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Developing an operating model and testing management procedures for pāua (*Haliotis iris*) fisheries in PAU 4

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TABLE OF CONTENTS

EXECUTIVE SUMMARY

Neubauer, P.[1]; Kim, K.[1] (2023). Developing an operating model and testing management procedures for pāua (*Haliotis iris*) fisheries in PAU 4.

***New Zealand Fisheries Assessment Report 2023/29*. 50 p.**

Quota management area (QMA) PAU 4 (Chatham Islands) is currently the largest pāua (*Haliotis iris*) fishery in New Zealand by landings; however, due to concerns over reported catch and effort, no formal integrated stock assessment of the resource has been successfully conducted to date, and the status of the fishery continues to be uncertain. The present project aimed to develop an operating model, and test management procedures that could formalise current pāua statistical-area scale industry management initiatives.

Operating models were developed as spatial length-based models. Due to a lack of sufficiently reliable time series of catch and catch-per-unit-effort (CPUE), stock assessment models could not be fitted statistically, but were conditioned on assumed catch times series. Conditioning assumes a current stock status, and produces a range of stock trajectories that produce assumed status.

Status assumptions were initially derived from a meta-analysis of stock status against CPUE in QMAs with accepted stock assessments. Results from this analysis suggested high status, and did not reflect industry concerns that led to the shelving of annual catch entitlements over the past decade. More conservative assumptions about stock status were, therefore, used to condition models, with conditioning scaled spatially from an analysis of recent spatial CPUE.

Management procedures were developed from a template applied in other pāua fisheries, and centred on a target catch rate provided by fishers. Rules were then scaled according to assumed spatial differences in abundance derived from spatial CPUE. These rules were used as a preliminary set of rules to test the potential of formalising current management practice.

Conditioned models suggested a range of outcomes across statistical areas. Nevertheless, while application of control rules still led to variable outcomes at the statistical-area scale, the spatial variability averaged out across the larger scale. This averaging led to highly stable trends at the QMA scale, and indicated low risk of further declines under the trialled harvest control rules.

[1] Dragonfly Data Science, New Zealand.

1. INTRODUCTION

In most pāua (*Haliotis iris*) quota management areas (QMAs), the management of stocks relies on stock assessments to estimate population status. In the Chatham Islands (PAU 4), the largest (by Total Allowable Commercial Catch) and most remote fishery, however, stock assessments were unsuccessful when attempted on a number of occasions, and have been deemed infeasible in recent times (Breen & Smith 2004, Fu et al. 2012, Neubauer 2019, Fisheries New Zealand 2022): pāua stock assessments are largely determined by trends in catch-per-unit-effort (CPUE). Reporting inconsistencies, from early mis-reporting of catch to limitations that persisted until recently (e.g., insufficient reporting detail for the use of underwater breathing apparatus (UBA)), have meant that CPUE has been repeatedly rejected as an index of abundance for the fishery.

Uncertainty surrounding the sustainability of the fishery has led to the shelving of 20% and 10% of the Annual Catch Entitlement (ACE) since 2010–11 and 2013–14, respectively. For the 2016–17 fishing year, the shelving level was increased to 20%, in an effort to safeguard the fishery. Recent concerns by divers and a current level of 40% catch reduction since 2017–18 suggest that the available biomass in the fishery may be under pressure from a high exploitation rate.

The lack of assessment and useful data resulted in a largely empirical approach to managing the fishery, led by industry initiatives to understand stock status and manage the fishery on small spatial scales. For example, adjusted CPUE based on diver interviews about reporting, and perceived abundance trends, led to scenarios that included a possibility of substantial declines since the early 2000s, with more stable adjusted CPUE in recent years, reflecting the substantial shelving of ACEs by industry (Neubauer 2019). Due to uncertainties around all indicators of abundance, fishers have been trailing an approach amounting to empirical harvest control rules. Under this approach, fishers meet regularly to discuss the status of each small-scale statistical area, and to adjust minimum harvest sizes and catch caps.

The present project developed a spatial operating model to test harvest control rules. The model was developed to align with management at the scale of pāua statistical areas (Figure 1). This management partitions catch among statistical areas, and allows the fishing industry to set area-specific minimum harvest sizes (MHSs). Similar to recent attempts in PAU 3B, where an assessment was not feasible, the present model used a direct meta-analysis across fisheries to constrain the stock assessment model *a priori* so that it would function as an operating model that can be used for testing management options. Management options were developed with stakeholders, and evaluated on the basis of the constrained model.

2. METHODS

2.1 Inputs

Inputs for the PAU 4 model consisted of commercial catch data, CPUE data for three years of electronic reporting system (ERS) data, and length-frequency data from commercial sampling (catch sampling length frequency, CSLF). Catch assumptions for recreational, customary, and illegal take were agreed by the Shellfish Working Group (SFWG), and considered as known.

All data sources were compiled and prepared through the Kahawai Collective reporting system, which implements reproducible and standardised prepared fisheries datasets for further analyses. Documentation for the Kahawai system is currently being developed (Middleton in prep.). For pāua in the current assessment, data preparation within the Kahawai database was minimal, consisting only of consistency assessments as part of database builds. Any substantial data preparation or analyses that were performed for individual analyses of datasets are detailed below.

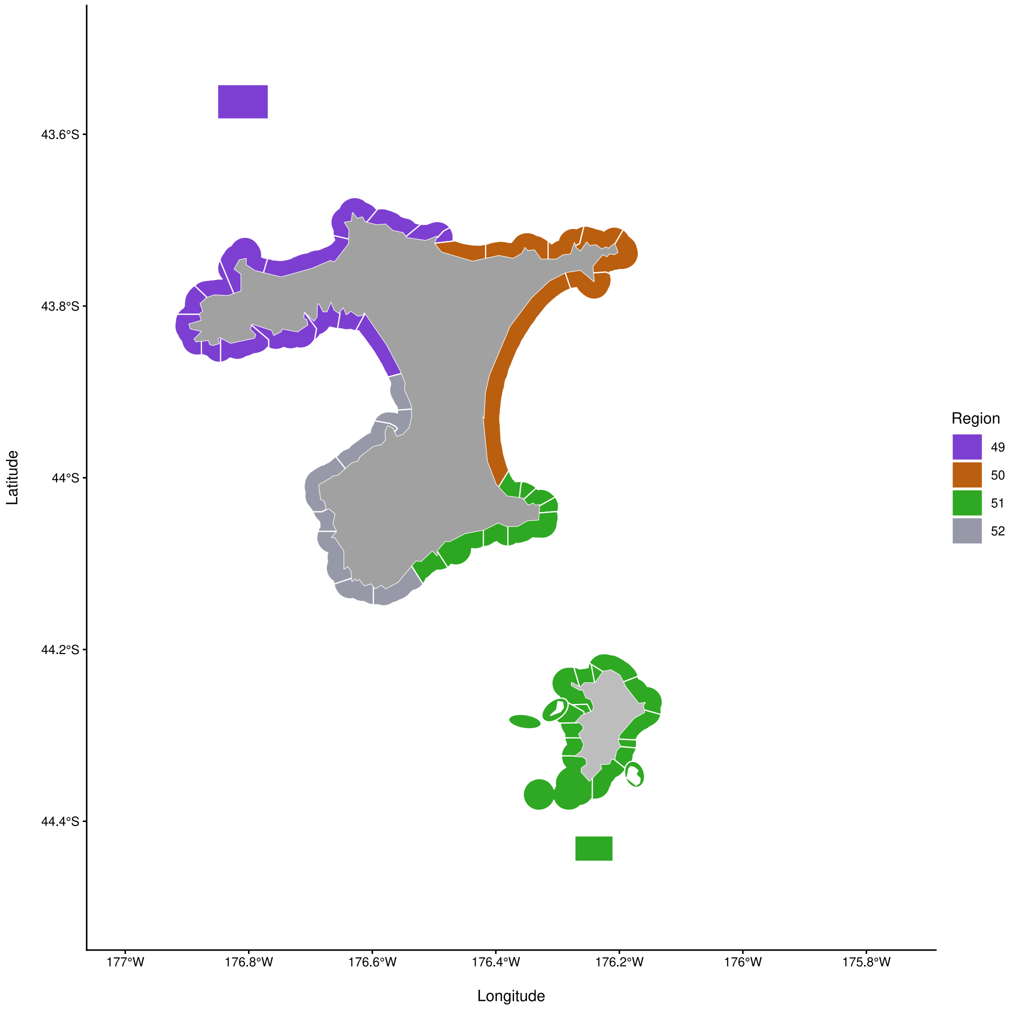

Figure 1: Pāua quota management area (QMA) PAU 4, including Catch Effort Landing Return (CELR) Statistical Areas 049–052. Catch reporting was initially at a lower spatial resolution of these CELR statistical areas (indicated by colours), and subsequently changed (in 2002) to fine-spatial scale pāua statistical areas shown here (coloured polygons). Rectangular shapes to the north and south of the main islands indicate statistical areas around small islands that are not discernible as land masses due to their size.

2.1.1 Catch

Commercial catch was assumed to be known without error in the assessment model, and was reconstructed from a range of sources for the model period (1965 to 2021). For the early part (1974–1983) of the catch history, the commercial catch reconstruction used data from Murray & Akroyd (1984); the FSU data were used from 1983 to 1988, whereas, from 1989 onwards, estimated catch data from Catch Effort Landing Return (CELR) forms were used to partition Monthly Harvest Return/Quota Management Report (MHR/QMR) returns into spatial strata (statistical areas; Table 1, Figure 2). Early data sources suggested a highly variable fishery (Figure 2). While this variability is considerably greater than variability reported in an earlier assessment by Breen & Smith (2004), it may be related to poor reporting practice at the time rather than reflecting actual variability.

Table 1: Sources of pāua catch data, by period. FSU, Fisheries Statistical Unit; (P)CELR, (Paua) Catch Effort Landing Return; ERS, electronic reporting system.

Period	Source
1965–1973	Linear increase from 1 t to 1974 value.
1974–1983	Murray & Akroyd (1984) as cited by Schiel (1989).
1984–1988	FSU database.
1990–2019	Estimated catch from (P)CELR.
2020–2022	Estimated catch from ERS.

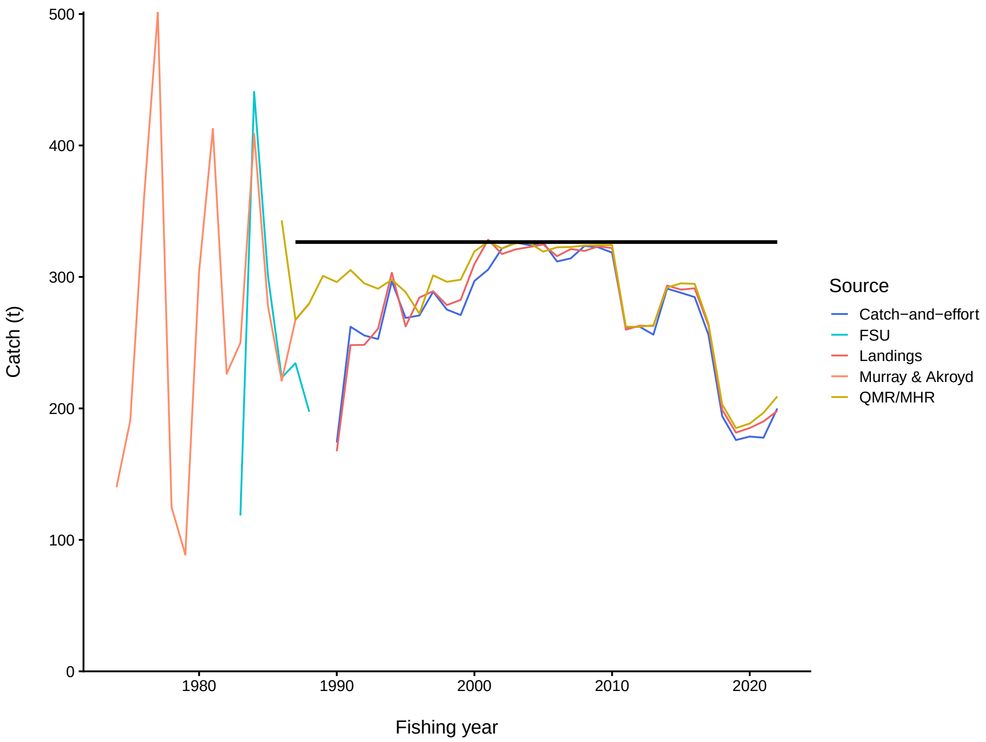

Figure 2: Commercial catch history for pāua quota management area (QMA) PAU 4 from 1974 to 2022. Catch to 1983 was reconstructed from data reported by Murray & Akroyd (1984; red line). Data for 1983–1986 were from the Fisheries Statistical Unit (FSU) database. Catch-effort and Monthly Harvest Return/Quota Management Report (MHR/QMR) return data from 1989 were provided by Fisheries New Zealand (catch-and-effort, blue).

Spatially explicit commercial catch for PAU 4 cannot be reconstructed with precision prior to the introduction of fine-scale statistical areas and Pāua Catch Effort Landing Return (PCELR) forms in 2002. Prior reporting on non-pāua-specific CELR forms was at the level of large-scale statistical areas, and was considered unreliable by the Shellfish Working Group in previous assessment attempts. Since 2002, reporting has been more consistent due to reporting on PCELR forms, with a relatively stable spatial distribution of catch (Figure 3). Recent reductions in catch after 2015 (see Figure 2) led to reductions in catch in some statistical areas, whereas other areas remained intensely fished. Given past data quality concerns, it is remains unclear if reported total catches were accurate. As a result, the early catch history is relatively uncertain.

No estimates exist for other sources of fishing from PAU 4, and a nominal take of 5 t was assumed for recreational, customary, and illegal take.

Based on the different catch components, catch declined over time in the north-eastern statistical areas, while it increased in the south-west (Figure 4). The north-west and south-east areas have maintained relatively consistent catch, with recent reductions as part of the shelving process affecting total catch since 2016 in all areas (Figure 5).

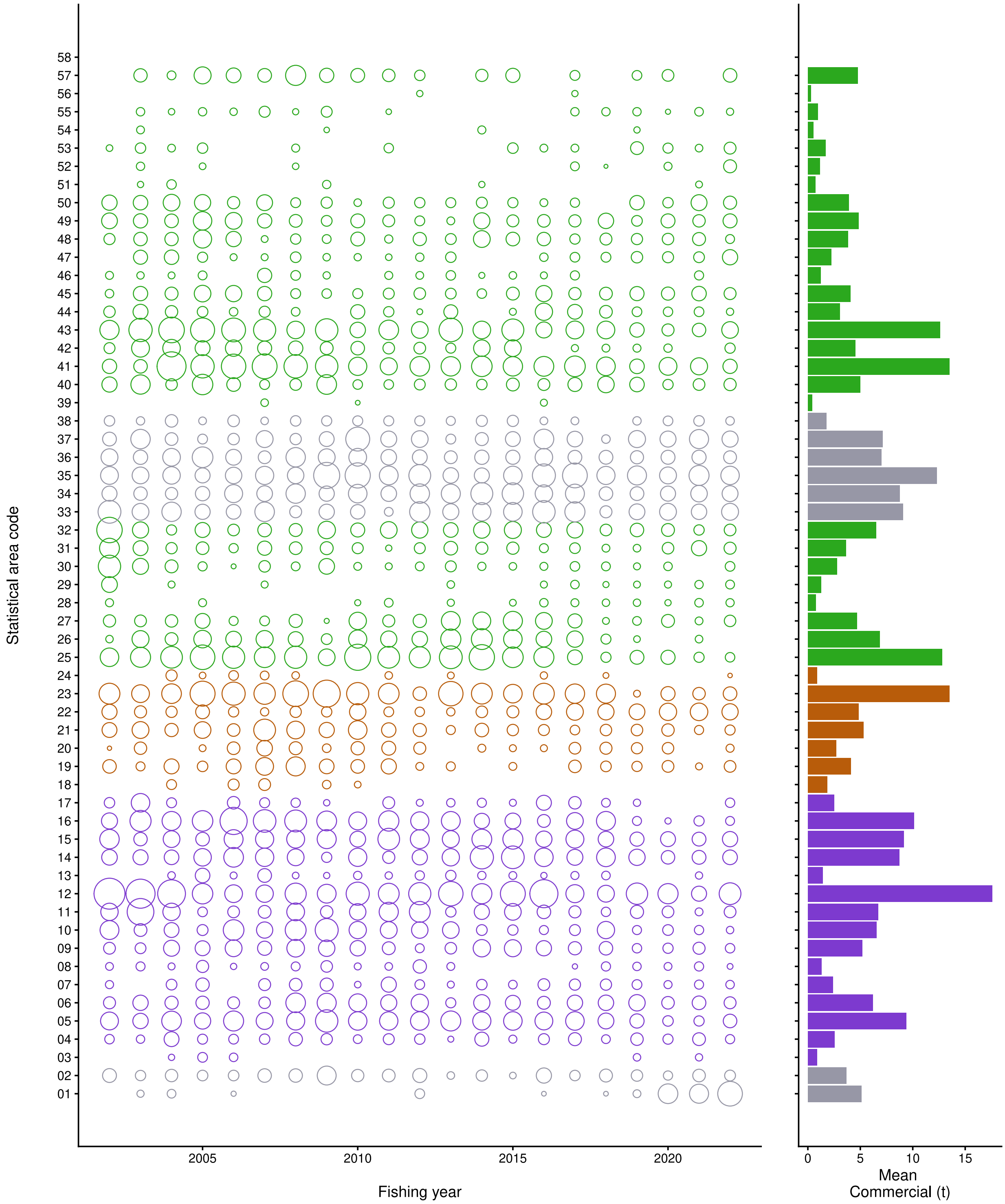

Figure 3: Relative trend in pāua catch (kg) over time by pāua statistical areas in quota management area PAU 4 for the period from 2002 to 2022, with total catch over the same time period (right-hand side). Catch Effort Landing Return statistical areas within PAU 4 are colour coded (see corresponding area number in Figure 1).

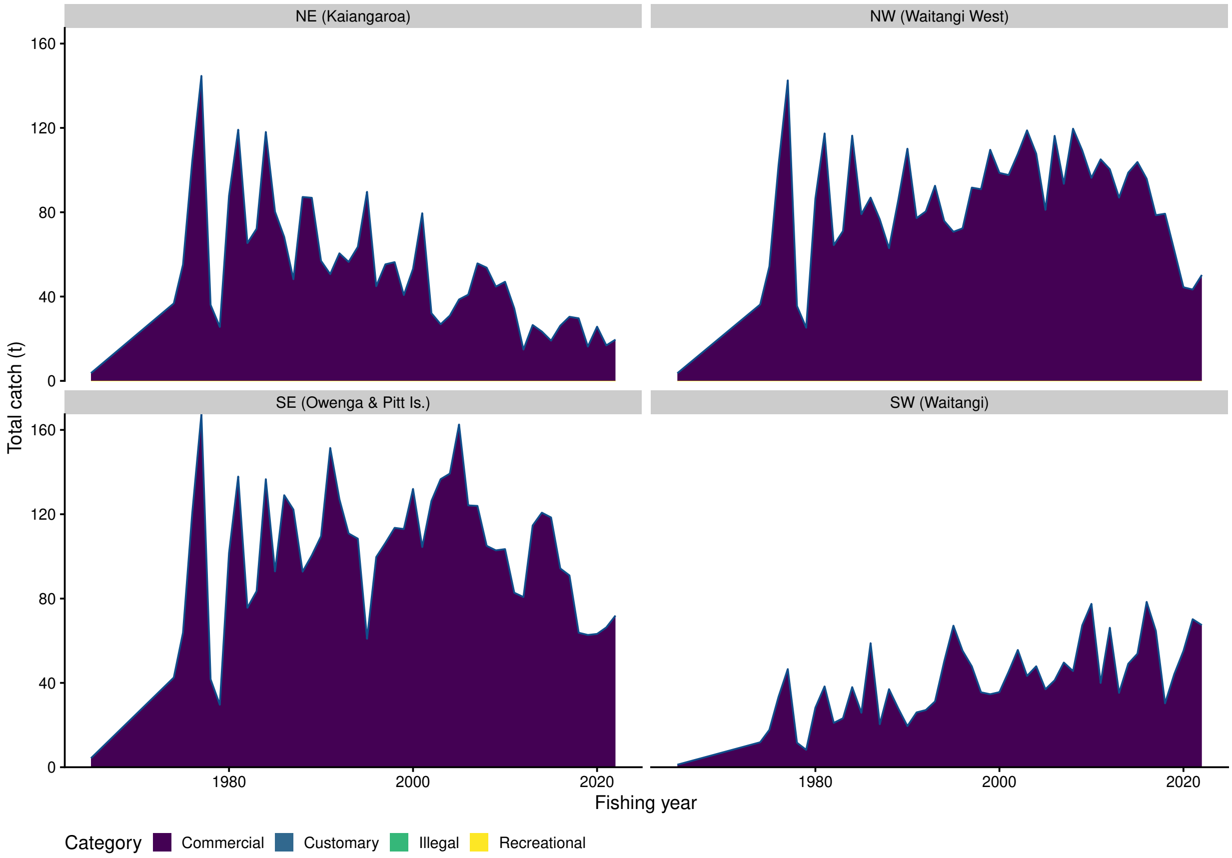

Figure 4: Estimated total pāua catch history for quota management area (QMA) PAU 4 from 1974 to 2022 by fishery component and reporting area. Fishery categories were commercial (Total Commercial Catch, TCC), customary, illegal, and recreational catch. The non-commercial components are not visible on the plot due to their small assumed contribution to overall catch.

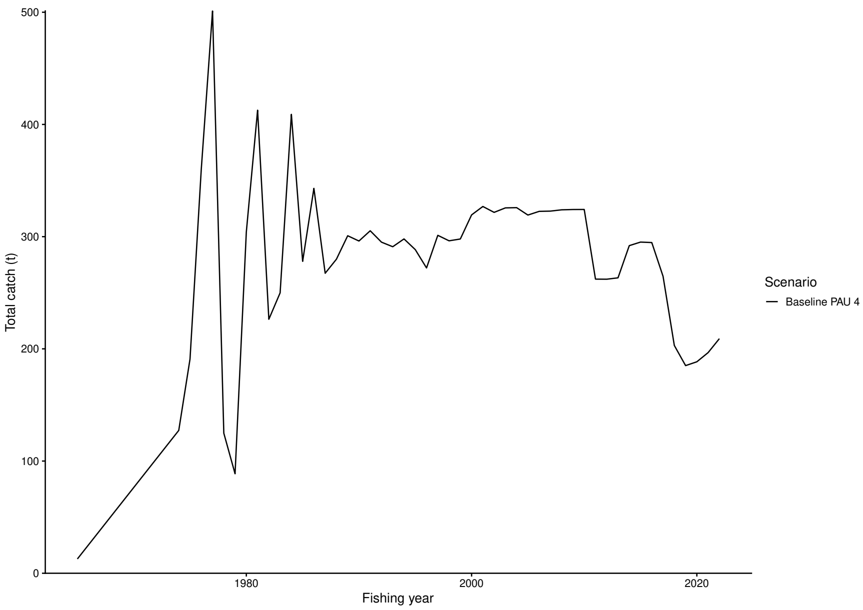

Figure 5: Total pāua catch history used in the single area stock assessment for quota management area PAU 4 from 1974 to 2022 as the sum of all catch components (commercial, customary, recreational, illegal).

2.1.2 Catch-per-unit-effort (CPUE)

The present modelling only considered ERS reported catch and effort data between 2020 and 2022. The CPUE was used only to derive relative statistical area status with respect to CPUE targets, and to scale depletion priors spatially. Although data from the FSU database, CELR, and PCELR forms were used in previous assessments (Breen & Smith 2004, Fu et al. 2012), these data have been rejected as being too unreliable to be a proxy for trends of relative abundance in PAU 4 due to evidence of misreporting in early years, and insufficient reporting of UBA use in recent years (Fisheries New Zealand 2019, Neubauer 2019).

Data preparation procedures for ERS data generally followed established protocols for PCELR data detailed by Fu et al. (2017) (see details of the data preparation in Table 2). Data preparation steps are summarised as follows:

1. Use only events with "diving" as method.
2. Remove items with missing fields needed for standardisation.
3. Remove clients who have not been active for extended periods of time (2 years), and divers with less than 2 years experience.
4. Retain only events with less than four recorded divers, and a recorded fishing duration of $\leq$10 h, as well as CPUE between 10 and 500 kg/h.

Table 2: Data preparation steps for catch and effort data for PAU 4; and number of records retained for data from Electronic Reporting System (ERS) reports by year and in total (as number and percentage of records retained). FIN, fisher (client) identification number; CPUE, catch-per-unit-effort.

Data preparation	2020	2021	2022	% retained
All	406	335	370	100.00
Missing fields	406	335	370	100.00
FIN years $\geq$2	406	335	370	100.00
Diver-years $\geq$2	348	331	357	93.28
No. of divers $\leq$4	348	331	357	93.28
Fishing duration $\leq$10h	348	331	357	93.28
10kg/h $\leq$CPUE $\leq$ 500kg/h	341	320	336	89.80

In usual practice a time series of relative change is derived from catch-per-unit effort. Nevertheless, here, the ERS data across three years were used to derive a single standardised, fishery-dependent index of spatial abundance. The CPUE modelling was carried out using Bayesian Generalised Linear Mixed Models (GLMM) which partitioned variation among fixed (statistical area) and random variables. The CPUE was defined as the log of daily catch. Variables in the model were fishing year, estimated fishing effort, client identification number, small-scale statistical area, and diver identification. The model was implemented in the Bayesian inference software brms (Bürkner 2017), using the following formulation (and accounting for truncation through the data preparation process):

```
Family: gaussian
 Links: mu = identity; sigma = identity;
Formula: log(GreenweightKgQuantity) | trunc(lb = log(unique(minGW)),
ub = log(unique(maxGW))) ~ (1 | ClientNumber) + StatArea + (1 | CatcherId)
+ FishingYear + lFishingDuration + UBA;
```

```
Data: ERS (Number of observations: 839);
Draws: 4 chains, each with iterateration = 2000; warmup = 1000; thin = 1;
Total post-warmup draws = 4000.
```

The fit of the log-normal CPUE model was considered reasonable (Figure 6), producing a map of estimated relative CPUE across statistical areas, showing large spatial variation in CPUE (Figure 7).

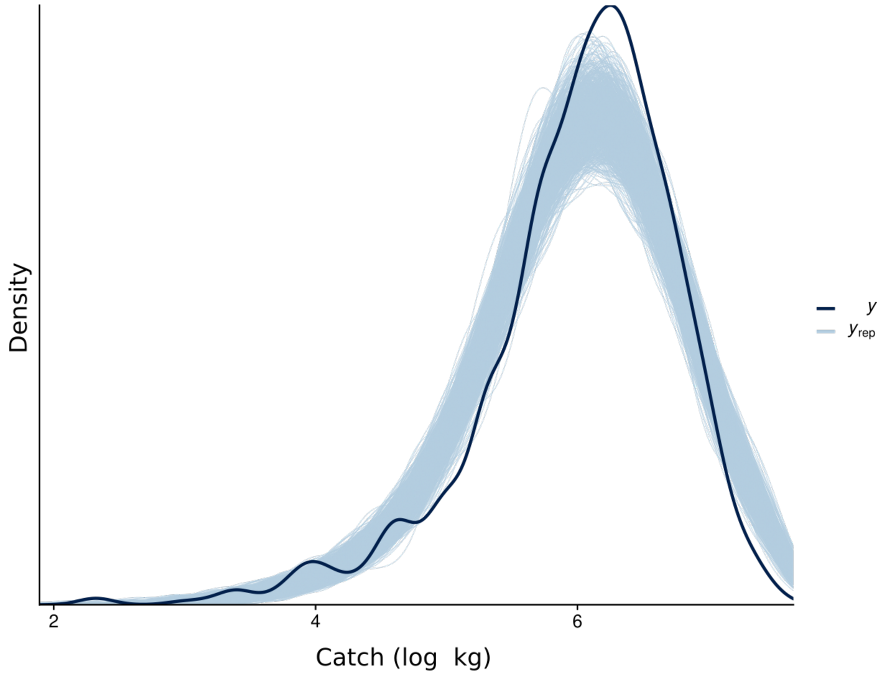

Figure 6: Fit of the log-normal generalised linear mixed model used for catch-per-unit-effort (CPUE) index standardisation (draws from the posterior distribution as blue lines, data as black line).

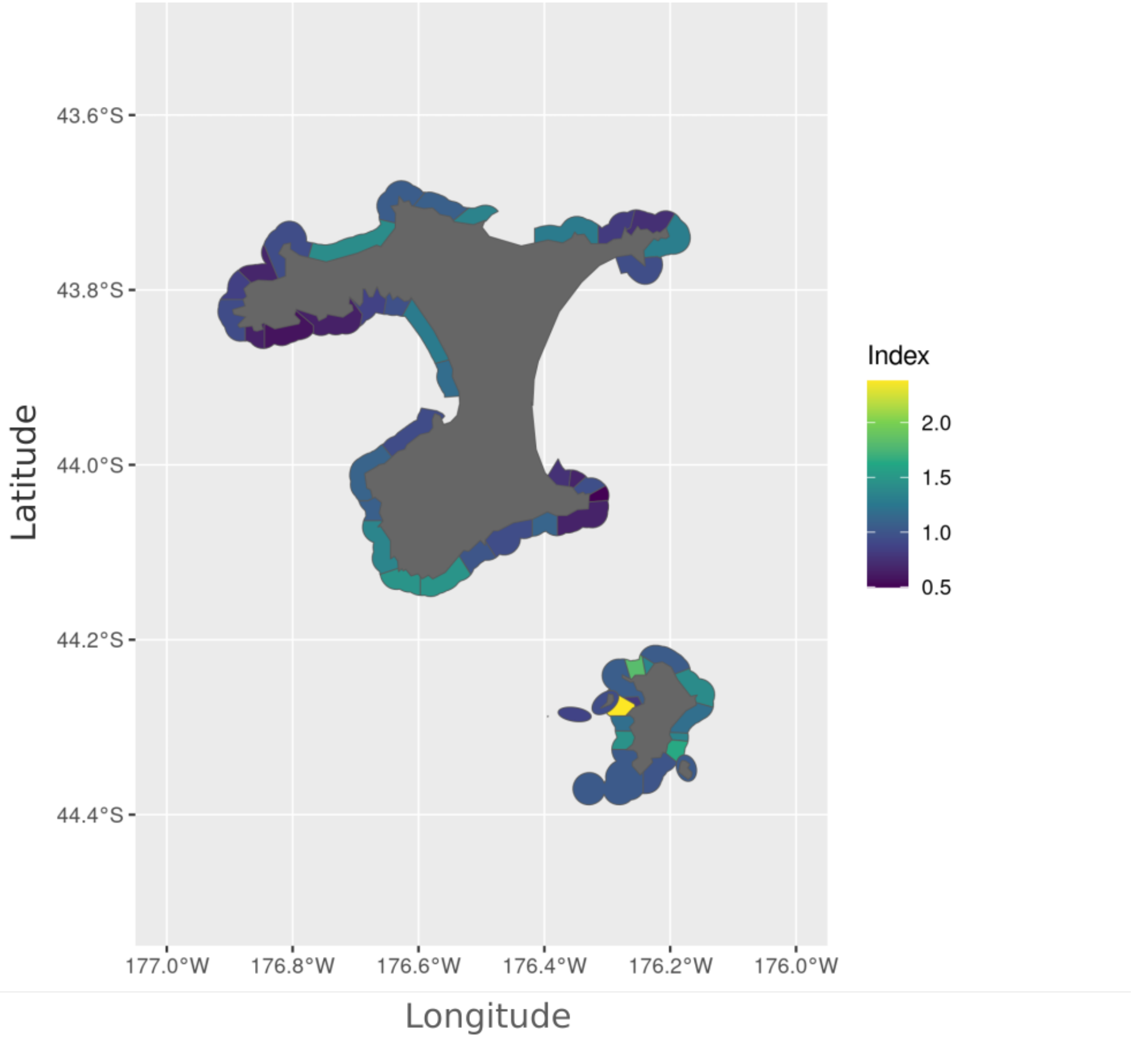

Figure 7: Spatial catch-per-unit-effort CPUE index as estimated from the Bayesian generalised linear mixed model. The model was fitted to catch and effort data (from the electronic reporting system) from quota management area PAU 4 for the period between 2020 and 2022.

2.1.3 Catch sampling length-frequency (CSLF) data

The present modelling 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, and adjusts the estimated length-frequency of removals. This procedure has the advantage that reasonably smooth length-frequency (LF) distributions (i.e., filtering out variance from highly multi-modal length-frequency 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 actual length frequencies. 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 2005–2006 (2006) to 2019–2020 (2020). The model used statistical area and area-year as standardising variables. Area and year were entered as fixed effects, and area-year was entered as a random effect.

Raw CSLF data showed clear geographical patterns in length composition of removals (Figure 8): in some areas, removals were largely of small pāua, including stunted growth (basal length <125 mm) individuals, whereas other areas had large-sized pāua that were fished at sizes near 140 mm length. In recent years, these patterns were determined by statistical area-scale minimum harvest sizes, which have generally increased and led to greater variation in harvest LFs (Figure 9).

The standardisation led to minor adjustments relative to raw removal estimates (see Figure 8) based on statistical areas for recent (2018–2020) and early (2006) fishing years (Figures 10, 11). In all cases, the models suggested that areas with small (stunted growth) individuals were over-sampled, leading to larger standardised removal estimates (Figure 11).

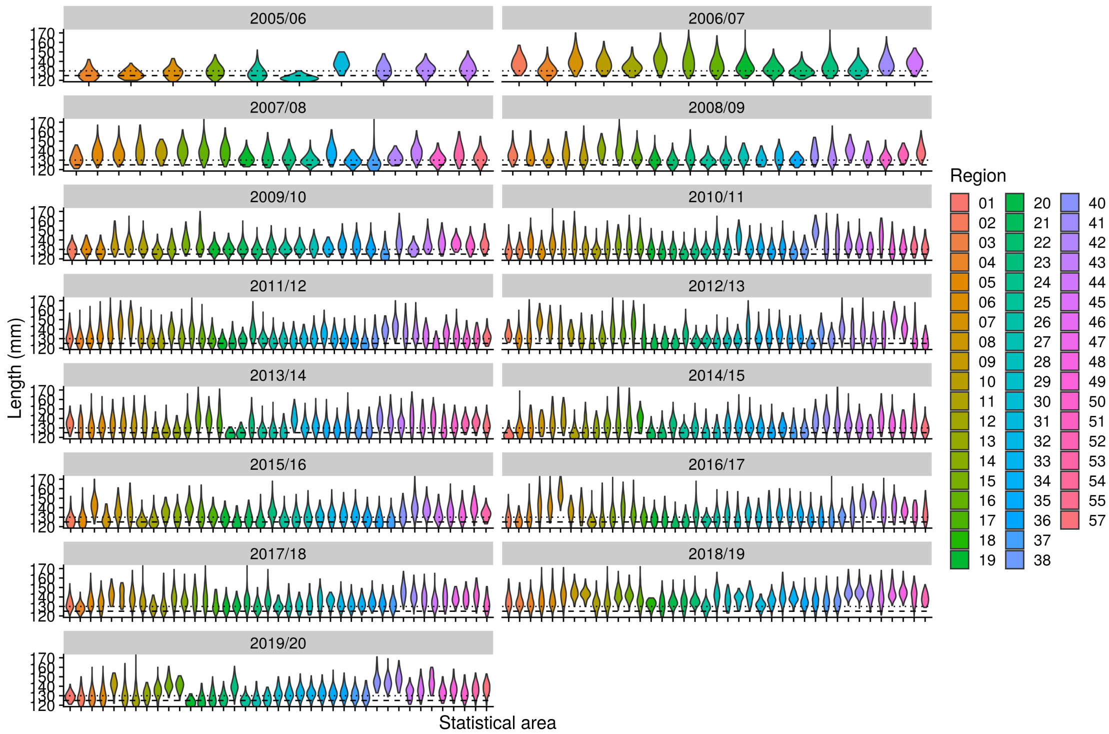

Figure 8: Catch sampling length-frequency samples of pāua by statistical area and year; statistical areas are ordered to show geographical trends. Region refers to statistical areas.

2.1.4 Growth and maturation

As for previous assessments and operating models since 2018, data from individual growth tagging sites in PAU 4 were not fitted. Recent developments in 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).

Similar to other recent stock assessments, an informed prior on growth across QMAs was used for the present models, which was derived from a meta-analysis of pāua growth. It allowed the model to adjust growth in accordance with other sources of information (priors on mortality M, CSLF, and CPUE input)(see priors for mean growth and growth standard deviation in Figure 12). 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 (i.e., stunted growth at length l; Figures 12 and 13). Maturation was estimated simultaneously with growth in the meta-analysis, but was not found to be linked to growth in the meta-analysis based on available data (Figure 14).

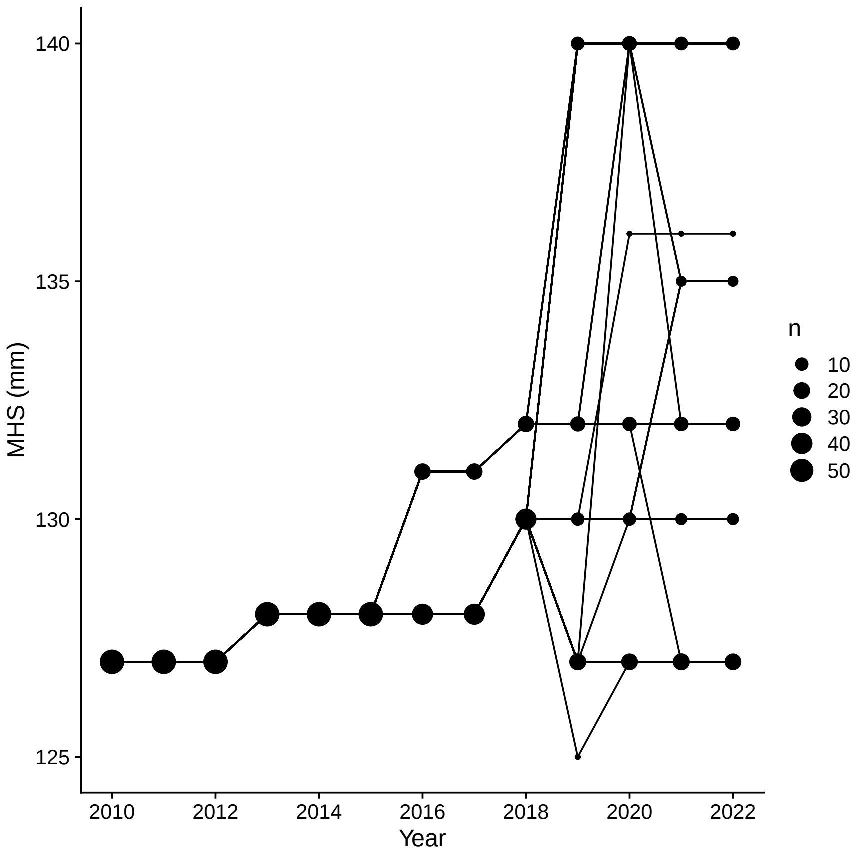

Figure 9: Evolution of pāua minimum harvest size (MHS) across statistical areas over time; points show the number (n) of statistical areas at a given harvest size in each year, and lines show increases or decreases in MHS across statistical areas.

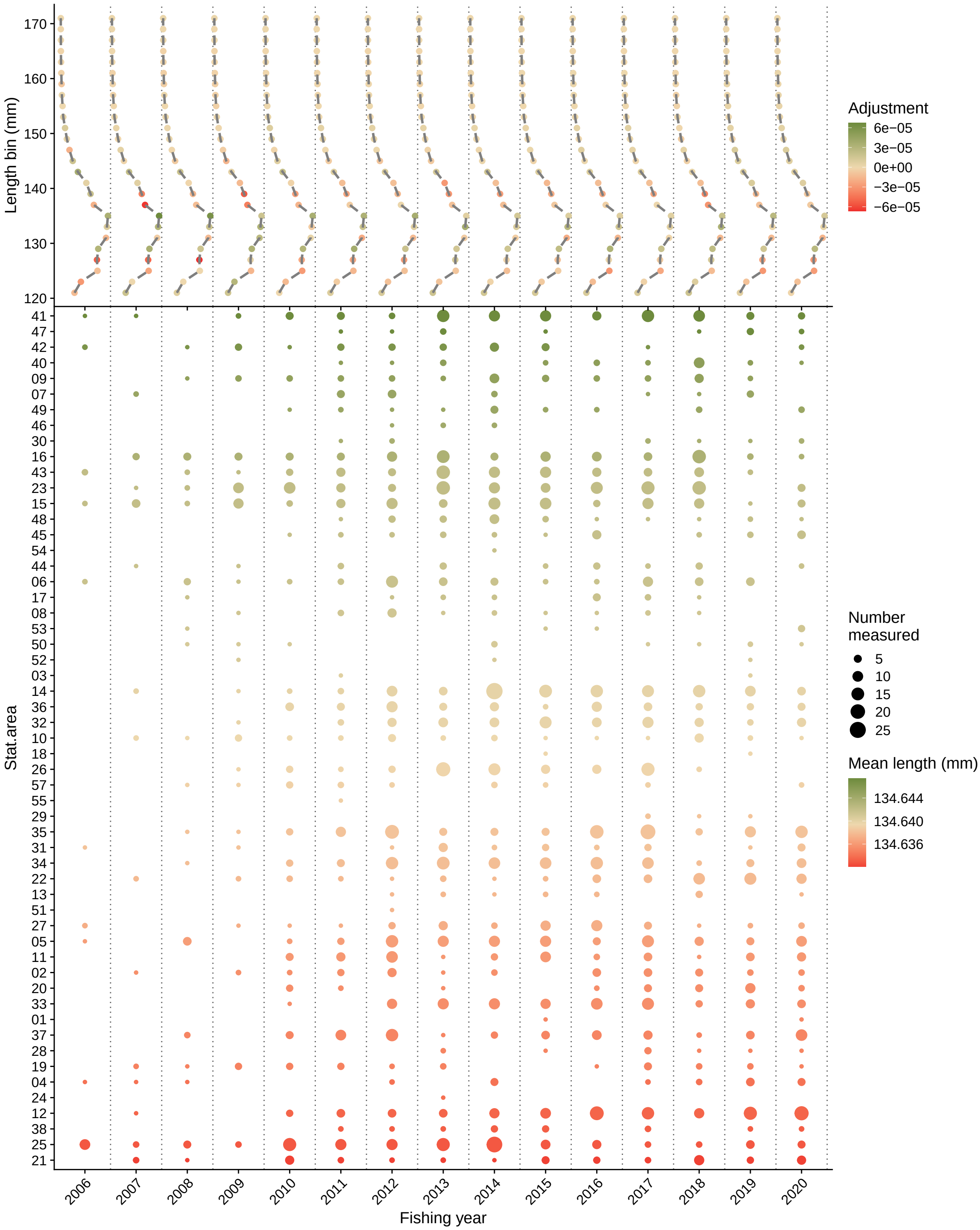

Figure 10: Effects plot for pāua statistical area for quota management area PAU 4. Top panel shows the direction of the adjustment from the raw catch sampling length-frequency (LF; coloured points for LF classes) in each year and length class in relation to the fishing pattern (shown in the lower panel). 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.

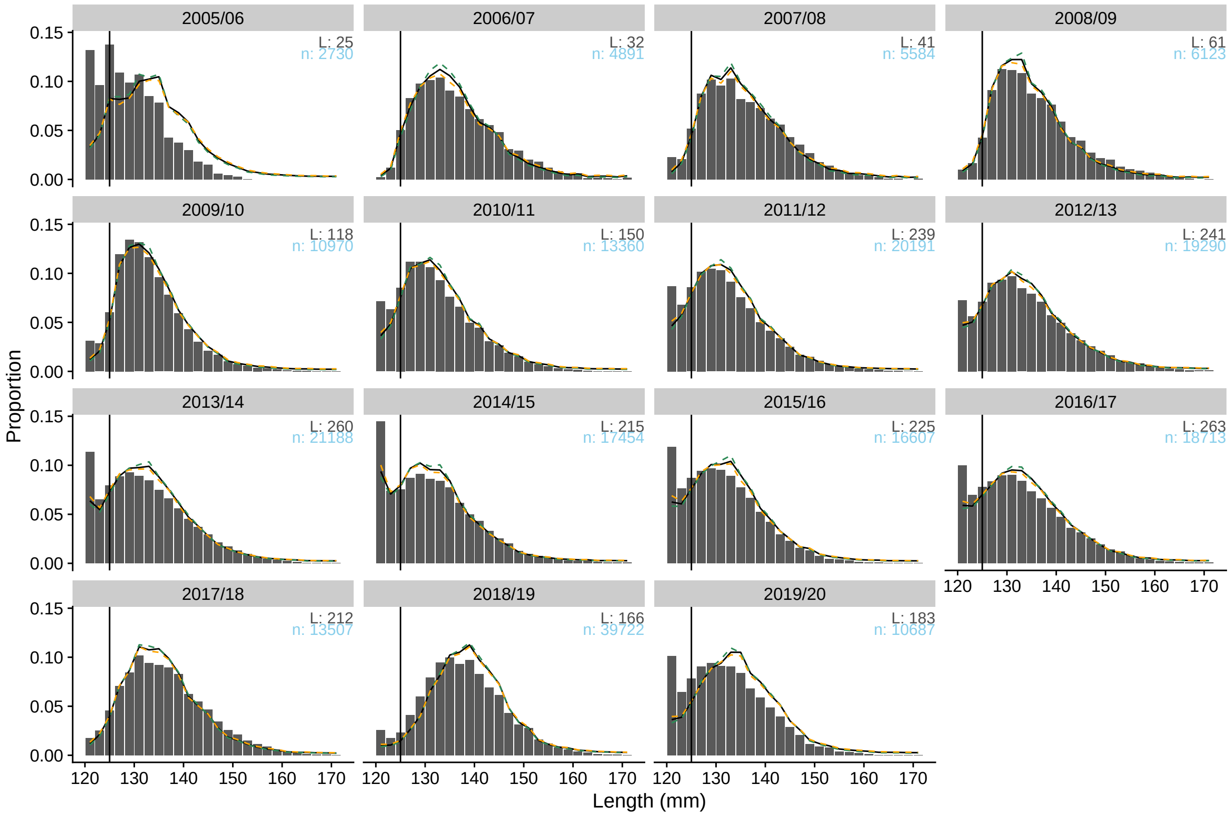

Figure 11: Dirichlet-Multinomial posterior distributions for yearly proportions $\pi_{r,y}$ (black line) in pāua quota management area PAU 4, with 95% confidence intervals (red and blue dashed line). Raw catch sampling length-frequency proportions in grey; number of landings (L) in black; number of measurements (n) in blue.

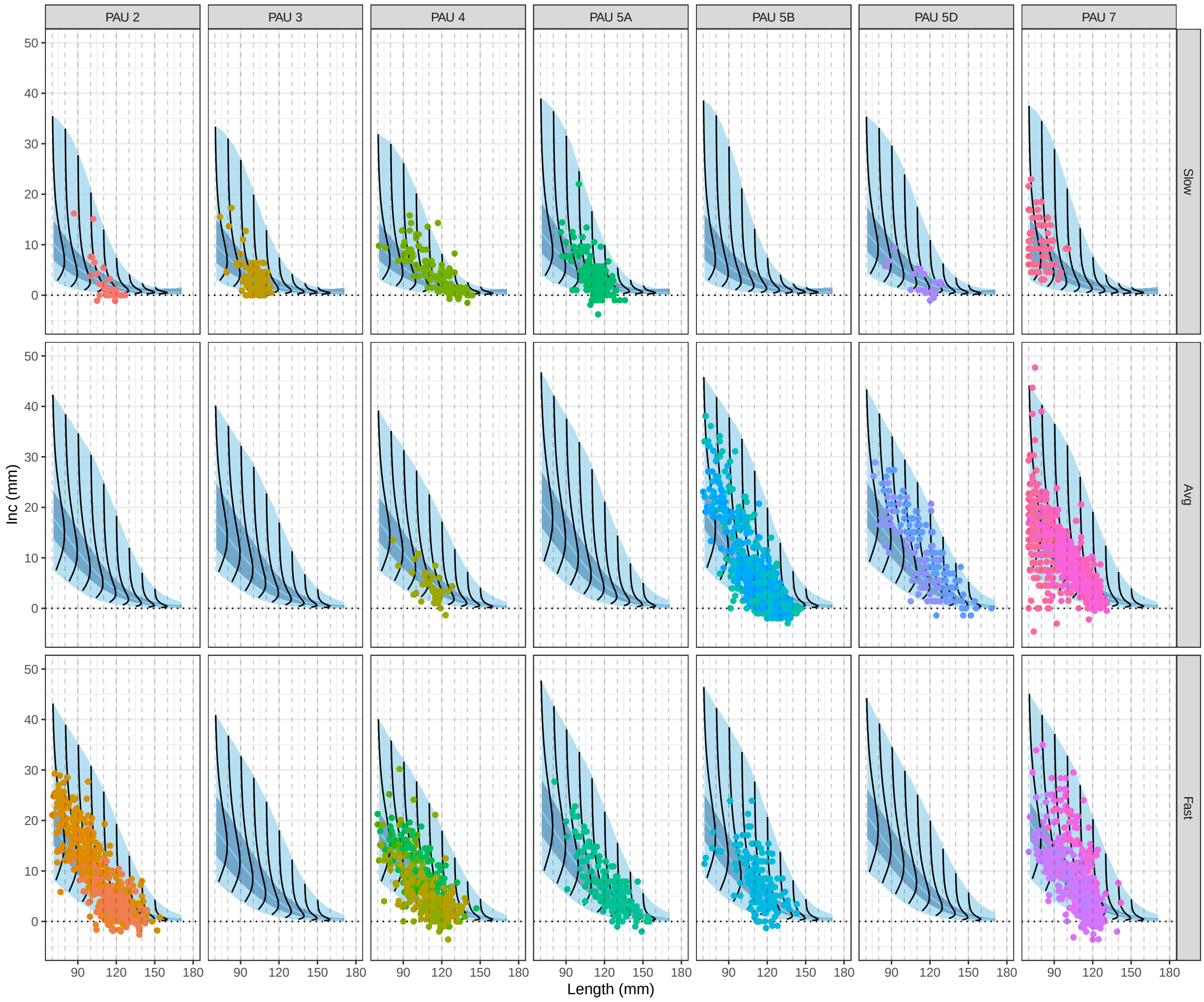

Figure 12: Priors derived from a meta-analysis of growth and maturity of pāua, based on model-fitting to all tag-increment and maturity data across quota management areas (QMAs). Shown is the joint prior for positive growth increments at size l by QMA and growth stratum. Dark blue shading shows uncertainty about mean growth; light blue line indicates posterior median for mean growth; light blue area shows the posterior median for the population standard deviation applied to mean growth; black lines indicate the implied distribution of growth at the median of the prior.

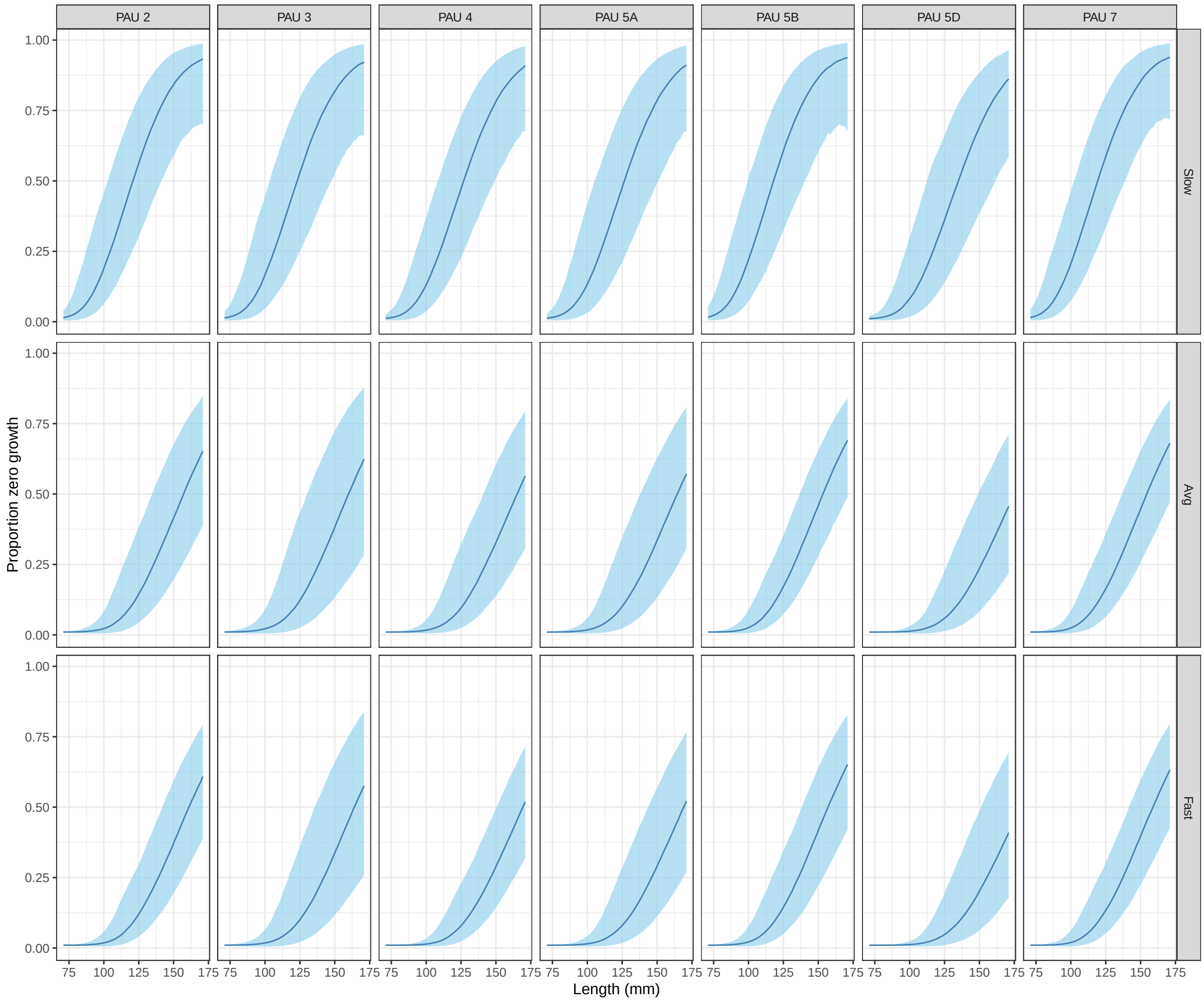

Figure 13: Priors derived from a meta-analysis of growth and maturity of pāua, based on model-fitting to all tag-increment and maturity data across quota management areas (QMAs). Shown is the expected proportion of local populations not growing at size l by QMA and growth stratum.

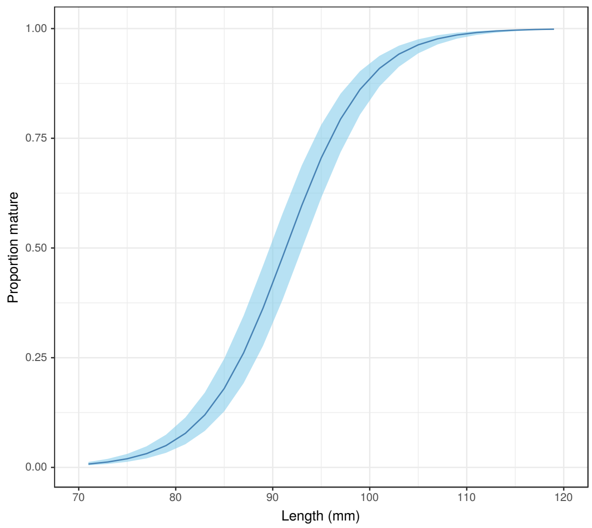

Figure 14: Priors derived from a meta-analysis of growth and maturity of pāua, based on model-fitting to all tag-increment and maturity data across quota management areas. Shown is the population level maturity.

2.2 Assessment model

2.2.1 Model 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 described by Neubauer & Tremblay-Boyer (2019b).

2.2.2 Prior distributions

Recruitment deviations (R_{dev}), equilibrium recruitment (R_0), 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 (Table 3). Priors were only initial guesses and were updated using depletion based stock reduction analysis.

Table 3: Default priors used in the pāua stock assessment model (LN=Lognormal), with prior mean and standard deviation (SD) shown on the log-scale (log) and on the positive scale (pos; CPUE, catch-per-unit-effort; CSLF, catch sampling length frequency).

Parameter	Symbol	Prior	Mean (log)	SD(log)	Mean (pos)	SD (pos)
Equilibrium recruitment	R_0	LN	13	5	1.19×10^{11}	3.19×10^{16}
Recruitment deviations	R_{dev}	LN	0	0.4	1.08	0.45
Natural mortality	M	Fixed	0.12 (0.09)			
Catchability	q	LN	-13	100	∞	∞
Length at 50% selectivity	D_{50}	LN	log(123)	0.05	123.15	6.16
95% selectivity offset	D_{95}	LN	log(5)	0.5	5.67	3.02
Steepness	h	Fixed	0.3			

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

2.2.3 Technical model details

The model was initialised using equilibrium conditions calculated from the theoretical numbers at length in the absence of fishing. All sampling was run using the Stan language for formulating Bayesian models (Stan Development Team 2018). All models used 1000 independent samples from the model after conditioning.

2.3 Model conditioning based on depletion priors

To derive an operating model, depletion predictions were used to estimate potential unfished stock size and productivity, using stochastic stock reduction analysis. This process is also known as depletion-based stochastic stock reduction analysis (DB-SRA; Dick & MacCall 2011). In this process, the model is iterated based on input priors (natural mortality, growth, unfished recruitment), and simulations are weighted according to the assumed output for (prior on) depletion. This process leads to a distribution over unfished stock size (technically, over unfished recruitment R_0, with unfished stock size the equilibrium conditioned under R_0 and priors/fixed growth and natural mortality). The present approach considered three independent assumptions about stock status for model conditioning:

1. Predicted status by statistical area derived from meta-analysis (see subsection 2.4 below).

2. Assuming a relatively low status of 50% of unfished biomass (with a CV of 10%), and scaling individual statistical areas using spatial CPUE (derived in 2.1.2). This prior assumed a log-normal distribution and was used as a basis for comparing main uncertainties in the management procedure evaluation.

3. A conservative estimate of stock size and depletion, via a uniform distribution of status between 0.4 and 0.8.

2.4 Deriving status estimates

The procedure for deriving stock status from meta-analysis of CPUE and stock status across assessed QMAs is detailed by Neubauer & Kim (2023). Estimated (standardised) spatial CPUE for the period between 2020 and 2022 was used as a reference, and compared with CPUE from QMAs with informative CPUE and assessment outcomes. Stock status was regressed against CPUE from each area and assessment year, using logistic regression with a random offset for each QMA. The regression model was then used to predict status for PAU 4 based on local spatial CPUE, accounting for differences between QMAs in the relationship between CPUE and estimated stock status.

The status meta-analysis models were set up in the Bayesian inference software brms (Bürkner 2017), allowing for error in both CPUE (via a measurement error model) and status or density (via an assumed meta-analysis type standard error) to be taken into account. For example, the brms model formulation was:

```
brm(logit(stock_status) | se(error) ~ me(CPUE,SD) + y(1|QMA),
                 data = assmnt_dfs ,
                 family = 'normal',
                 iter = 1000,
                 warmup = 500,
                 cores = 16,
                 chains = 2,
                 threads = 8,
                 prior = set_prior('normal(0,1)', class="sd") +
                   set_prior('normal(0,2)', class="b"),
                 backend = 'cmdstanr',
                 seed = 14).
```

2.5 Management procedure evaluation

Potential management procedures were determined with fishers at a special meeting in 2021. A general proposal was to build control rules based on examples from PAU 5 QMAs, which adopted a set of three-step control rules, centred around a desired catch rate and corresponding catch (see Table 4). Fishers suggested that a catch rate of 100 kg/h was desirable, and the rule was developed assuming a $\pm$20% increment for steps around a 100 kg/h target CPUE, with the current catch set as the mid-plateau of the control rule (see Figures 15, 16, Table 4). Control rules were scaled such that areas with low (high) CPUE (i.e., more than 20% deviation) relative to the target were placed on the low (high) plateau (see Figure 15 for an illustration).

The proposed control rules were evaluated based on conditioned models with a range of assumptions:

- Growth according to the meta-analytic prior mean (base model), with sensitivities with 20% increased and decreased growth.

- No dispersal between adjacent statistical areas was assumed in the base model, with a sensitivity of high connectivity (auto-correlation in recruitment of 0.8 between adjacent areas).
- Natural mortality was assumed to be 0.12 (with sensitivity at 0.09).
- R_0 was constrained using DB-SRA.
- Steepness was fixed to a low value (0.3) to emulate low resilience that is often attributed to abalone stocks.

Catch splits were assumed to be consistent with control rules, with catch fully-aligned with control catch. Although this aspect is not the case in practice, the level of compliance with spatial control rule settings is difficult to predict. The ongoing industry management in the fishery and poor spatial data quality make it difficult to obtain a precedent. For this reason, it was assumed that the control rules were implemented without variation in spatial catch. The CV of CPUE observation error was based on the residual error in CPUE in recent stock assessments, and was assumed to be 10%. Applying the management procedure evaluation with a CV of 20% did not notably affect outcomes.

The control rule was tested for a validity period of five years, with simulations projecting the stock for 20 years to ascertain long-term performance of the control rule. In addition, all simulations assumed average recruitment with no auto-correlation. Periods of prolonged below-average recruitment would significantly degrade fishery performance. For this reason, any indication of poor recruitment periods should lead to a review of the operating model assumptions and control rules. In addition, the evaluation performed here assumed a starting point based on recent (2020–2022) conditions; however, implementation starting from a markedly different starting point (i.e., a lower starting point due to delayed implementation) would affect risk estimates, so that the control rule should be re-evaluated.

Table 4: Parameters used for initial management procedure evaluations in pāua quota management area PAU 4: target commercial catch (TCC) by pāua statistical area taken from 2021 PAU 4 annual operating plan, with associated assumed target catch-per-unit-effort (CPUE) and CPUE reference points (in kg/h) for fishery closure, and the CPUE at which a linear increase in catch is taken. Minimum harvest size (MHS) and standardised recent CPUE (Std CPUE) as the median of the estimated posterior distribution for each statistical area are given for reference. All other parameters of the control rules were derived from the targets.

Stat area	Target TCC (t)	Target CPUE (kg/h)	Closure (kg/h)	Linear incr. from (kg/h)	MHS (mm)	Std. CPUE (kg/h)
02	3.00	100.00	20	150	127.00	110.09
04	4.00	100.00	20	150	127.00	90.84
05	4.00	100.00	20	150	127.00	81.16
06	1.20	100.00	20	150	135.00	60.87
07	1.20	100.00	20	150	135.00	54.02
08	1.20	100.00	20	150	135.00	60.71
09	2.00	100.00	20	150	140.00	87.58
10	2.00	100.00	20	150	140.00	80.09
11	6.00	100.00	20	150	127.00	63.57
14	6.00	100.00	20	150	136.00	99.26
15	4.50	100.00	20	150	140.00	101.35
16	2.40	100.00	20	150	135.00	125.01
17	1.80	100.00	20	150	135.00	61.87
19	5.00	100.00	20	150	127.00	119.07
20	3.60	100.00	20	150	127.00	76.82
21	3.60	100.00	20	150	127.00	69.31
22	6.40	100.00	20	150	127.00	121.41
23	5.00	100.00	20	150	132.00	88.95
25	8.40	100.00	20	150	127.00	70.74
26	3.60	100.00	20	150	127.00	62.29
27	2.00	100.00	20	150	127.00	89.32
28	4.80	100.00	20	150	127.00	46.79
29	1.20	100.00	20	150	127.00	61.59
30	2.00	100.00	20	150	127.00	104.46
31	3.00	100.00	20	150	127.00	88.55
32	4.00	100.00	20	150	130.00	94.38
33	5.60	100.00	20	150	130.00	135.75
34	6.40	100.00	20	150	130.00	136.18
36	4.00	100.00	20	150	130.00	100.79
37	8.50	100.00	20	150	130.00	103.47
38	3.00	100.00	20	150	127.00	87.76
40	2.40	100.00	20	150	140.00	125.37
41	7.00	100.00	20	150	140.00	98.65
42	0.40	100.00	20	150	140.00	129.92
43	5.00	100.00	20	150	140.00	110.72
44	1.60	100.00	20	150	127.00	125.95
45	4.00	100.00	20	150	132.00	149.34
46	1.00	100.00	20	150	132.00	96.92
47	2.00	100.00	20	150	140.00	94.15
48	4.00	100.00	20	150	140.00	97.36
49	4.00	100.00	20	150	132.00	134.84
50	4.00	100.00	20	150	132.00	111.26
52	1.20	100.00	20	150	132.00	75.70
53	2.00	100.00	20	150	132.00	100.52
55	1.00	100.00	20	150	132.00	88.00
57	4.00	100.00	20	150	132.00	149.55

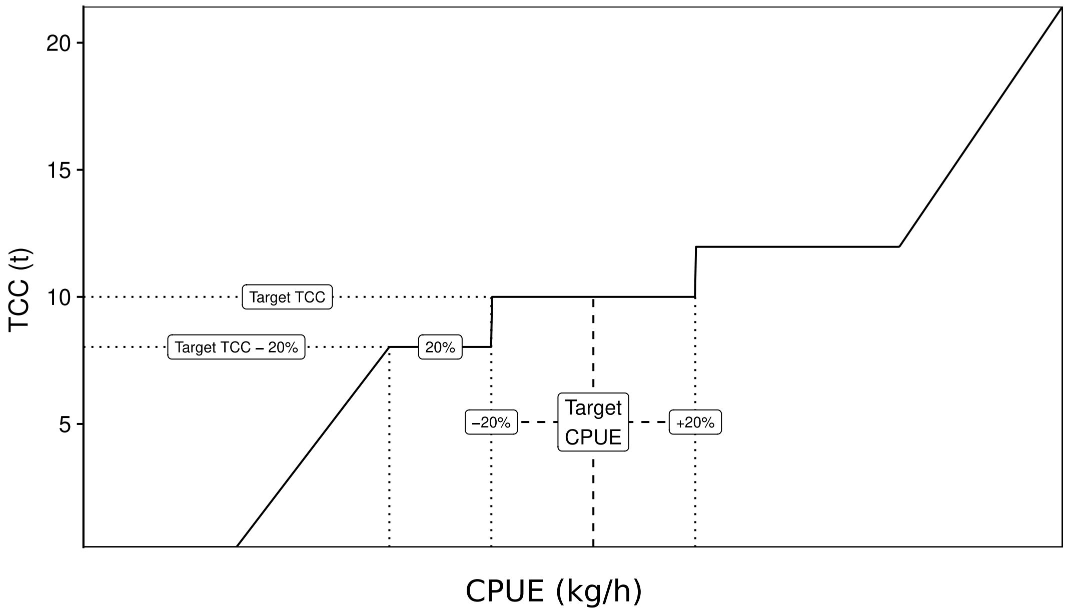

Figure 15: Conceptual graph of harvest control rules proposed for quota management area PAU 4, illustrated for a single pāua statistical area with a target catch of 10 t. Control rules show total commercial catch (TCC) as a function of catch-per-unit-effort (CPUE), including key parameters. The latter include the width of the target plateau for expected CPUE and for natural variation around the target (here 20% of target), a lower buffer (20% of target), and catch and catch increments corresponding to the target and limit catch rates.

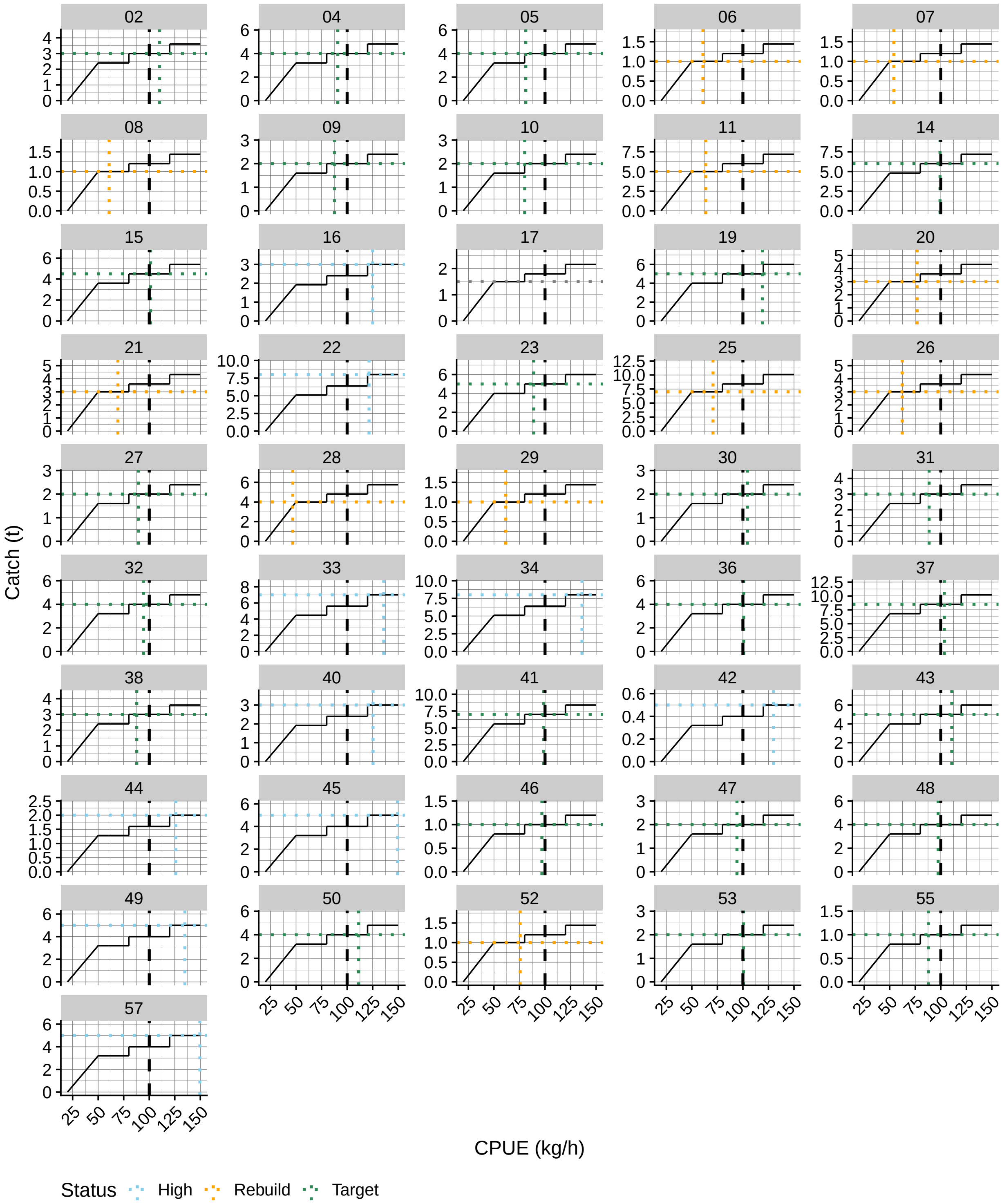

Figure 16: Harvest control rules proposed for quota management area PAU 4 (by pāua statistical area): total commercial catch (TCC) as a function of catch-per-unit-effort (CPUE). Target CPUE is shown as the dashed vertical line, recent CPUE, and corresponding control rule catch are shown in coloured dotted lines, corresponding to estimates of areas being below ("Rebuild"), at ("Target"), or above target ("High").

3. RESULTS

3.1 Deriving alternative status estimates

The meta-analysis of stock status against CPUE suggested higher standing biomass and status in PAU 4 than in any assessed QMA, with a status above 75% of unfished biomass (Figure 17), but with considerable spatial variation. Due to these relatively high estimates, alternative formulations with lower status (lognormal distribution with mean 0.5, CV 10%) was assumed as a base assumption, and adjusted for spatial differences in CPUE according to the spatial CPUE index.

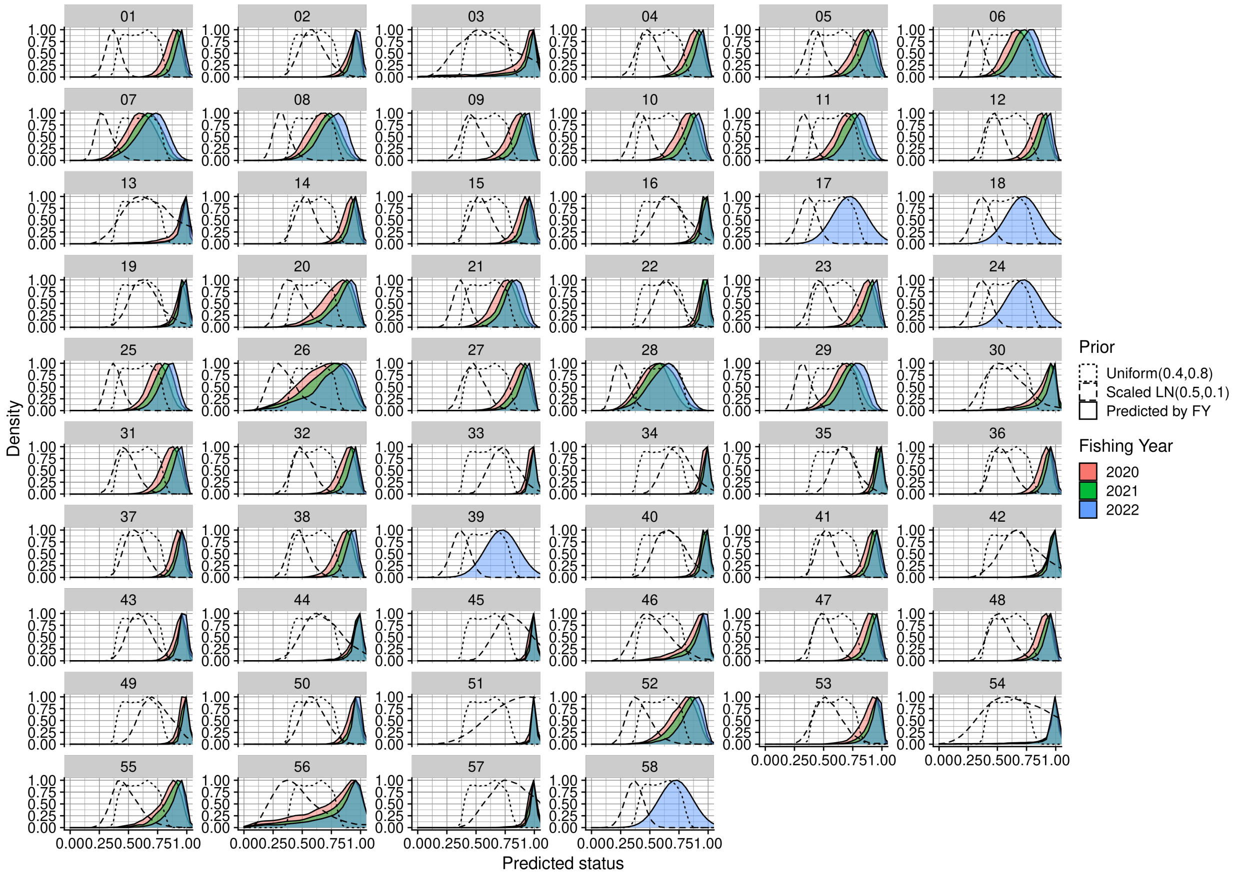

Figure 17: Predicted status (coloured density by year) for quota management area PAU 4 from a meta-analysis relating catch-per-unit-effort (CPUE) to stock assessment outcomes (stock status, biomass) across pāua statistical areas. Dashed line represents the "low" status assumption, using a spatially scaled lognormal distribution with mean 0.5 and CV of 0.1. Dotted line shows the alternative status assumption of a uniform distribution between 0.4 and 0.8.

3.2 Operating model and management procedure evaluation

The conditioned base models with stock size conditioned either on low or uniform stock status assumptions, suggested a stabilising effect from pāua statistical area-scale control rules at the QMA-wide scale (Figure 18): despite a range of outcomes and variable trends at small spatial scales (Appendix A, Figures A-1 to A-7); trends at the QMA scale remained slow and suggested an overall stable fishery.

The model suggested potential declines in statistical areas with low CPUE and low past catch (e.g., pāua statistical area 52). In these statistical areas, the model forced considerable declines prior to application of management procedures (Figure A-1), with often little catch before their application. Any catch that was applied as part of the management procedures had a large impact in these areas, because low CPUE and catch led the models to assume a low standing biomass, especially in the context of conditioning based on the spatially scaled log-normal low-status assumption. However, due to their low biomass, these areas contribute relatively little to the QMA-wide trends (Figures A-2, A-3).

Over the course of a realistic implementation period (e.g., 5 years), the conditioning assumptions did not lead to marked differences in outcomes between models, and no models approached limit reference points either over time frames of implementation or long term periods (Appendix B; Table B-1). Only over the longer time period did the low status assumption lead to a slow downward trend in available biomass (Figure 18), which corresponded to minor declining trends in catch. There was also little variability or uncertainty about catch levels QMA-wide, despite considerably larger uncertainty at the statistical area level (Figure A-6).

Different model productivity assumptions forced after conditioning had a minor effect at the QMA scale (Figure 19), despite marked differences at the statistical area scale between models using different productivity assumptions (Appendix C, Figures C-1 to C-7). Although none of the models suggested a risk of breaching Harvest Strategy Standard limit reference points (Table C-1), the application of rules at the small spatial scale mitigates the risk of model mis-specification for any area, leading to stable catch and biomass at the QMA-wide scale.

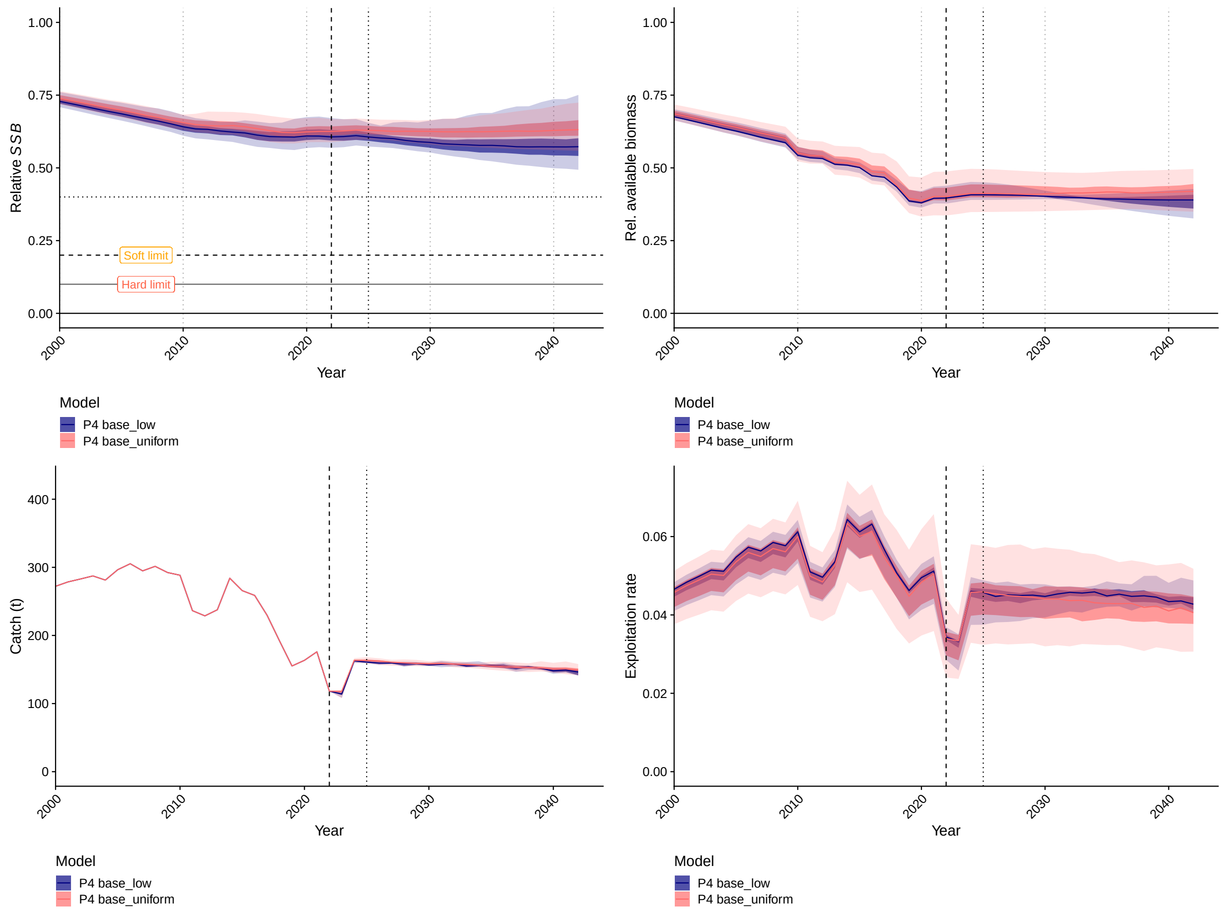

Figure 18: Projected relative spawning stock biomass (SSB), available biomass (at current minimum harvest size), long-term catch, and exploitation rate under two different conditioning assumptions (Low: scaled lognormal (0.5, 0.1) stock status assumption; uniform status was assumed to be between 0.4 and 0.8). Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

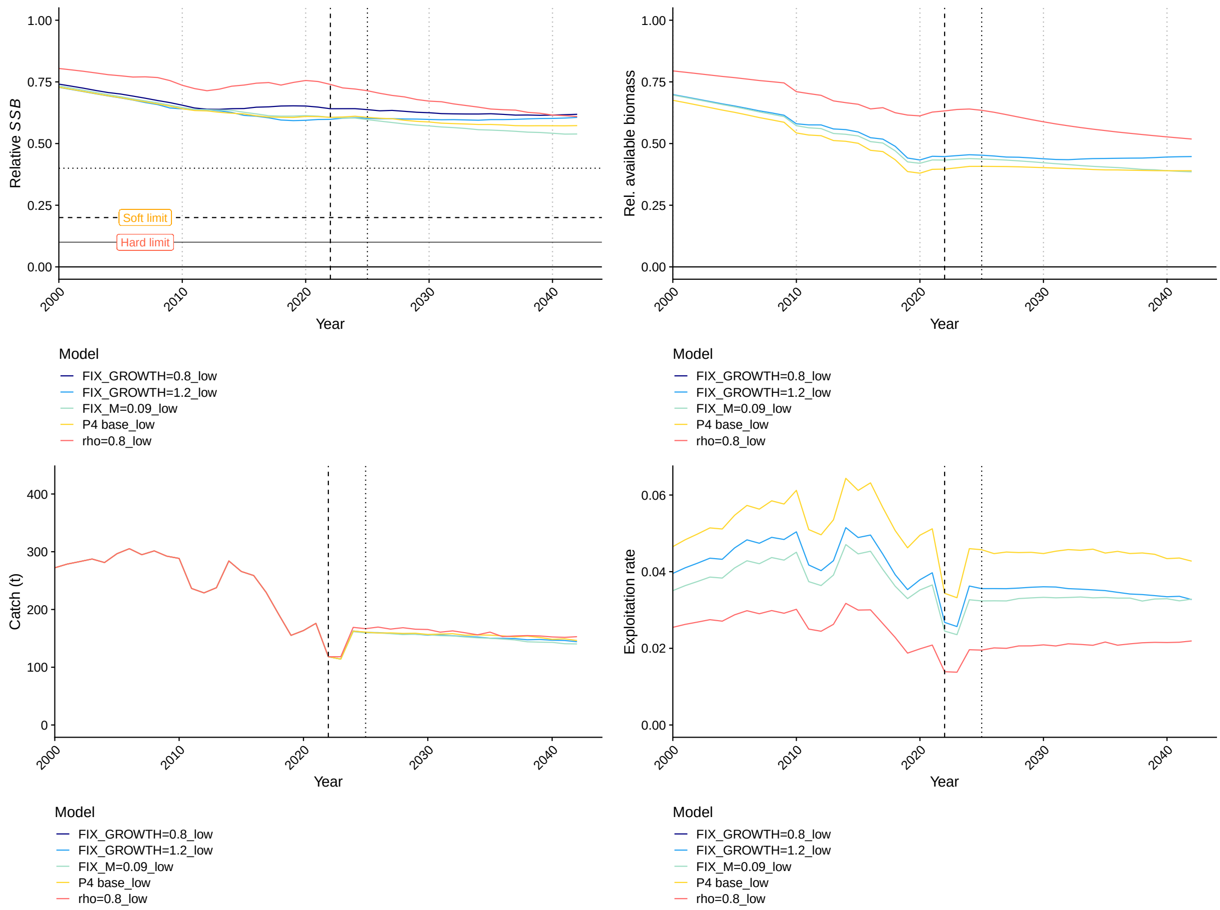

Figure 19: Projected relative spawning stock biomass (SSB), available biomass (at current minimum harvest size), long-term catch, and exploitation rate under different biological assumptions for the lognormal (0.5, 0.1) conditioning assumption. Fixed growth assumptions were 20% changes from base growth, the rho model allowed for dispersion of recruits between adjacent statistical areas, M=0.9 represents a sensitivity with lower natural mortality. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

4. DISCUSSION

Due to previous difficulties with assessments for PAU 4, the present project attempted to develop credible operating models, and evaluate management for the area. Previous reports have highlighted the shortcomings of CPUE and catch data in PAU 4 (Breen & Smith 2004, Fu et al. 2012, Fisheries New Zealand 2019, Neubauer 2019), both of which are essential components in stock assessments for pāua stocks.

In the absence of sufficiently accurate and representative CPUE time series, models can only be conditioned on available data, but not fitted using statistical procedures (e.g., Bayesian inference). Conditioning via catch alone can be seen as a Bayesian prior prediction, with no updating of the Bayesian posterior distribution from CPUE of length-frequency likelihoods (Walters et al. 2006). Therefore, the present approach of conditioning the model based on catch and status assumptions only, could be readily extended into a complete statistical stock assessment in the future if data of sufficient quality are collected over a sufficient period of time.

For model conditioning, we assumed a lower-than-predicted status for all areas. Predicted status based on CPUE was notably high, owing to markedly high CPUE relative to other pāua fisheries in New Zealand.

The reason for this difference is unknown; the spatial CPUE standardisation accounts for reported use of UBA, and standardises CPUE to a free-diving index, therefore, accounting for the use of UBA. Despite high CPUE, however, it is unlikely that the notably high status predictions are accurate, given the catch history of large catches in excess of 300 t for a number of years. For this reason, a more conservative assumption was made around stock status, adjusted for spatial variability in CPUE.

With the conservative status assumptions, the model conditioning effectively forces the model to an assumed status that may be too low in many areas, leading to depletion in these areas under application of control rules. Nevertheless, these small-scale deletions are unlikely to be realistic, because they occur in areas that have had little catch in the past, and are likely relatively marginal areas which would not be fished at low densities. In addition, periodic reviews of control rules allow for adjustments in areas where targets were poorly identified, so that long-term mismatches between control rules and local productivity are unlikely. As a result, the small-scale trends simulated here are likely relatively extreme.

A key advantage of relatively frequent catch-limit adjustments, coupled with fine-scale monitoring of CPUE, is that models can be rapidly improved, as adjustments in management provide the necessary contrast in time series to allow for statistical estimation of stock productivity. At a large scale, buffering via portfolio effects (a large number of small stocks spreading risk and slowing trends at large scales; Schindler et al. 2010). When spatial trends in effort are not constant, large-scale trends will obscure small-scale trends, leading to biased indicators (Neubauer 2017). By modelling directly at small scales relevant to the fishery, the present model may be able to provide more accurate assessments than have been possible in other pāua quota management areas with relatively short time series of reliable data. Obtaining reliable data of catch, effort, and fished lengths remains a priority to ensure the model can eventually provide assessment advice.

Future updates of this study could include the testing of alternative rules that account for fisher knowledge and are more relevant to individual statistical areas. The present approach used a broad approach to highlight the benefit of management at small spatial scales in determining stable catches and biomass at the QMA scale. Nevertheless, optimised rules at small scales may significantly improve the short- and long-term performance of the fishery overall. This type of optimisation was not attempted here, but could be performed before rules are considered for adoption.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

Breen, P.A.; Kim, S.W.; Andrew, N.L. (2003). A length-based Bayesian stock assessment model for the New Zealand abalone *Haliotis iris*. *Marine and Freshwater Research 54 (5)*: 619–634.

Breen, P.A.; Smith, A.N.H. (2004). The 2004 assessment of paua (*Haliotis iris*) in PAU 4. *New Zealand Fisheries Assessment Report 2004/55*. 79 p.

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software 80*: 1–28. https://doi.org/10.18637/jss.v080.i01

Butterworth, D.S.; Haddon, M.; Haist, V.; Helidoniotis, F. (2015). Report on the New Zealand paua stock assessment model; 2015. *New Zealand Fisheries Science Review 2015/4*. 31 p.

Dick, E.; MacCall, A.D. (2011). Depletion-based stock reduction analysis: A catch-based method for determining sustainable yields for data-poor fish stocks. *Fisheries Research 110 (2)*: 331–341.

Fisheries New Zealand. (2019). *Fisheries Assessment Plenary May 2019: Stock assessment and stock status. Volume 2: Hake to pilchard*. Fisheries New Zealand, Wellington, New Zealand.

Fisheries New Zealand. (2022). *Fisheries Assessment Plenary May 2022: Stock assessment and stock status. Volume 2: Horse mussel to red crab*. Fisheries New Zealand, Wellington, New Zealand.

Fu, D.; McKenzie, A.; Marsh, C. (2017). Summary of input data for the 2016 PAU 5D stock assessment. *New Zealand Fisheries Assessment Report 2017/32*. 79 p.

Fu, D.; McKenzie, A.; Naylor, R. (2012). Summary of input data for the 2011 PAU 7 stock assessment. *New Zealand Fisheries Assessment Report 2012/26*. 50 p.

Middleton, D.A.J. (in prep.). The Kahawai database.

Murray, T.; Akroyd, J.M. (1984). The New Zealand paua fishery: an update of biological considerations to be reconciled with management goals. Fisheries Research Centre Internal Report No. 5. Unpublished report held by National Institute of Water and Atmospheric Research, Wellington. 34 p.

Neubauer, P. (2017). Spatial bias in pāua *Haliotis iris* catch-per-unit-effort. *New Zealand Fisheries Assessment Report 2017/57*. 33 p.

Neubauer, P. (2019). Trend scenarios and status of quota management area PAU 4 based on adjusted CPUE. Unpublished report prepared for Fisheries New Zealand. 16 p.

Neubauer, P. (2020). Development and application of a spatial stock assessment model for pāua (*Haliotis iris*). *New Zealand Fisheries Assessment Report 2020/30*. 42 p.

Neubauer, P.; Kim, K. (2023). Developing an operating model and testing management procedures for pāua (*Haliotis iris*) fisheries in PAU 3B. *New Zealand Fisheries Assessment Report 2023/27*. 65 p.

Neubauer, P.; Tremblay-Boyer, L. (2019a). Input data for the 2018 stock assessment of pāua (*Haliotis iris*) for PAU 5D. *New Zealand Fisheries Assessment Report 2019/38*. 40 p.

Neubauer, P.; Tremblay-Boyer, L. (2019b). The 2018 stock assessment of pāua (*Haliotis iris*) for PAU 5D. *New Zealand Fisheries Assessment Report 2019/39*. 58 p.

Ohnishi, S.; Yamakawa, T.; Okamura, H.; Akamine, T. (2012). A note on the von Bertalanffy growth function concerning the allocation of surplus energy to reproduction. *Fishery Bulletin 110 (2)*: 223–229.

Schiel, D.R. (1989). Paua fishery assessment 1989. Unpublished New Zealand Fisheries Assessment Research Document 89/9 (held by NIWA, Wellington).

Schindler, D.E.; Hilborn, R.; Chasco, B.; Boatright, C.P.; Quinn, T.P.; Rogers, L.A.; Webster, M.S. (2010). Population diversity and the portfolio effect in an exploited species. *Nature 465 (7298)*: 609–612.

Stan Development Team. (2018). RStan: the R interface to Stan. R package version 2.17.3. http://mc-stan.org/.

Walters, C.J.; Martell, S.J.; Korman, J. (2006). A stochastic approach to stock reduction analysis. *Canadian Journal of Fisheries and Aquatic Sciences 63 (1)*: 212–223.

APPENDIX A: MANAGEMENT PROCEDURE EVALUATION: BASE MODEL, LOW STATUS (SCALED LOGNORMAL) ASSUMPTION

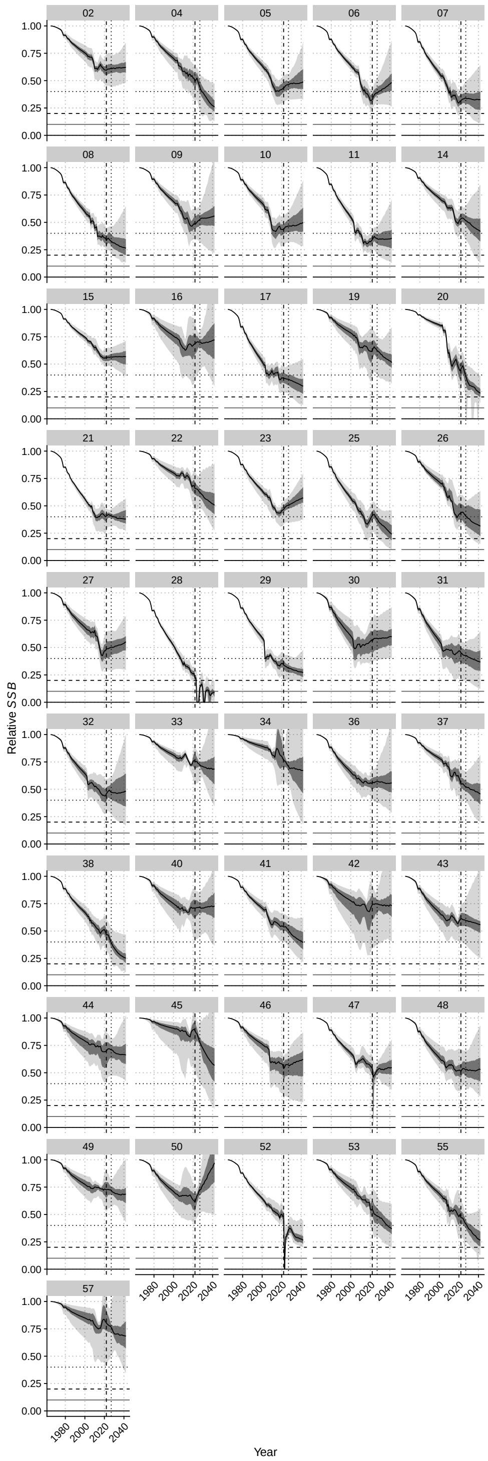

Figure A-1: Simulated relative spawning stock biomass (SSB) trend for pāua for the base operating model, with management according to the tested control rules for each statistical area of quota management area PAU 4; median line, inter-quartile range (dark shaded area) and 95% confidence interval (lighter shading). Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

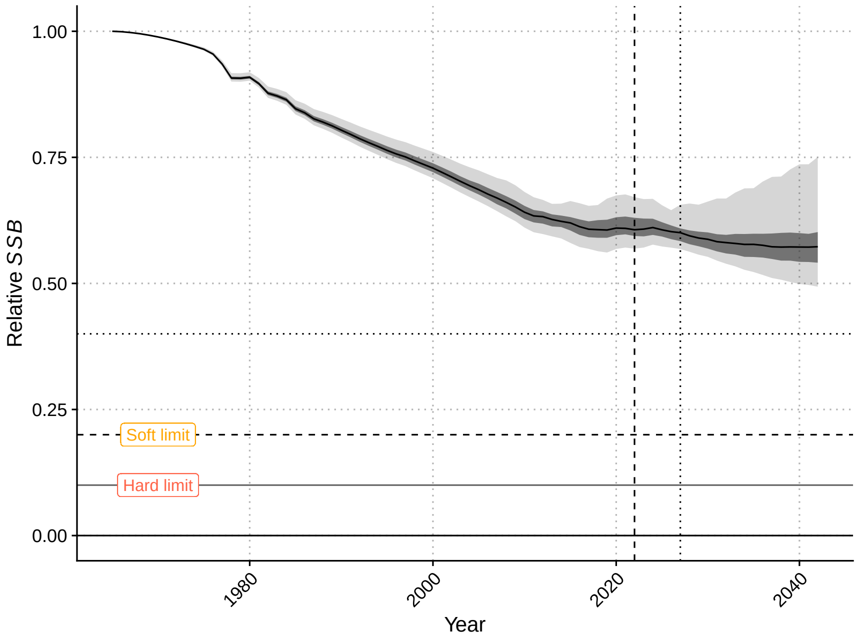

Figure A-2: Simulated relative spawning stock biomass (SSB) trend for pāua for the base operating model, with management according to the tested control rules for quota management area PAU 4; median line, inter-quartile range (dark shaded area) and 95% confidence interval (lighter shading). Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

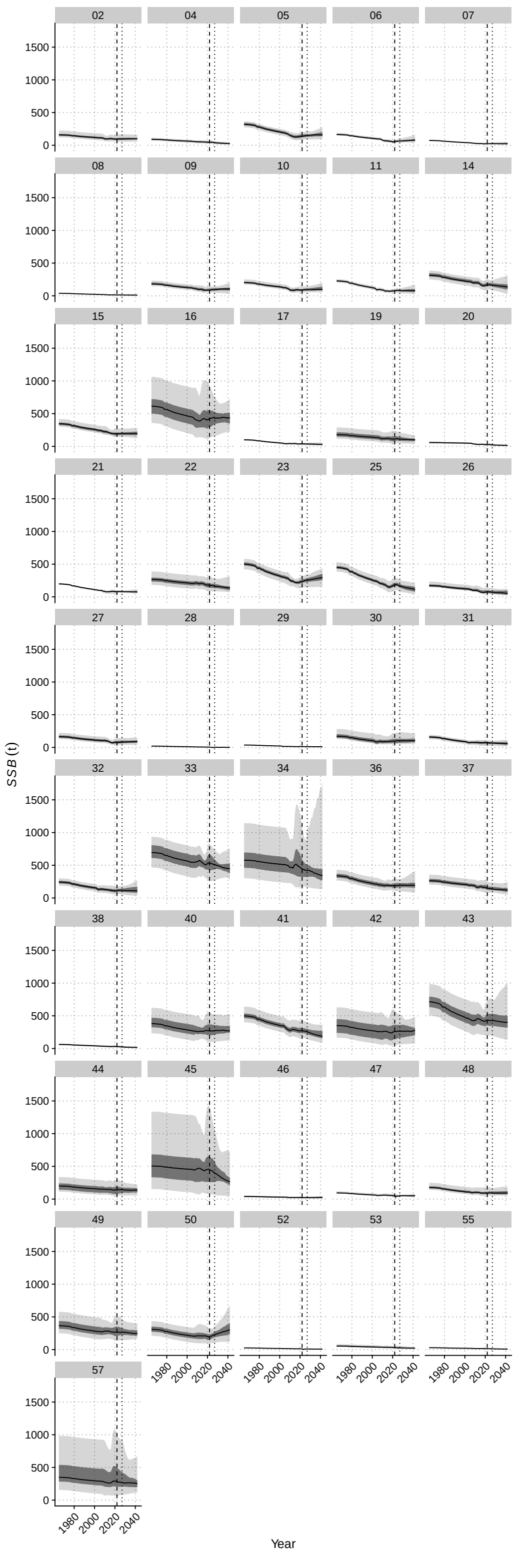

Figure A-3: Simulated spawning stock biomass (SSB) trend for pāua for the base operating model, with management according to the tested control rules for each statistical area of quota management area PAU 4 (median line, inter-quartile range (dark shaded area) and 95% confidence interval (lighter shading)). Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

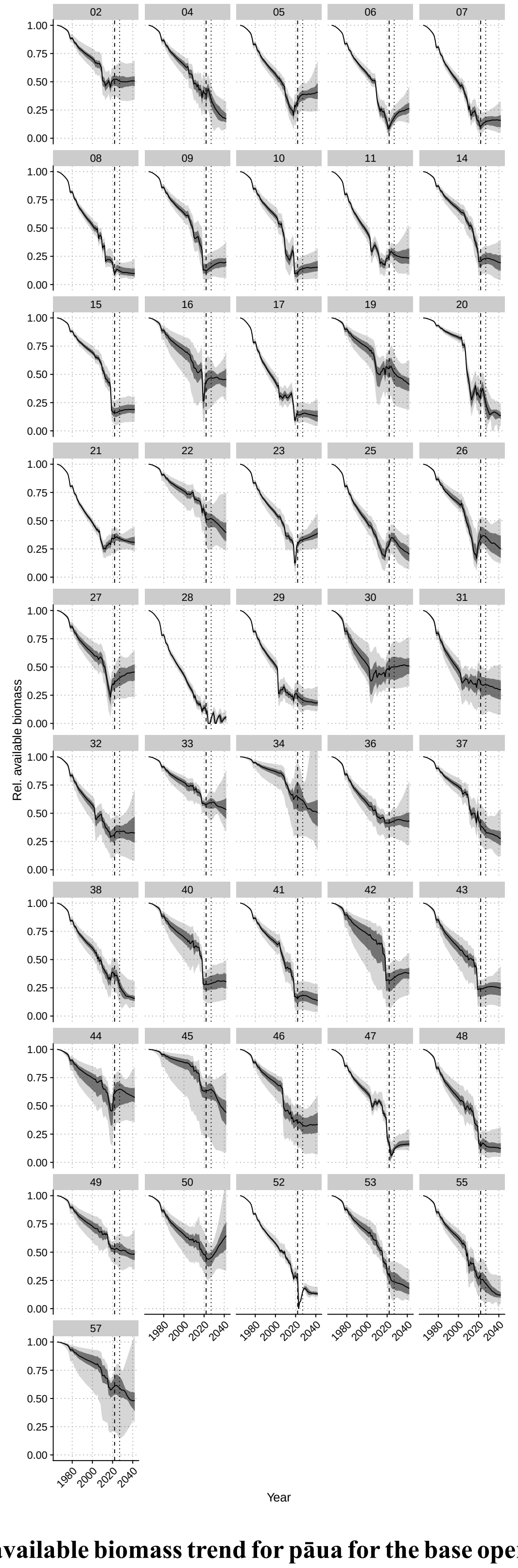

Figure A-4: Simulated relative available biomass trend for pāua for the base operating model, with management according to the tested control rules for each statistical area of quota management area PAU 4; median line, inter-quartile range (dark shaded area) and 95% confidence interval (lighter shading). Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

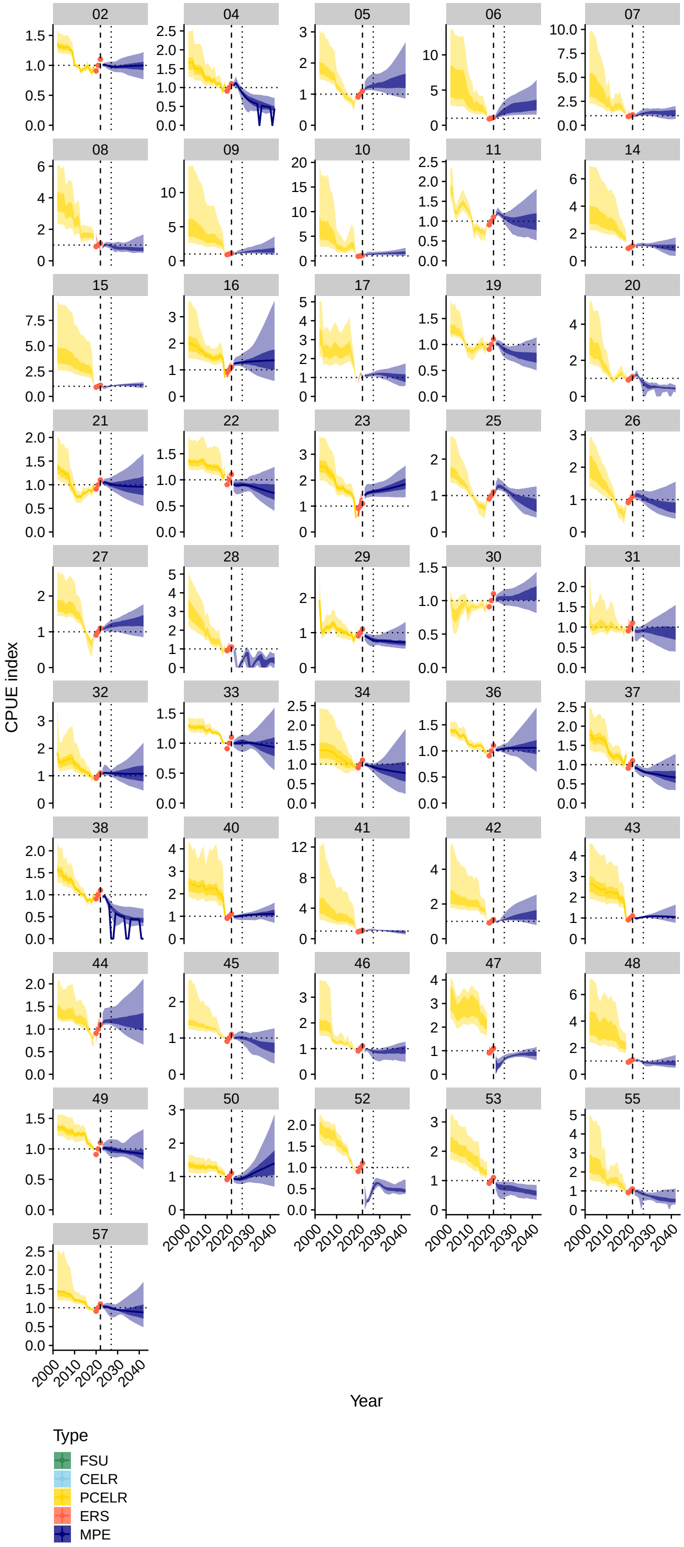

Figure A-5: Predicted catch-per-unit-effort (CPUE) trends for past and future fishery for pāua for the base operating model, with management according to the tested control rules for each statistical area of quota management area PAU 4; median line, inter-quartile range (dark shaded area) and 95% confidence interval (lighter shading).

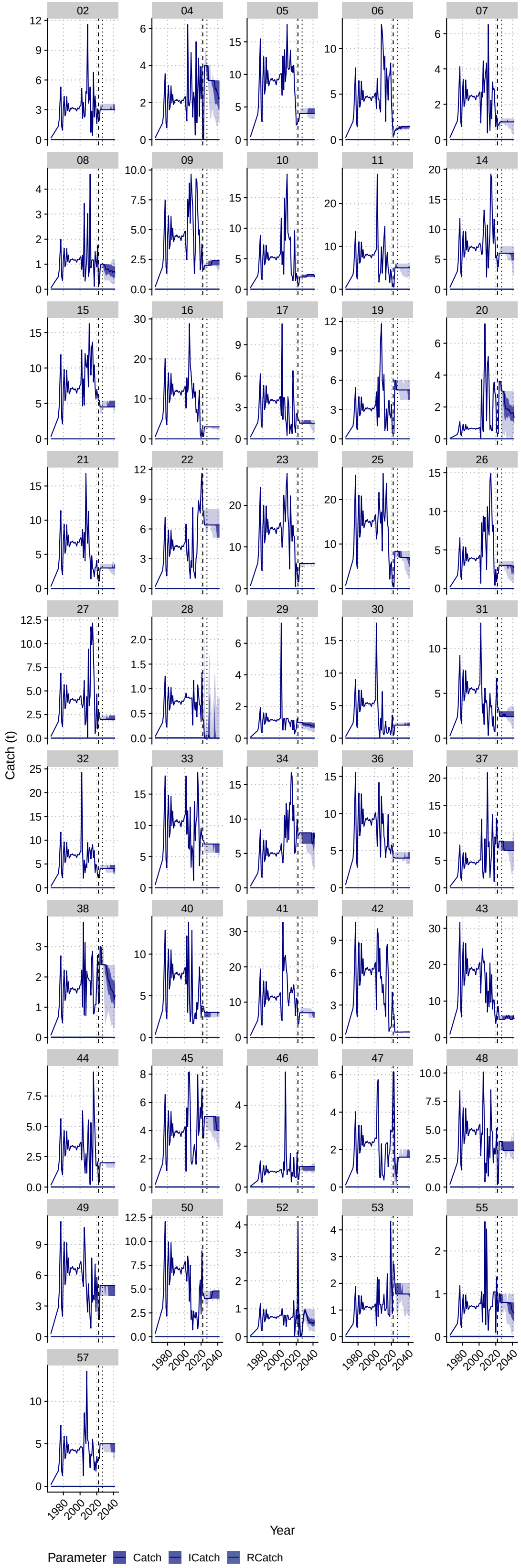

Figure A-6: Assumed and simulated catch by sector for the base operating model, with management according to the tested control rules for each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

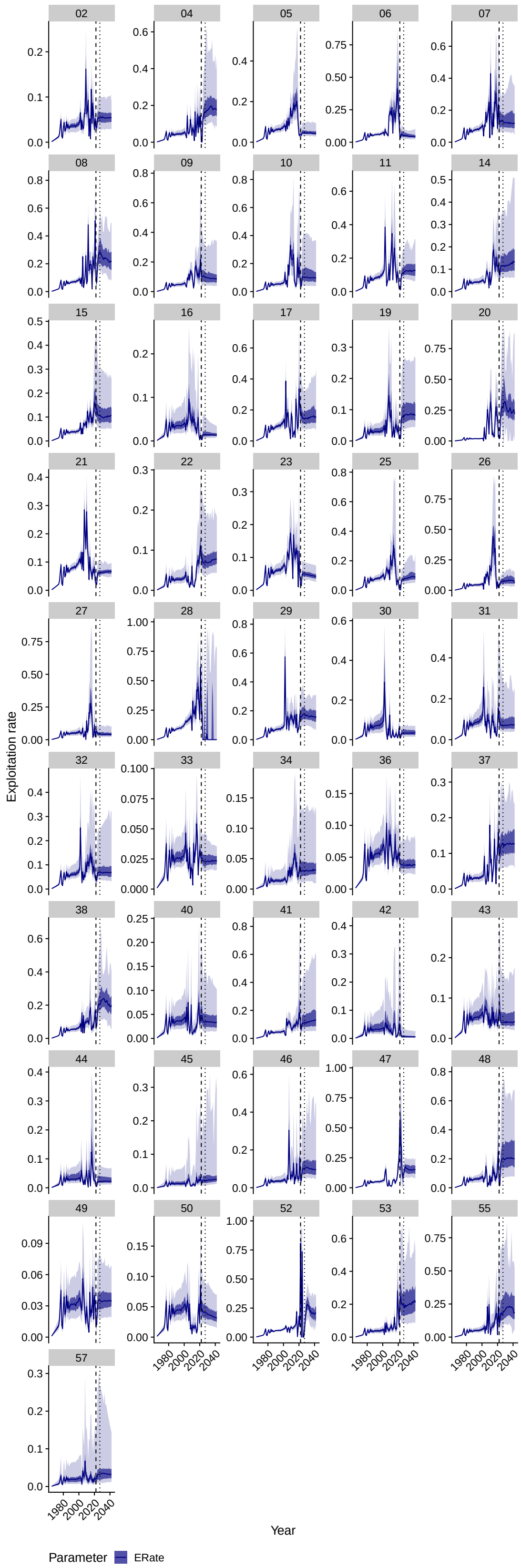

Figure A-7: Simulated exploitation rate (median line and 95% confidence interval) for the base operating model, with management according to the tested control rules for quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

APPENDIX B: MANAGEMENT PROCEDURE EVALUATION MODEL COMPARISON: CONDITIONING STATUS

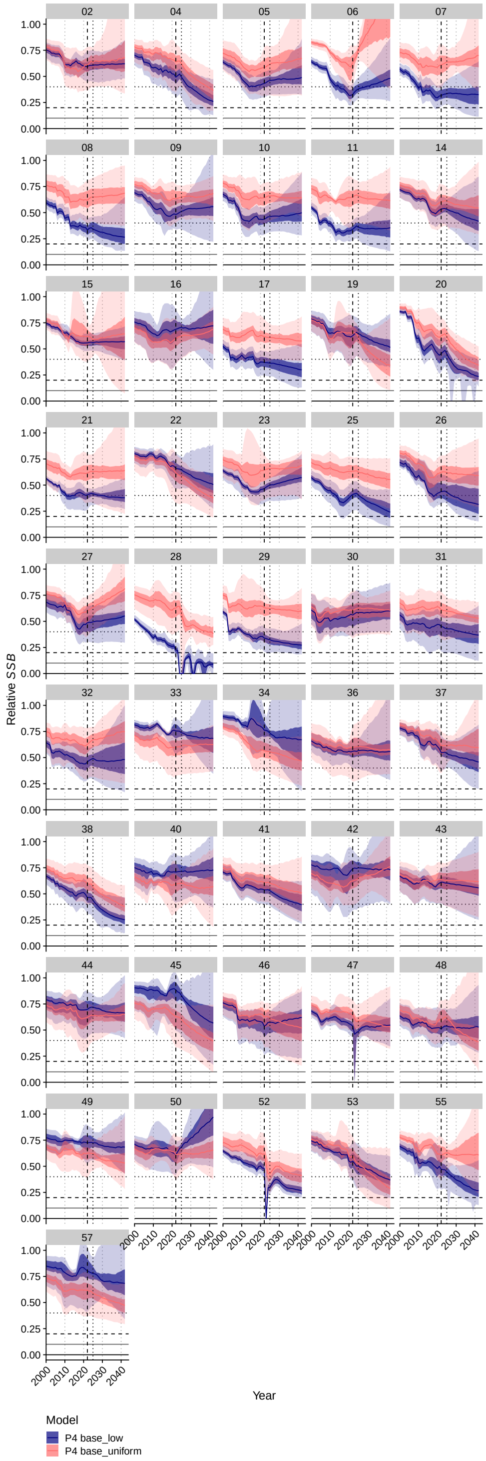

Figure B-1: Simulated relative spawning stock biomass (SSB) trend for pāua, comparing models (posterior medians (line) and confidence interval (shaded area) from simulations are compared) conditioned on different status assumptions, with management according to the tested control rules in each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

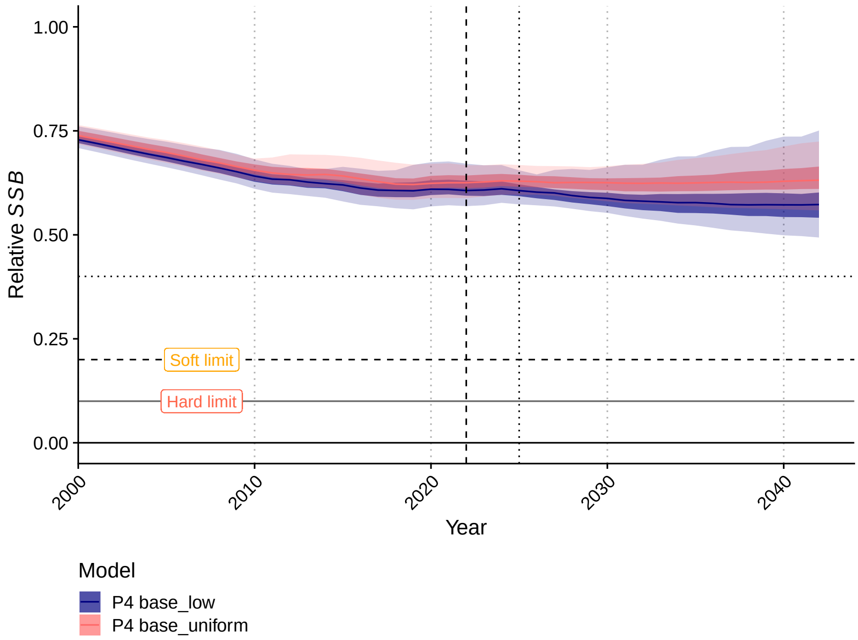

Figure B-2: Simulated relative spawning stock biomass (SSB) trend for pāua, comparing models (posterior medians (line) and confidence interval (shaded area) from simulations are compared) conditioned on different status assumptions, with management according to the tested control rules in in quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

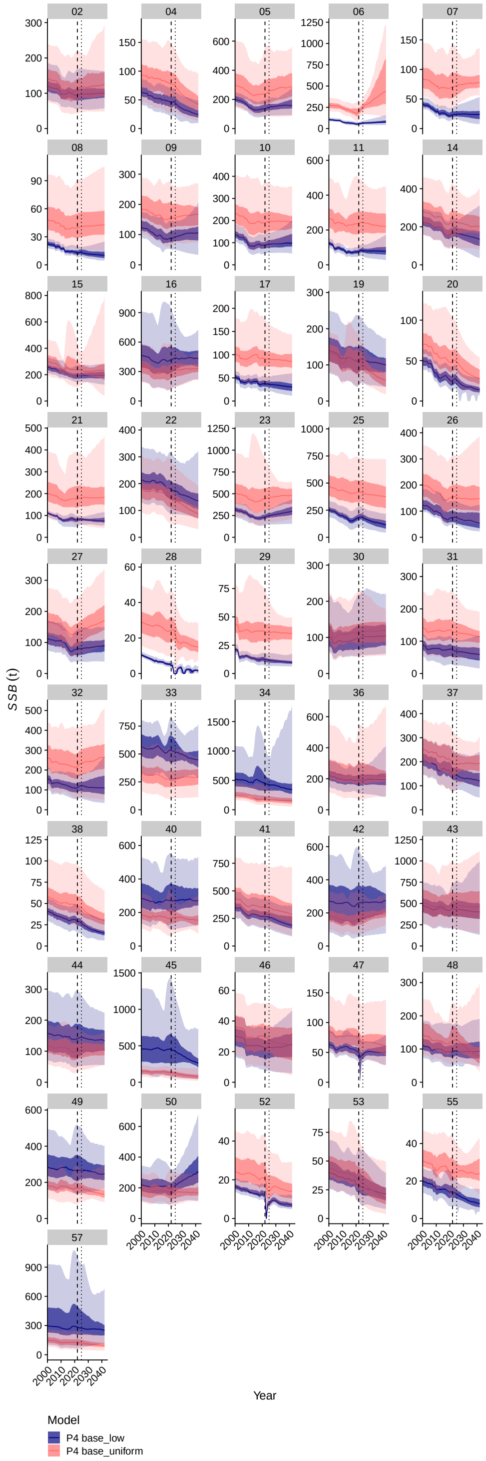

Figure B-3: Simulated spawning stock biomass (SSB; in tonnes) trend for pāua, comparing models (posterior medians (line) and confidence interval (shaded area) from simulations are compared) conditioned on different status assumptions, with management according to the tested control rules in each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

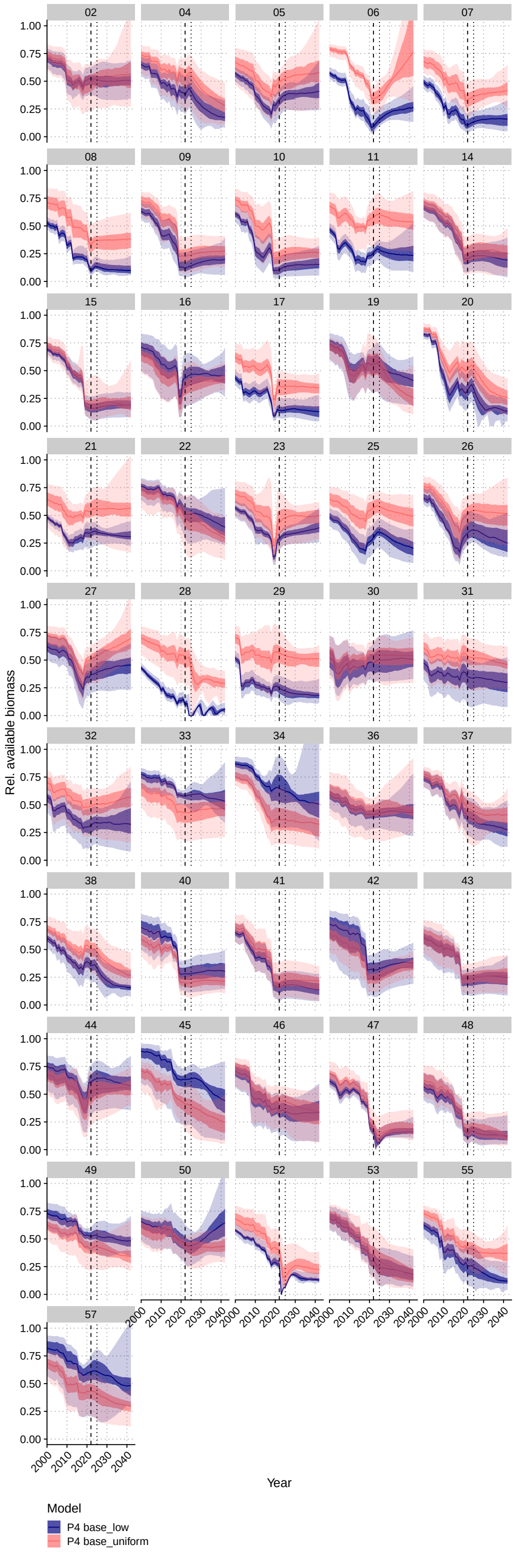

Figure B-4: Simulated relative available biomass trend for pāua, comparing models (posterior medians (line) and confidence interval (shaded area) from simulations are compared) conditioned on different status assumptions, with management according to the tested control rules in each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

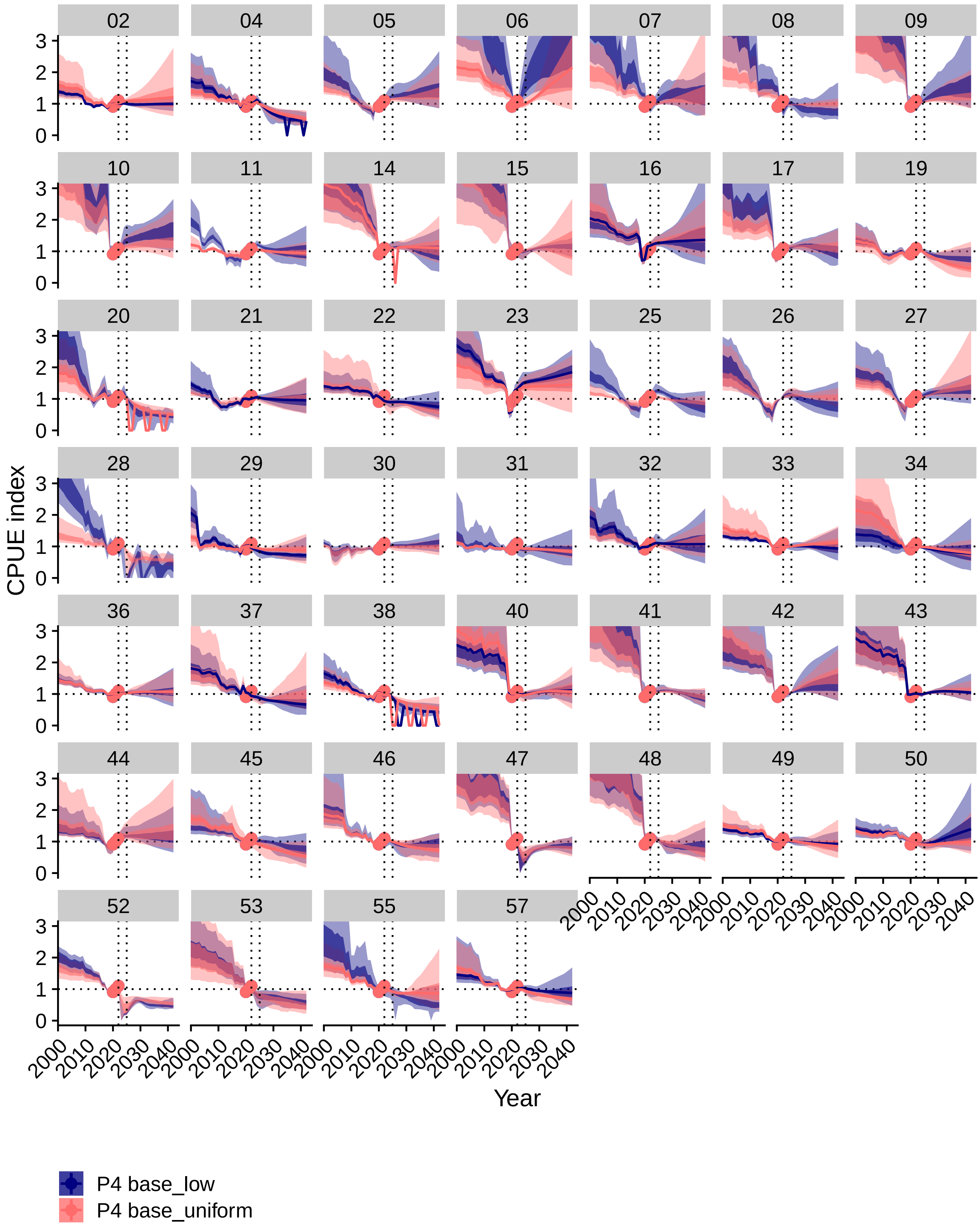

Figure B-5: Simulated relative spawning stock biomass (SSB) trend for pāua, comparing models (posterior medians (line) and confidence interval (shaded area) from simulations are compared) conditioned on different status assumptions, with management according to the tested control rules in each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. Management Procedure Evaluation projections are indicated as a new CPUE type.

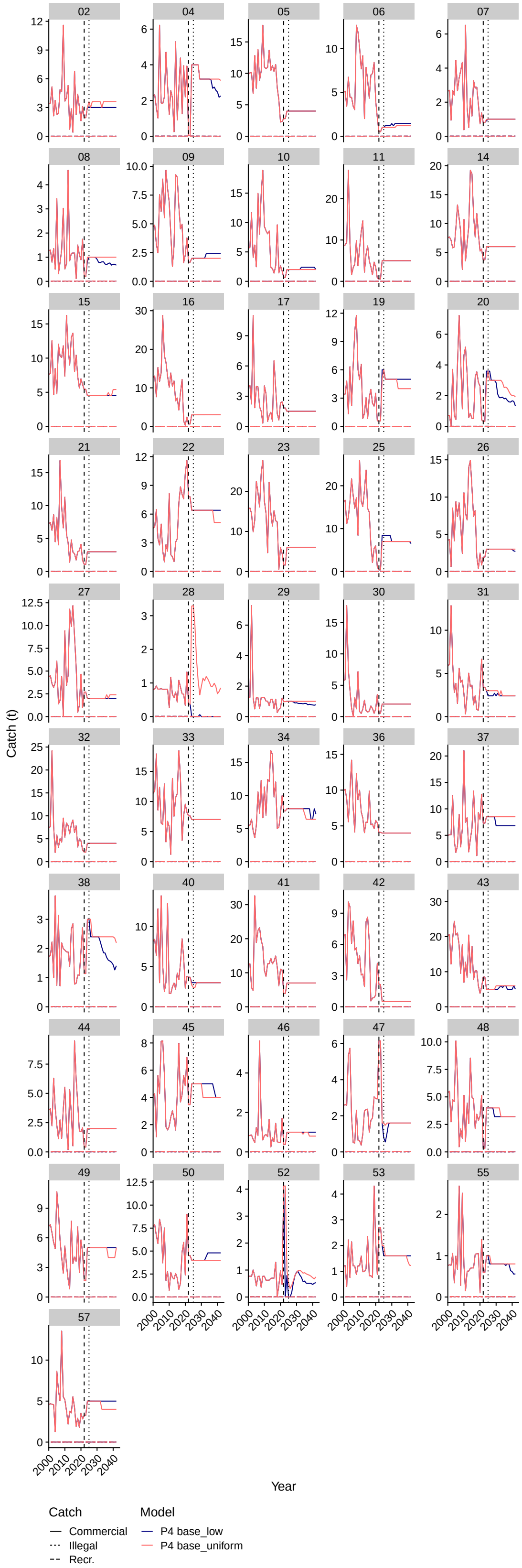

Figure B-6: Assumed and simulated catch, comparing models (posterior medians (line) and confidence interval (shaded area) from simulations are compared) conditioned on different status assumptions, with management according to the tested control rules in each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule.

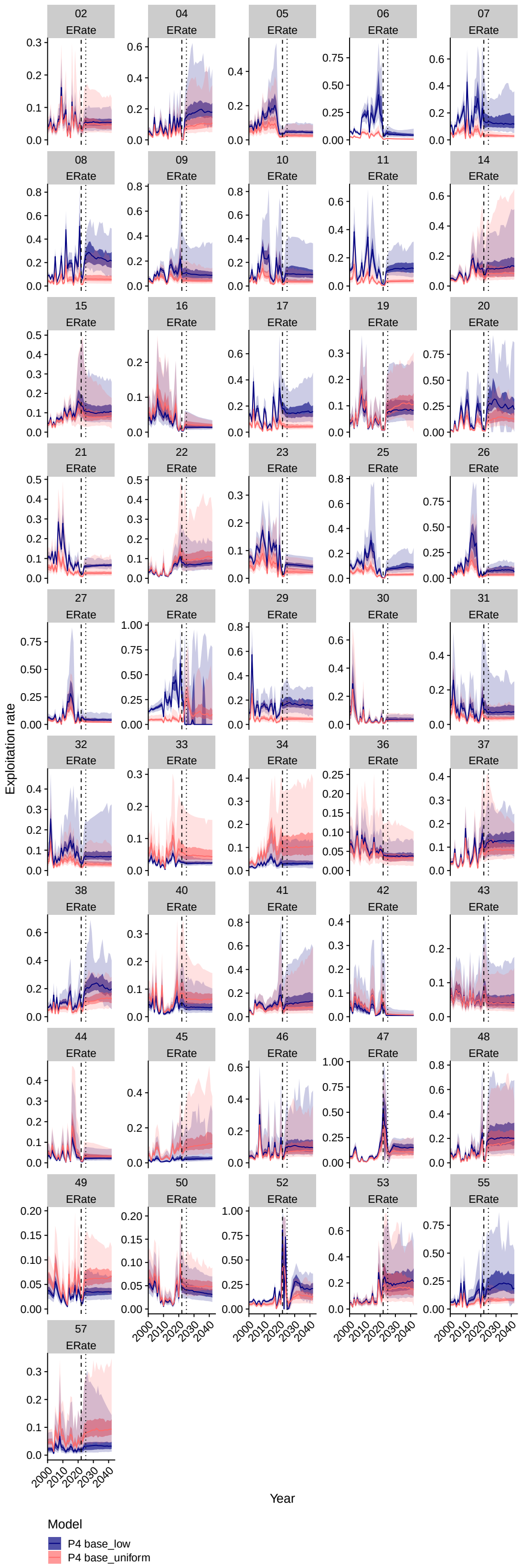

Figure B-7: Simulated exploitation rate (median line), comparing models (posterior medians (line) and confidence interval (shaded area) from simulations are compared) conditioned on different status assumptions, with management according to the tested control rules in each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

Table B-1: Performance of tested management procedures, comparing management procedures for quota management area (QMA) PAU 4. Results are shown aggregated across the overall QMA. SSB, spawning stock biomass; CPUE, catch-per-unit-effort.

Model	Region	Mean rel. SSB (2026)	Mean rel. SSB (2041)	P(rel. SSB (2026) > 0.4)	P(rel. SSB (2041) > 0.4)	P(relSSB (2026) < 0.2)	P(relSSB (2041) < 0.2)	P(rel. SSB (2026) < 0.1)	P(rel. SSB (2041) < 0.1)	mean rel. SSB (2021–2041)	Mean catch (kg)	Mean CPUE(kg/h)
P4 base_low	All	0.61	0.58	1.00	1.00	0.00	0.00	0.00	0.00	0.59	153212.75	104.81
P4 base_uniform	All	0.63	0.63	1.00	1.00	0.00	0.00	0.00	0.00	0.63	154756.14	101.68

APPENDIX C: MANAGEMENT PROCEDURE EVALUATION MODEL COMPARISON: PRODUCTIVITY ASSUMPTIONS

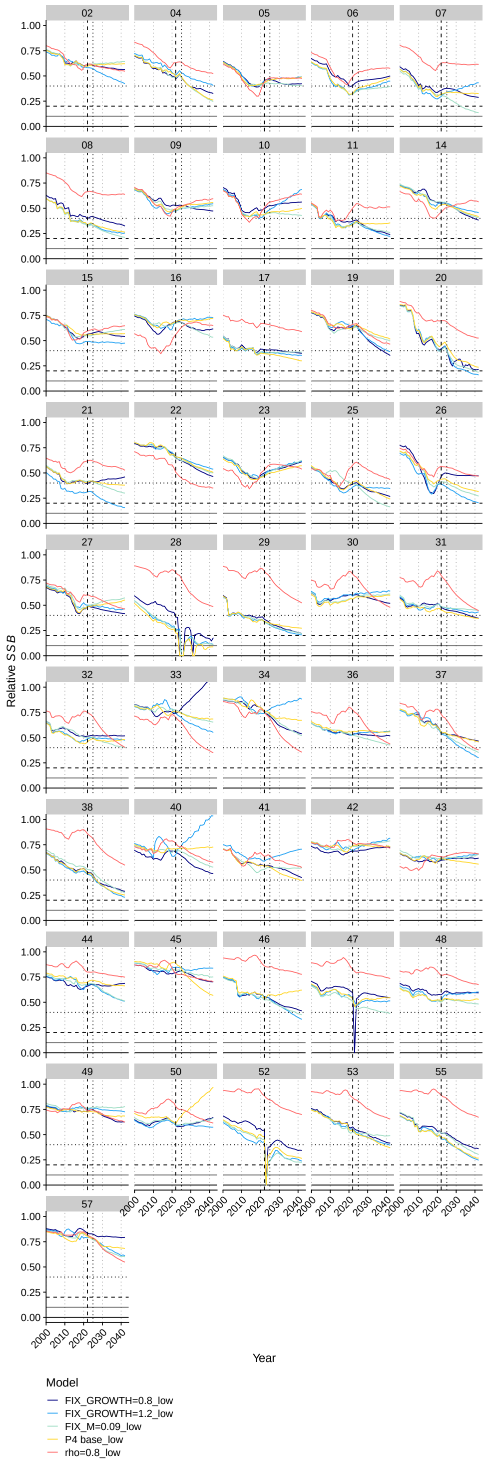

Figure C-1: Simulated relative spawning stock biomass (SSB) trend for pāua, comparing models (only medians from simulations are compared) assuming different productivity parameters, with management according to the tested control rules each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

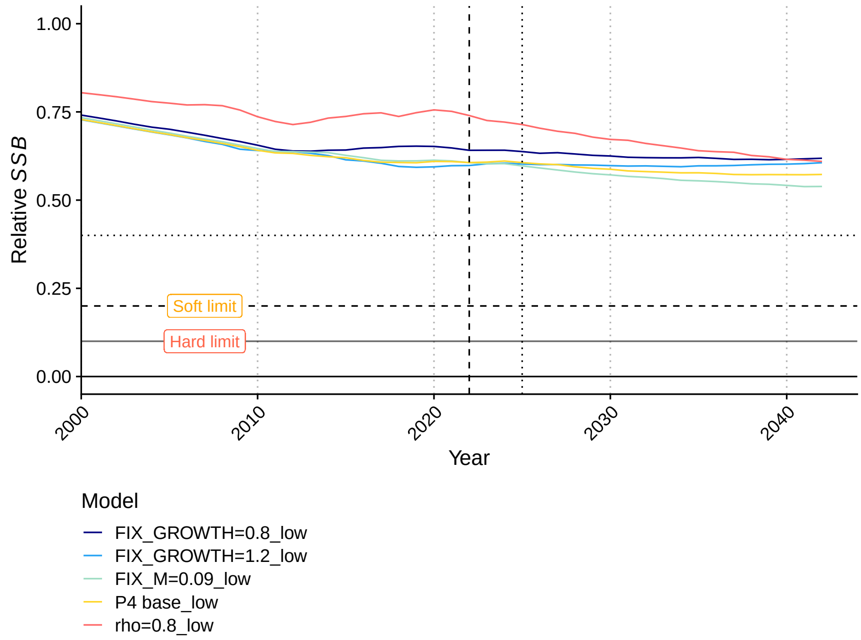

Figure C-2: Simulated relative spawning stock biomass (SSB) trend for pāua, comparing models (only medians from simulations are compared) assuming different productivity parameters, with management according to the tested control rules in quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

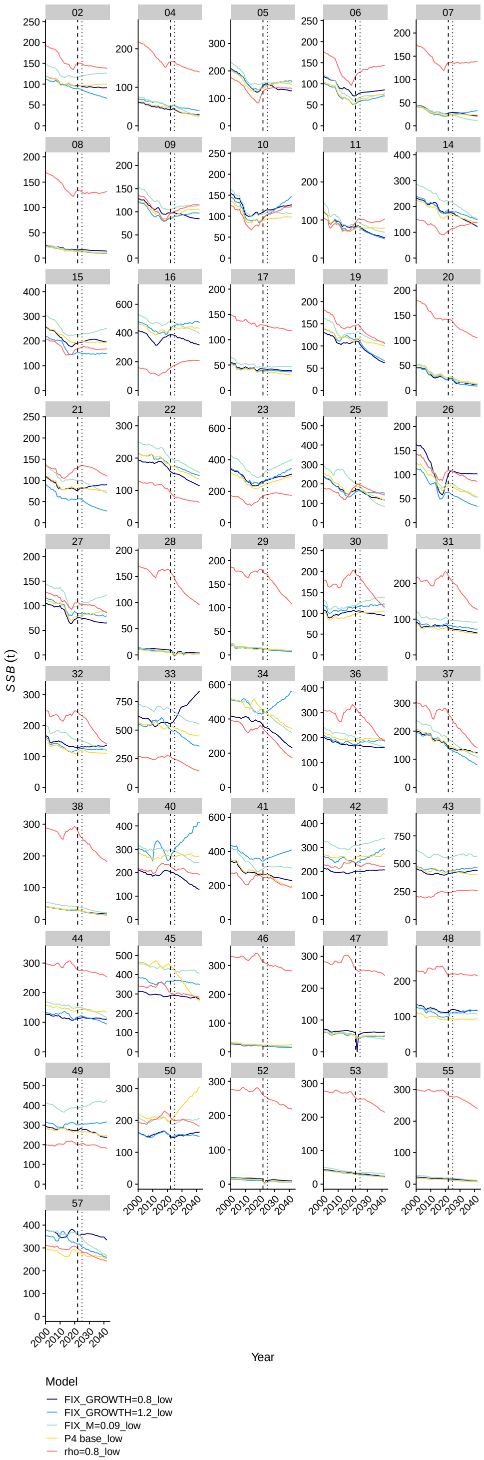

Figure C-3: Simulated spawning stock biomass (SSB; in tonnes) trend for pāua, comparing models (only medians from simulations are compared) assuming different productivity parameters, with management according to the tested control rules each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

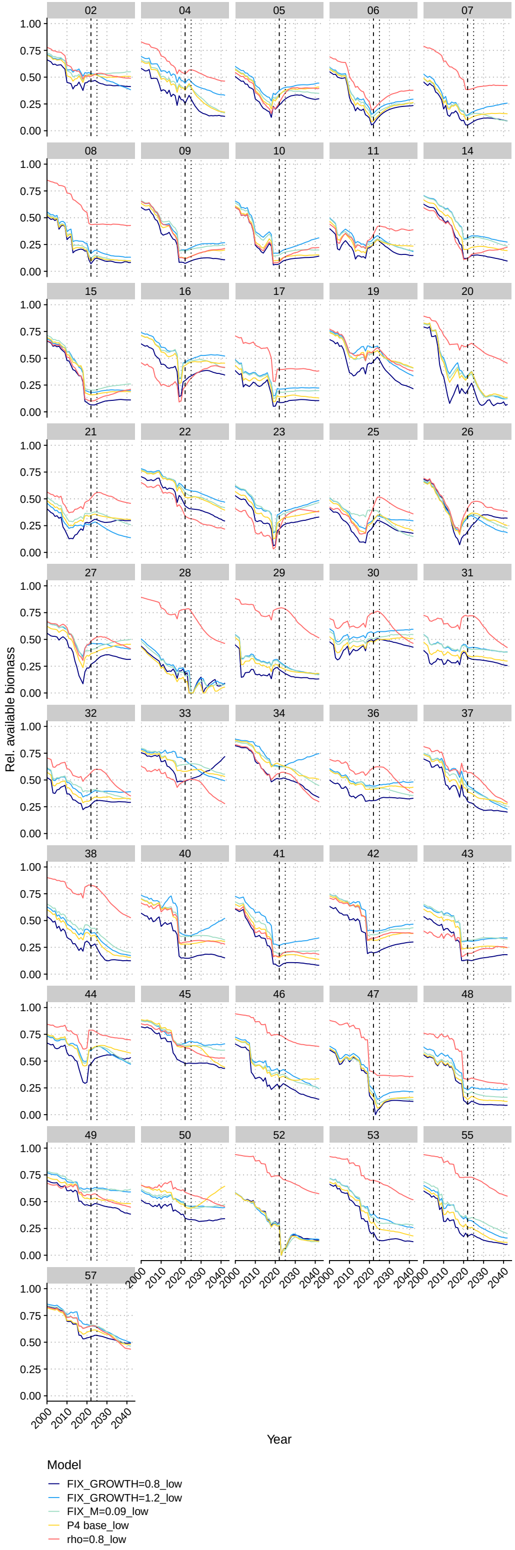

Figure C-4: Simulated relative available biomass trend for pāua, comparing models (only medians from simulations are compared) assuming different productivity parameters, with management according to the tested control rules each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

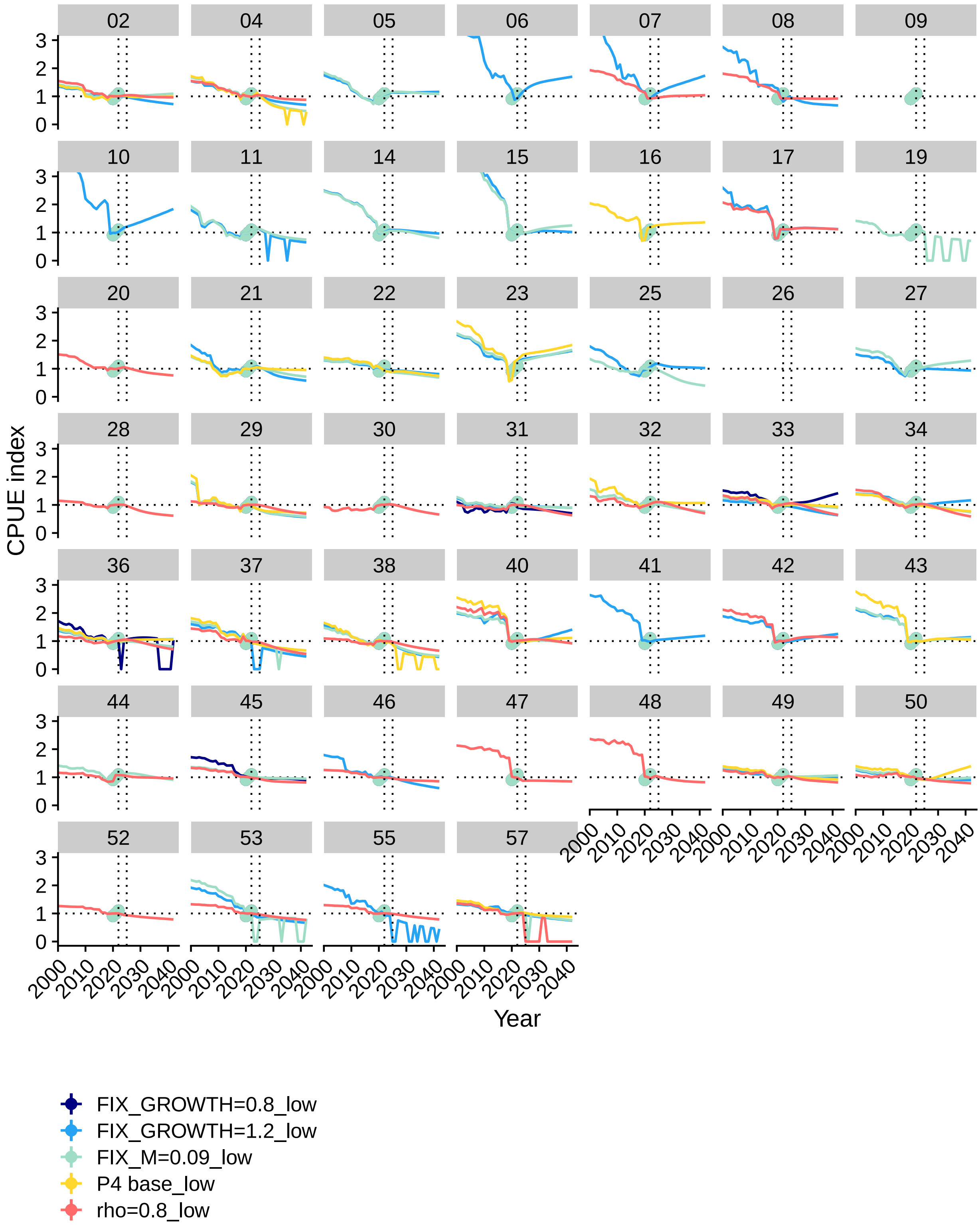

Figure C-5: Simulated relative spawning stock biomass (SSB) trend for pāua, comparing models (only medians from simulations are compared) assuming different productivity parameters, with management according to the tested control rules each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. Management Procedure Evaluation projections are indicated as a new CPUE type.

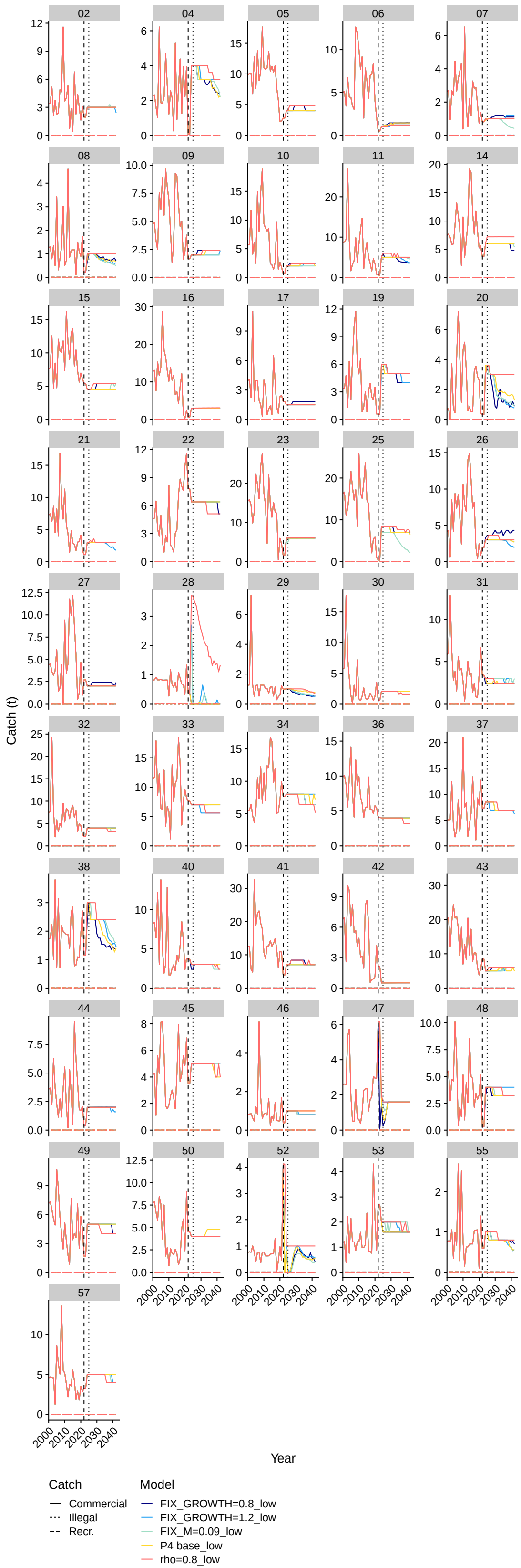

Figure C-6: Assumed and simulated catch, comparing models (only medians from simulations are compared) assuming different productivity parameters, with management according to the tested control rules each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule.

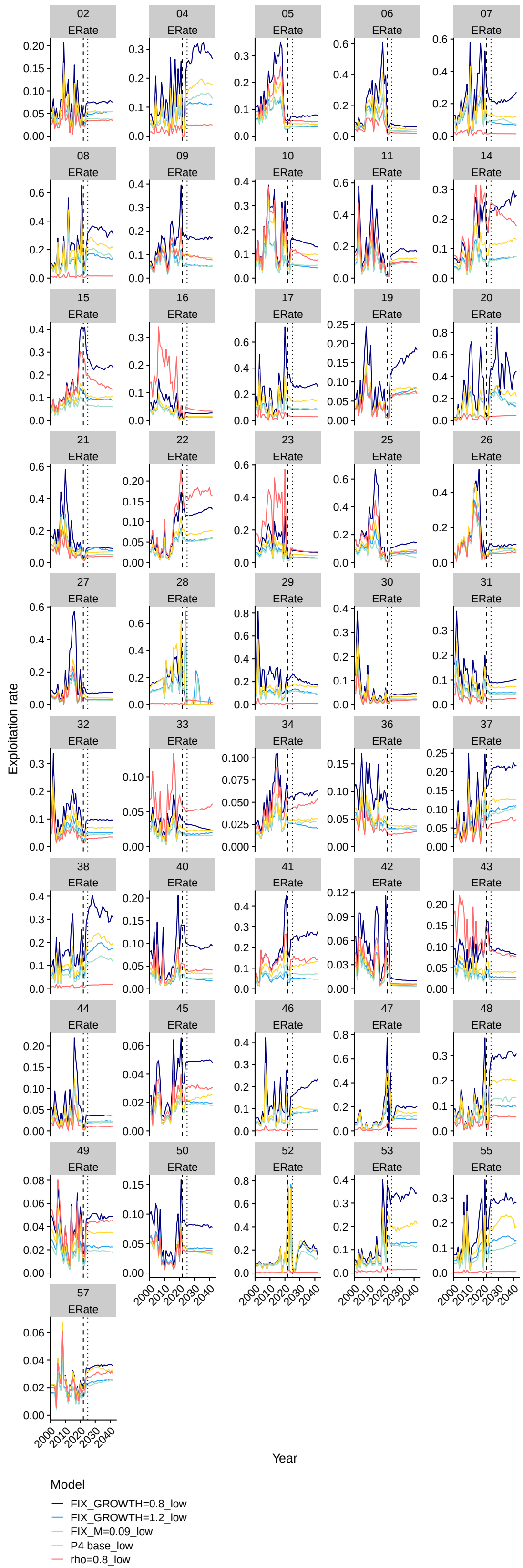

Figure C-7: Simulated exploitation rate (median line), comparing models (only medians from simulations are compared) assuming different productivity parameters, with management according to the tested control rules each statistical area of quota management area PAU 4. Dashed vertical line shows the beginning of simulated trends based on the assessed harvest control rule, dotted vertical line shows the tested limit of validity (5 years) of the tested rule. The final projection year was 2041.

Table C-1: Performance of tested management procedures, comparing management procedures for quota management area (QMA) PAU 4. Results are shown aggregated across the overall QMA. SSB, spawning stock biomass; CPUE, catch-per-unit-effort.

Model	Region	Mean rel. SSB (2026)	Mean rel. SSB (2041)	P(rel. SSB (2026) > 0.4)	P(rel. SSB (2041) > 0.4)	P(relSSB (2026) < 0.2)	P(relSSB (2041) < 0.2)	P(rel. SSB (2026) < 0.1)	P(rel. SSB (2041) < 0.1)	mean rel. SSB (2021–2041)	Mean catch (kg)	Mean CPUE(kg/h)
P4 base_low	All	0.61	0.58	1.00	1.00	0.00	0.00	0.00	0.00	0.59	153212.75	104.81
rho=0.8_low	All	0.71	0.62	1.00	0.93	0.00	0.00	0.00	0.00	0.66	161019.54	117.41
FIX_GROWTH=0.8_low	All	0.64	0.64	1.00	1.00	0.00	0.00	0.00	0.00	0.63	153799.36	113.14
FIX_GROWTH=1.2_low	All	0.60	0.61	1.00	1.00	0.00	0.00	0.00	0.00	0.60	151373.31	103.18
FIX_M=0.09_low	All	0.60	0.54	1.00	1.00	0.00	0.00	0.00	0.00	0.57	149276.58	99.82