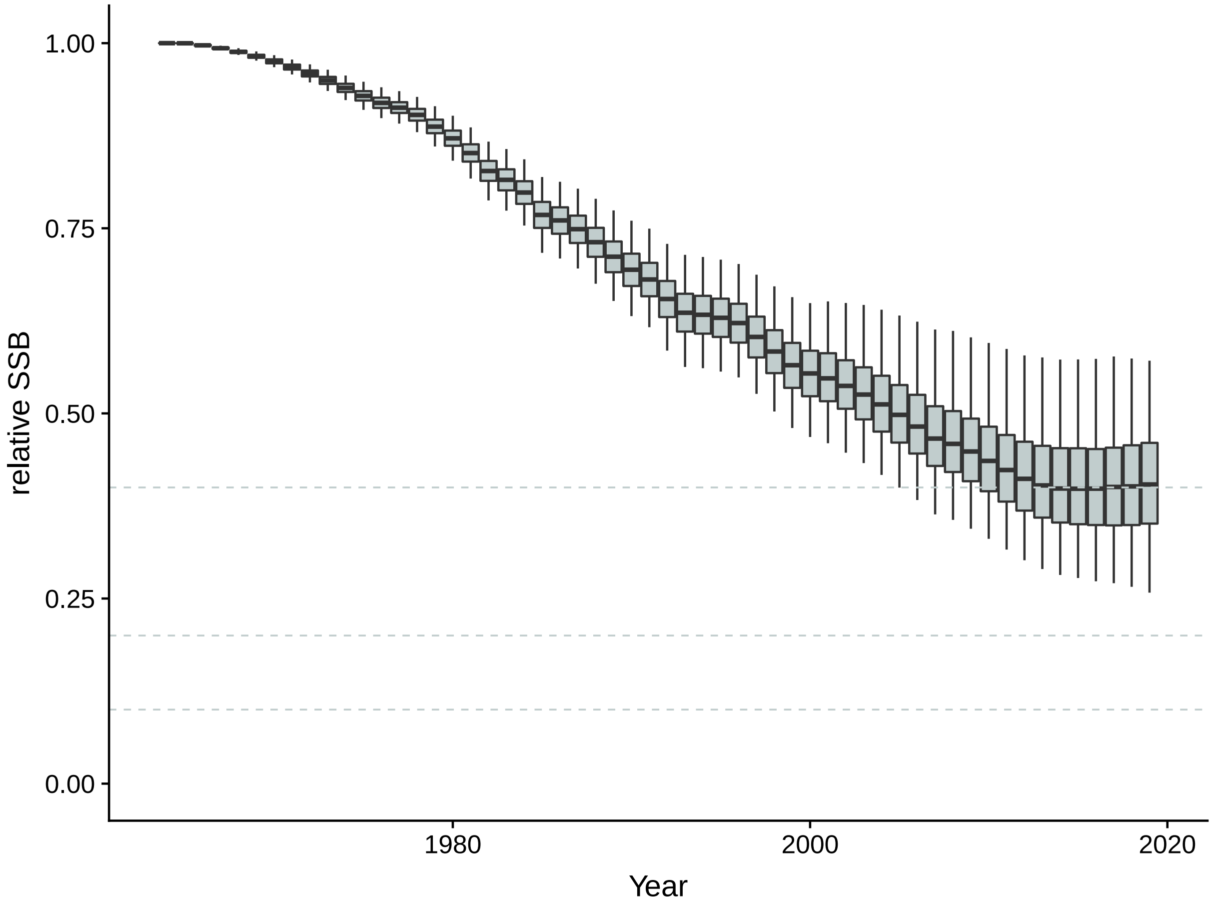

Figure B-25: Predicted relative spawning stock biomass (SSB) trend for pāua for the main sensitivity run 1 of the stock assessment model for quota management area PAU 5A (black line and 95% confidence interval).

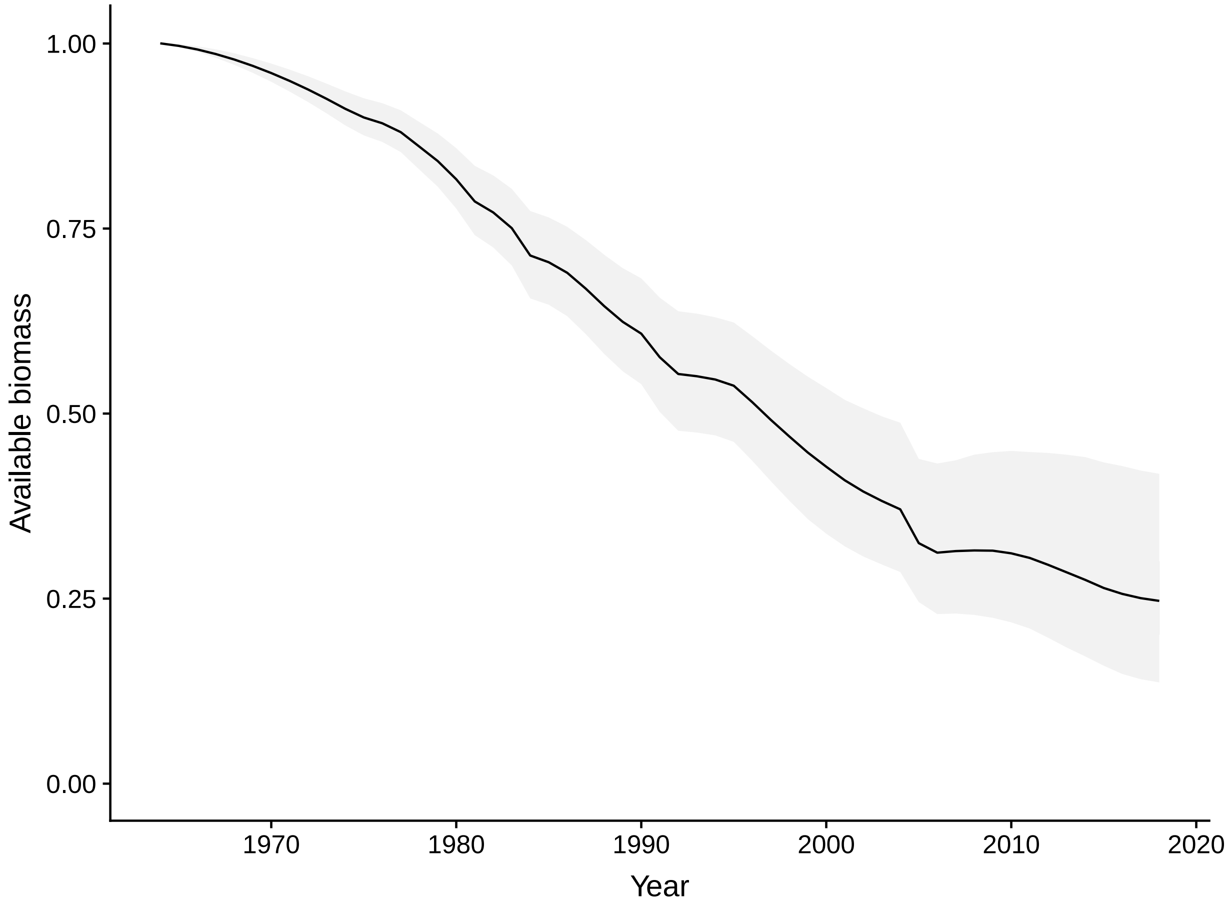

Figure B-26: Predicted relative available biomass trend for pāua for the main sensitivity run 1 of the stock assessment model for quota management area PAU 5A (black line and 95% confidence interval).

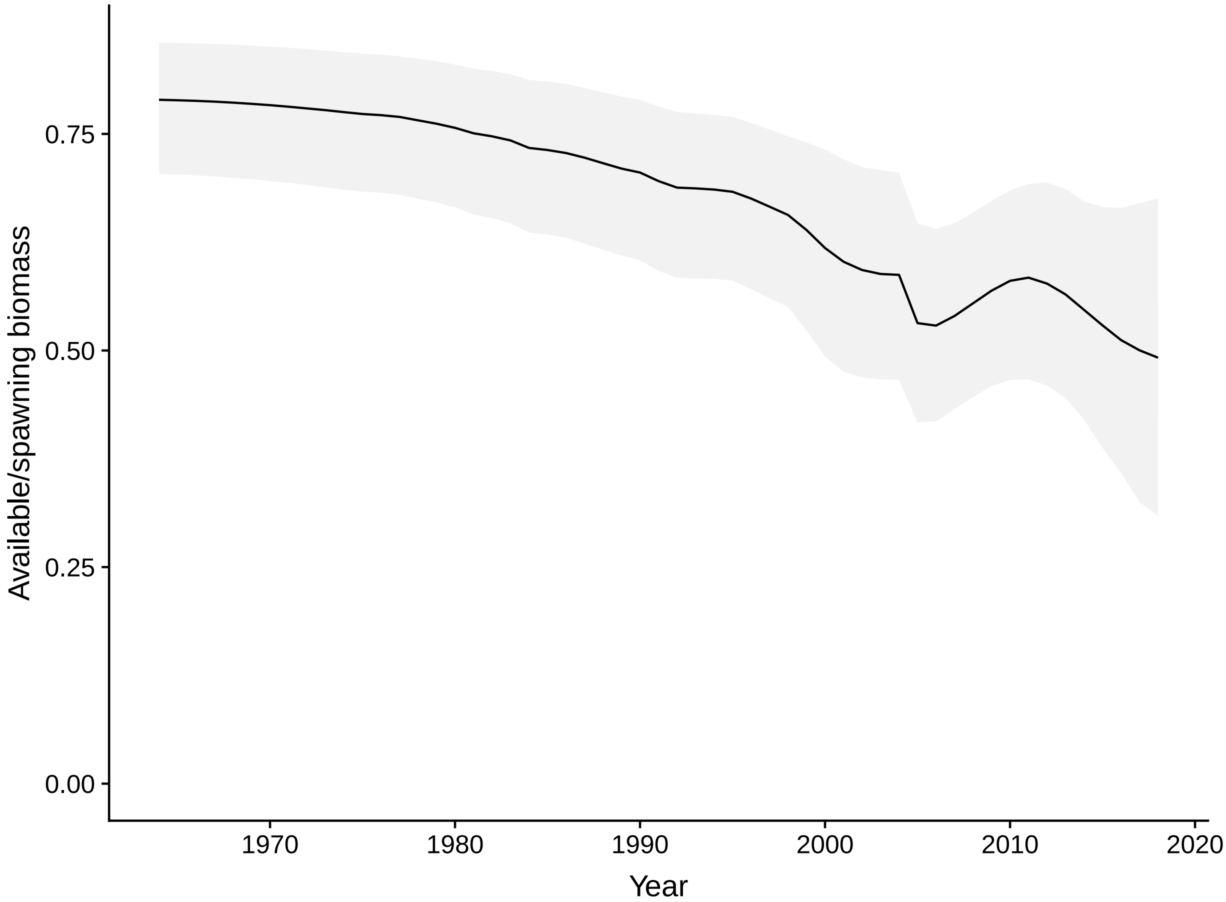

Figure B-27: Predicted relative available pāua biomass (relative to spawning stock) for the main sensitivity run 1 of the stock assessment model for quota management area PAU 5A (black line and 95% confidence interval).

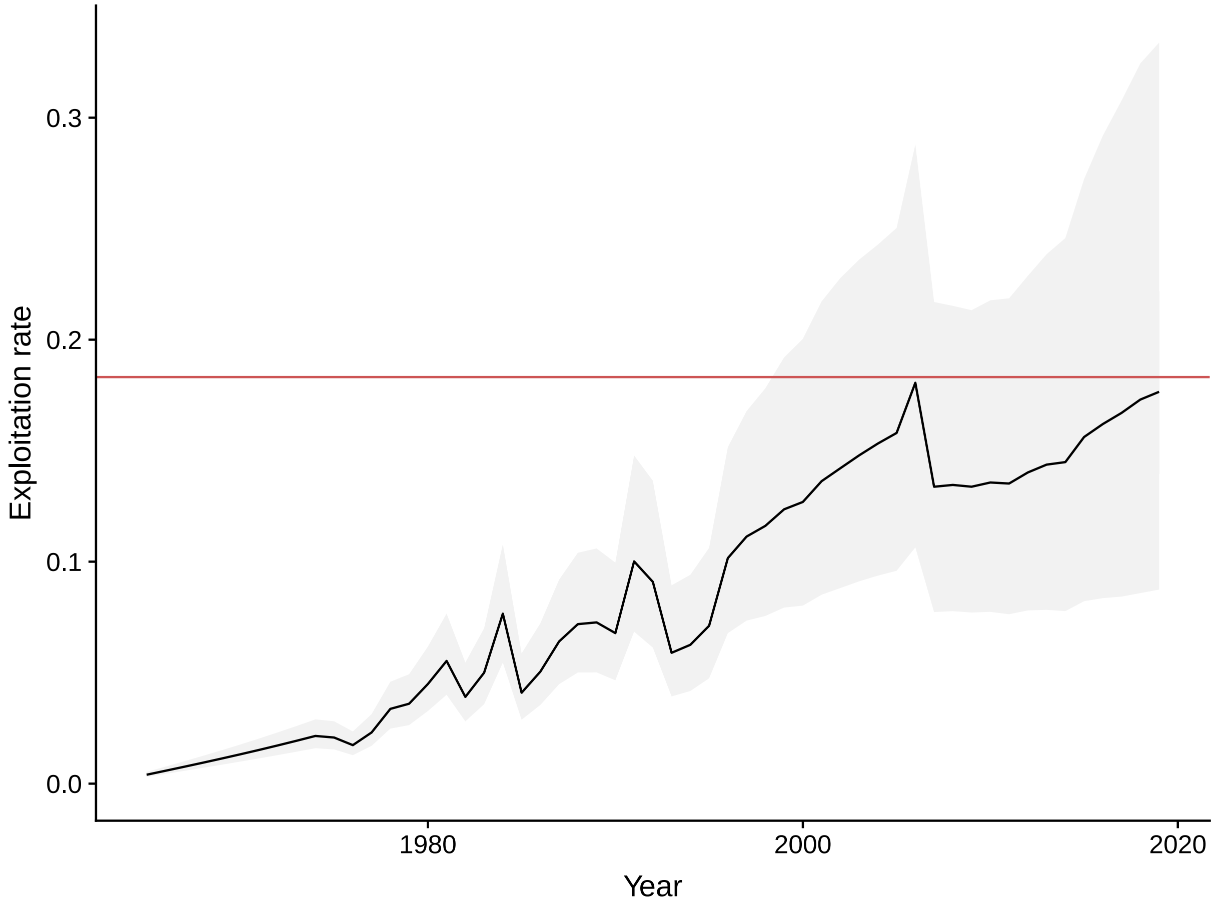

Figure B-28: Predicted exploitation rate (black line and 95% confidence interval) for the main sensitivity run 1 of the relative to the posterior median estimate of the explotiation rate (U) leading to 40% SSB $U_{40\%\mathrm{SSB}_0}$ (red line) of pāua for quota management area PAU 5A.

B.2.8 Status and projections

Table B-4: Stock status and fishery indicators for the last fishing year considered in this assessment and projections for key fishery indicators from the main sensitivity run 1 of the stock assessment model of pāua for quota management area PAU 5A for three years, for current catch (indicated by the asterisk), and 20% and 50% increases and reductions from current catch. Results at equilibrium (Eq.) are also given (assumed to be reached after 50 years). Columns are: probabilities of being above 40% (P(SSB>0.4SSB$_0$)) and 20% (P(SSB>0.2SSB$_0$)) of unfished spawning stock biomass (SSB), the probability that SSB in the projection year is above current SSB, the posterior median relative SSB, the posterior median relative available biomass (B^{avail}), the posterior median relative available spawning biomass (B^{avail}), the probability that B^{avail} in the projection year is above current B^{avail}, and the probability that the exploitation rate (U) is greater than the exploitation rate leading to 40% SSB (TCC, total commercial catch).

TCC (t)	Year	Fishery indicator							
		P(SSB>0.4SSB$_0$)	P(SSB>0.2SSB$_0$)	P(SSB>SSB$_{\text{current}}$)	Median rel. SSB	Median rel. B^{avail}	Median rel. SSB$^{\text{avail}}$	P($B^{\text{avail}} > B^{\text{avail}}_{\text{current}}$)	P($U > U_{40\%\text{SSB}_0}$)
52.14	2019	0.51	1.00	0.00	0.41	0.26	0.50	0.00	0.44
	2020	0.52	1.00	0.45	0.41	0.26	0.49	0.00	0.10
	2021	0.61	1.00	0.64	0.43	0.27	0.50	0.00	0.07
	2022	0.68	1.00	0.73	0.44	0.29	0.51	0.01	0.06
	Eq.	0.98	1.00	0.96	0.79	0.69	0.68	0.77	0.00
83.43	2019	0.51	1.00	0.00	0.41	0.26	0.50	0.00	0.44
	2020	0.52	1.00	0.45	0.41	0.26	0.49	0.00	0.30
	2021	0.57	1.00	0.54	0.42	0.26	0.49	0.00	0.29
	2022	0.61	1.00	0.59	0.43	0.27	0.50	0.00	0.27
	Eq.	0.86	0.98	0.83	0.65	0.51	0.60	0.49	0.13
104.29*	2019	0.51	1.00	0.00	0.41	0.26	0.50	0.00	0.44
	2020	0.52	1.00	0.45	0.41	0.26	0.49	0.00	0.43
	2021	0.54	1.00	0.48	0.41	0.25	0.49	0.00	0.44
	2022	0.55	1.00	0.50	0.42	0.25	0.48	0.00	0.44
	Eq.	0.70	0.92	0.68	0.54	0.39	0.52	0.32	0.30
125.14	2019	0.51	1.00	0.00	0.41	0.26	0.50	0.00	0.44
	2020	0.52	1.00	0.45	0.41	0.26	0.49	0.00	0.56
	2021	0.51	1.00	0.41	0.40	0.25	0.48	0.00	0.58
	2022	0.50	0.99	0.42	0.40	0.24	0.47	0.00	0.59
	Eq.	0.51	0.83	0.49	0.44	0.27	0.42	0.19	0.54
156.43	2019	0.51	1.00	0.00	0.41	0.26	0.50	0.00	0.44
	2020	0.52	1.00	0.45	0.41	0.26	0.49	0.00	0.70
	2021	0.47	0.99	0.33	0.40	0.24	0.47	0.00	0.75
	2022	0.43	0.98	0.31	0.39	0.22	0.45	0.00	0.78
	Eq.	0.28	0.70	0.27	0.33	0.15	0.30	0.07	0.84