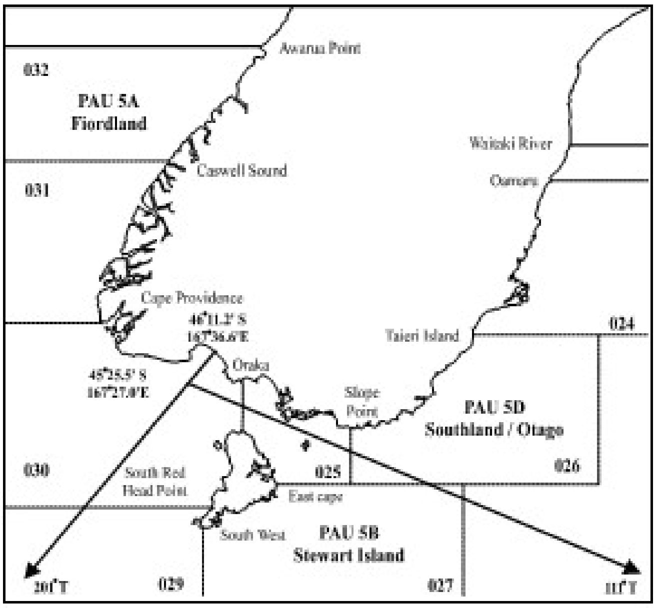
PĀUA (PAU 5D) - Southland / Otago

(*Haliotis iris*)
Pāua



1. FISHERY SUMMARY

Before 1995, PAU 5D was part of the PAU 5 QMA, which was introduced into the QMS in 1986 with a TACC of 445 t. As a result of appeals to the Quota Appeal Authority, the TACC increased to 492 t for the 1991–92 fishing year; PAU 5 was then the largest QMA by number of quota holders and TACC. Concerns about the status of the PAU 5 stock led to a voluntary 10% reduction in the TACC in 1994–95. On 1 October 1995, PAU 5 was divided into three QMAs (PAU 5A, PAU 5B, and PAU 5D; see figure above) and the TACC was divided equally among them; the PAU 5D quota was set at 148.98 t.

On 1 October 2002 a TAC of 159 t was set for PAU 5D, comprising a TACC of 114 t, customary and recreational allowances of 3 t and 22 t respectively, and an allowance of 20 t for other mortality. The TAC and TACC have been changed since then, but customary, recreational and other mortality allowances have remained unchanged (Table 1).

Table 1: Total allowable catches (TAC, t) allowances for customary fishing, recreational fishing, and other sources of mortality (t) and Total Allowable Commercial Catches (TACC, t) declared for PAU 5 and PAU 5D since introduction to the QMS.

Year	TAC	Customary	Recreational	Other mortality	TACC
1986–1991*	-	-	-	-	445
1991–1994*	-	-	-	-	492
1994–1995*	-	-	-	-	442.8
1995–2002	-	-	-	-	148.98
2002–2003	159	3	22	20	114
2003–present	134	3	22	20	89

*PAU 5 TACC figures

1.1 Commercial fishery

The fishing year runs from 1 October to 30 September. On 1 October 2001, it became mandatory to report catch and effort on Paua Catch Effort Landing Return (PCELR) forms using fine-scale reporting areas that had been developed by the New Zealand Pāua Management Company for their voluntary logbook programme (Figure 1). Since 2010, the commercial industry has adopted some voluntary management initiatives which include raising the minimum harvest size for commercial fishers over specific statistical reporting areas. The industry has also voluntarily closed, to commercial harvesting, specific areas that are of high importance to recreational pāua fishers. In recent years commercial fishers have been voluntarily shelving a percentage of their Annual Catch Entitlement (ACE), which is reflected by the annual catch landings falling below the TACC (Figure 2, Table 2).

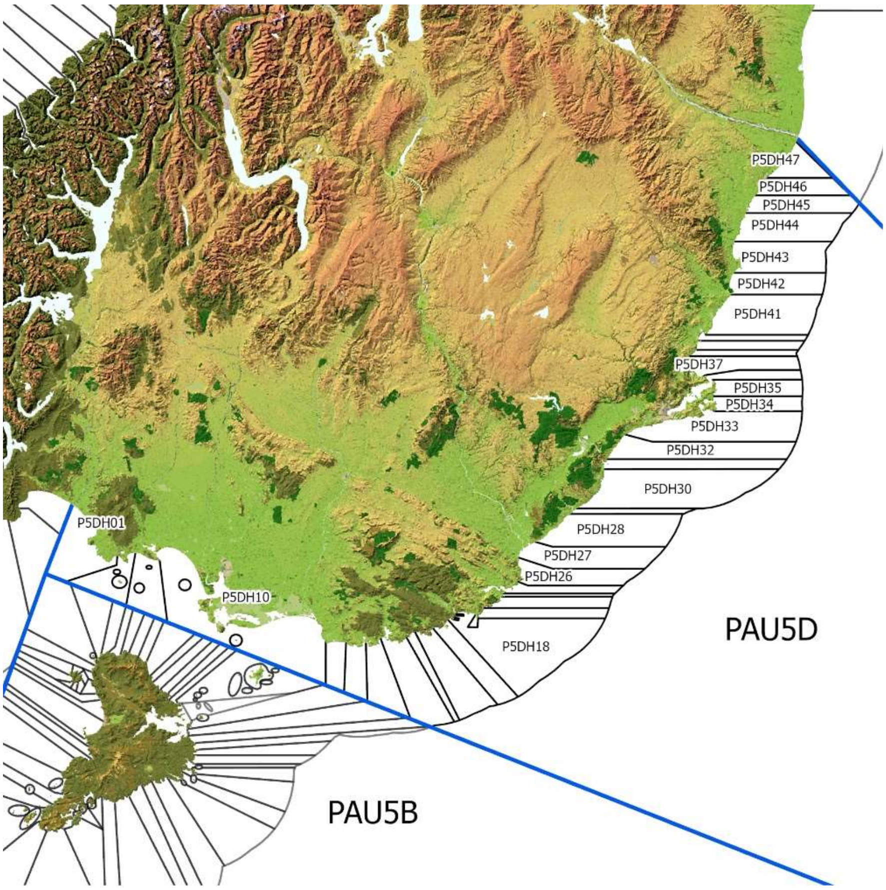


Figure 1: Map of fine scale statistical reporting areas for PAU 5D.

Commercial landings for PAU 5D are shown in Table 2 and Figure 2. Landings matched the TACC until 2012–13, and then declined to an average of 56 t in 2018–19 and 2019-20.

Table 2: TACC and reported landings (t) of pāua in PAU 5D from 1995–96 to the present.

Year	Landings	TACC
1995–96	167.42	148.98
1996–97	146.6	148.98
1997–98	146.99	148.98
1998–99	148.78	148.98
1999–00	147.66	148.98
2000–01	149.00	148.98
2001–02	148.74	148.98
2002–03	111.69	114.00
2003–04	88.02	89.00
2004–05	88.82	89.00
2005–06	88.93	89.00
2007–08	88.98	89.00
2006–07	88.97	89.00
2008–09	88.77	89.00
2009–10	89.45	89.00
2010–11	88.70	89.00
2011–12	89.23	89.00
2012–13	87.91	89.00
2013–14	84.59	89.00
2014–15	71.87	89.00
2015–16	65.95	89.00
2016–17	63.12	89.00
2017–18	62.48	89.00
2018–19	55.55	89.00
2019–20	56.55	89.00
2020–21	57.78	89.00

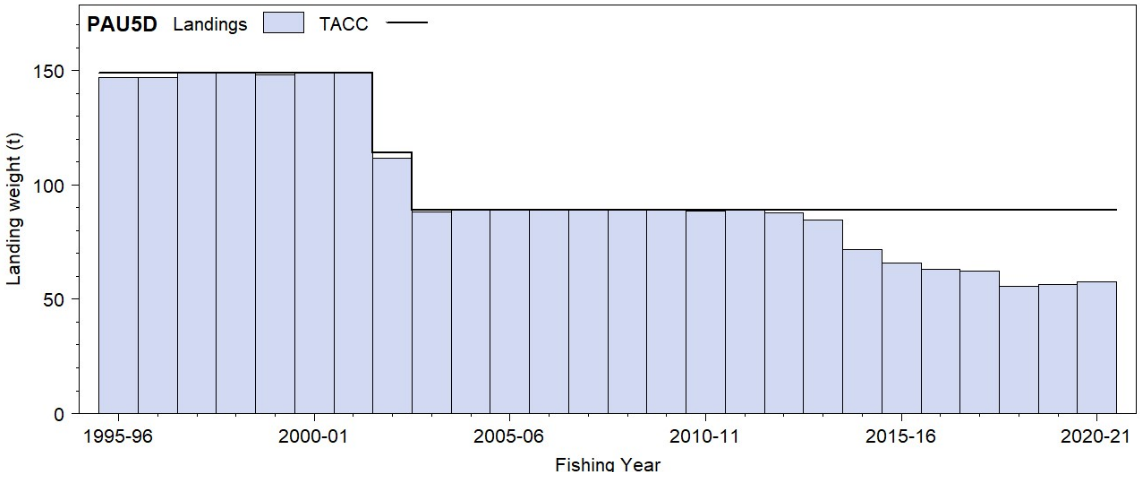


Figure 2: Reported commercial landings and TACC for PAU 5D from 1995–96 to present. For reported commercial landings in PAU 5 prior to 1995–96 refer to Figure 1 and Table 1 of the Introduction – Pāua chapter.

1.2 Recreational fisheries

The 'National Panel Survey of Marine Recreational Fishers 2011–12: Harvest Estimates' estimated that the recreational harvest for PAU 5D was 80 290 pāua and of 22.45 t with a CV of 30% (Wynne-Jones et al 2014). The National Panel Survey was repeated in the 2017–18 fishing year (Wynne-Jones et al 2019). The estimated recreational catch for that year was 55 pāua and 19.28 tonnes with a CV of 21%.

For the purpose of the 2019 stock assessment model, the SFWG agreed to assume that the recreational catch in 1974 was 2 t and that it increased linearly to 10 t by 2005, where it has remained unchanged to date. For further information on recreational fisheries refer to the Introduction – Pāua chapter.

1.3 Customary fisheries

Pāua is a taonga species and as such there is an important customary use of pāua by Maori for food, and the shells have been used extensively for decorations and fishing devices.

For information on customary catch regulations and reporting refer to the Introduction – Pāua chapter.

Estimates of customary catch for PAU 5D are shown in Table 3. These numbers are likely to be an underestimate of customary harvest as only the catch approved and harvested in numbers is reported in the table. In addition, many tangata whenua also harvest pāua under their recreational allowance and these are not included in records of customary catch.

Table 3: Fisheries New Zealand records of customary harvest of pāua (approved and reported in numbers) in PAU 5D since 2000-01. – no data.

	Numbers	
Fishing year	Approved	Harvested
2000–01	665	417
2001–02	5 530	3 553
2002–03	2 435	1 351
2003–04	–	–
2004–05	–	–
2005–06	1 560	1 560
2006–07	2 845	2 126
2007–08	5 600	5 327
2008–09	6 646	6 094
2009–10	4 840	4 150
2010–11	15 806	15 291
2011–12	7 935	7 835
2012–13	10 254	8 782
2013–14	5 720	5 358
2014–15	–	–
2015–16	15 922	13 110
2016–17	3 676	3 576
2017–18	3 588	3 310
2018–19	950	894
2019–20	6 905	6 439
2020–21	9 247	9 020

For the purpose of the stock assessment model, the SFWG agreed to assume that, for PAU 5D, the customary catch has been constant at 2 t from 1974 to the current stock assessment. The reported customary catch in 2018–19 was 894 kg.

1.4 Illegal catch
For the purpose of the stock assessment model, the SFWG agreed to assume that, for PAU 5D, illegal catches have been constant at 10 t from 1974 to the current stock assessment. For further information on illegal catch refer to the Introduction – Pāua chapter.

1.5 Other sources of mortality
For further information on other sources of mortality refer to the Introduction – Pāua chapter.

2. BIOLOGY

For further information on pāua biology refer to the Introduction – Pāua chapter. A summary of biological parameters used in the PAU 5D assessment is presented in Table 4.

3. STOCKS AND AREAS

For further information on stocks and areas refer to the Introduction – Pāua chapter.

Table 4: Estimates of biological parameters (*H. iris*).

		Estimate	Source
1. Natural mortality (*M*)			
		0.15(0.12-0.19)	Median (5–95% range) of posterior estimated by the base case model
2. Weight = a(length)^b (Weight in g, length in mm shell length)			
All	a	b	
	2.99 x 10^{-5}	3.303	Schiel & Breen (1991)
3. Size at maturity (shell length)			
		50% maturity at 91 mm (89–93)	Median (5–95% range) estimated outside of the assessment
		95% maturity at 103 mm (103–105)	Median (5–95% range) estimated outside of the assessment
4. Estimated annual growth increments (both sexes combined)			
	16.65 (15.96–24.29)	4.57 (3.27–6.40)	

4. STOCK ASSESSMENT

The stock assessment was implemented as a length-based Bayesian estimation model, with uncertainty of model estimates investigated using the marginal posterior distributions generated from Markov chain-Monte Carlo simulations. The most recent stock assessment was conducted for the fishing year ended 30 September 2018. A base case model (0.0 - referred to as the reference model henceforth) was chosen from the assessment. Data weighting had the strongest impact on assessment outcomes, and a range of scenarios with varying weights for CPUE and commercial length-frequency data were explored. QMA specific growth patterns remain highly uncertain due to high spatial variability in growth and relatively low spatial coverage of the tag-recapture programme to estimate pāua growth. This uncertainty translates into uncertainty about stock status and stock trajectories.

4.1 Estimates of fishery parameters and abundance indices
Parameters estimated in the assessment model and their assumed Bayesian priors are summarized in Table 5.

Table 5: A summary of estimated model parameters, lower bound, upper bound, type of prior, (U, uniform; N, normal; LN = lognormal; Beta = beta distribution), mean and CV of the prior.

Parameter	Prior	μ	sd	Bounds Lower	Upper
ln(*R0*)	LN	exp(13.5)	0.5	10	20
D_{50}(Length at 50% selectivity for the commercial catch)	LN	123	0.05	100	145
$D_{95\text{-}50}$(Length between 50% and 95% selectivity the commercial catch)	LN	5	0.5	0.01	50
Steepness (h)	Beta				
ϵ (Recruitment deviations)	LN	0	2	0	-

The observational data were:
1. A standardised CPUE series covering 1989–2018 based on combined CELR and PCELR data.
2. A commercial catch sampling length frequency series for 1991–93, 1997, 1999–2016
3. Tag-recapture length increment data.
4. Maturity at length data

4.1.1 Relative abundance estimates from standardised CPUE analyses

The 2019 stock assessment used a combined series of standardised CPUE indices that included both CELR data covering 1990–2001, and PCELR data covering 2002–2018. CPUE standardisation was carried out using a Bayesian Generalised Linear Mixed Model (GLMM) which partitioned variation among fixed (research strata) and random variables, and between fine-scale reporting (PCELR) and larger scale variables (CELR). The variation explained by fine-scale variables (e.g. fine scale statistical areas or divers) in PCELR data was considered unexplained in the CELR portion of the model and therefore added to observation error.

For the CELR data, there was ambiguity in what was recorded for estimated daily fishing duration: either incorrectly recorded as hours per diver, or correctly as total hours for all divers. For PAU 5D, fishing duration appeared to have been predominantly recorded as hours per diver. A model-based correction procedure was developed to detect and correct for misreporting, using a mixture model that determines the characteristics of each reporting type by fishing crew and assigns years to correct (reporting for all divers) or incorrect (by diver) reporting regimes with some probability. Only records with greater than 95% certainty of belonging to one or the other reporting type were retained for further analysis.

CPUE was defined as the log of daily catch-per-unit-effort. Variables in the model were fishing year, FIN (Fisher Identification Number), Statistical Area (024, 026), dive condition, diver ID, and fine-scale statistical area. Variability in CPUE was mostly explained by differences among divers and crews (FINs), with dive conditions strongly affecting CPUE. The CPUE data showed a slight decline in the 1990s followed by a strong downturn in CPUE in the early 2000s, followed by a strong recovery of CPUE to levels above those seen in the early 1990s (Figure 3). However, CPUE subsequently declined to below-average levels, where it has remained relatively stationary since 2013. In some circumstances, commercial CPUE may not be proportional to abundance because it is possible to maintain catch rates of pāua despite a declining biomass. This occurs because pāua tend to aggregate and divers move among areas to maximise their catch rates. Apparent stability in CPUE should therefore be interpreted with caution. The assumption of CPUE being proportional to biomass was investigated using the assessment model.

4.1.2 Relative abundance estimates from research diver surveys

The relative abundance of pāua in PAU 5D has also been estimated from a number of independent research diver surveys (RDSI) undertaken in various years between 1994 and 2004. The survey strata (Catlins East and Catlins West) cover the areas that produced about 25% of the recent catches in PAU 5D. This data was not included in the assessment because there is concern that the data is not a reliable enough index of abundance and the data is not representative of the entire PAU 5D QMA.

Concerns about the ability of the data collected in the independent Research Dive surveys to reflect relative abundance instigated reviews in 2009 (Cordue 2009) and 2010 (Haist 2010). The reviews assessed the reliability of the research diver survey index as a proxy for abundance and whether the RDSI, when used in the pāua stock assessment models, results in model outputs that adequately reflect the status of the stocks. Both reviews suggested that outputs from pāua stock assessments using the RDSI should be treated with caution. For a summary of the review's conclusions refer to the Introduction – Pāua chapter.

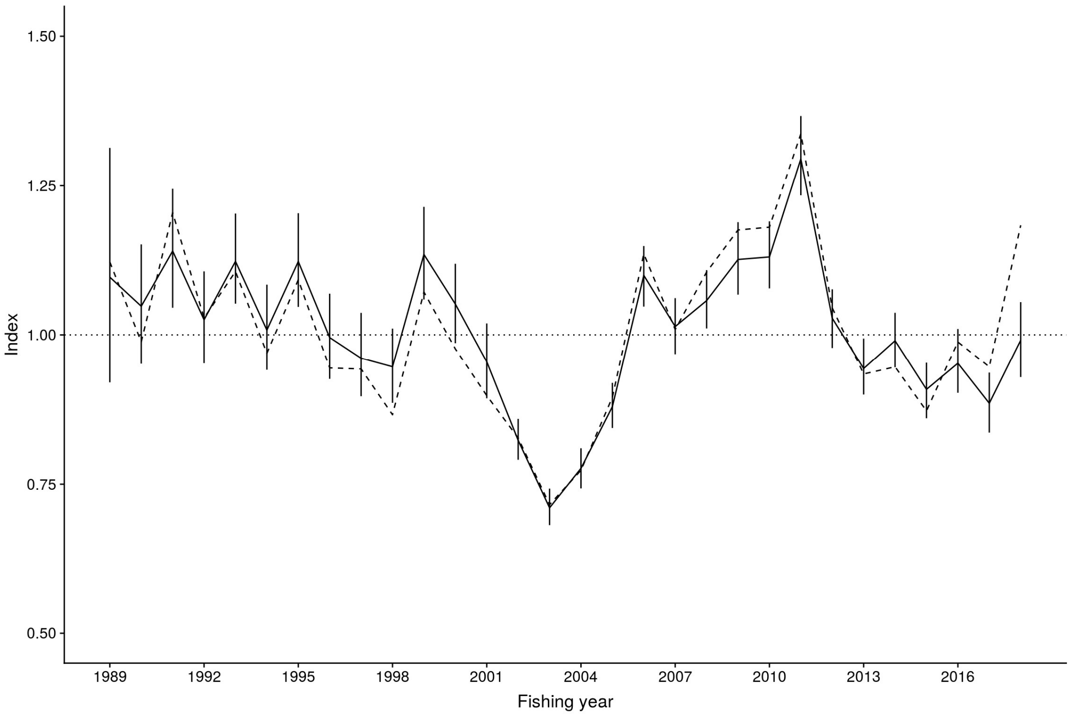


Figure 3:The standardised CPUE indices with 95% confidence intervals (solid line and vertical error bars) and unstandardized geometric CPUE (dashed line) for the combined CELR and the PCELR series.

4.2 Stock assessment methods

The 2019 PAU 5D stock assessment used the length-based population dynamics model first described by Breen et al (2003). PAU 5D was last assessed using data up to the 2015–2016 fishing year (Marsh & Fu 2017), and the most recent assessment uses data up to the 2017–2018 fishing year (Neubauer & Tremblay-Boyer 2019). Although the overall population-dynamics model remained unchanged, the most recent iteration of the PAU 5D stock assessment incorporates a number of changes to the previous methodology:

1. CPUE likelihood calculations reverted to predicting CPUE from beginning of year biomass since the previous change to mid-year predictions did not affect the assessment and caused potential for error and an increased computational burden.
2. A Bayesian statistical framework across all data inputs and assessments (MPD runs were not performed; all exploration was performed using full Markov Chain Monte Carlo runs).
3. The assessment model framework was moved to the Bayesian statistical inference engine Stan (Stan Development Team 2018), including all data input models (the assessment model was previously coded in ADMB).
4. Catch sampling length-frequency (CSLF) data handling was modified to a model-based estimation of observation error with partitioning between observation and process error for CSLF and CPUE, and use of a multivariate normal model for centred-log-ratio-transformed mean CSLF and observation error.
5. The data weighting procedure was to use a scoring rule (log score) and associated divergence measure (Kullbach-Liebler divergence) to measure information loss and goodness of fit for CPUE and CSLF.
6. Growth and maturation were fit to data across all QMAs outside of the assessment model, and the resulting mean growth and estimate of proportions mature at age were supplied as an informed prior on growth to the model; no growth or maturation data were explicitly fitted in the model.

The model structure assumed a single sex population residing in a single homogeneous area, with length classes from 70 mm to 170 mm, in groups of 2 mm. Growth is length-based, without reference to age, mediated through a growth transition matrix that describes the probability of each length class changing in each year. Pāua entered the partition following recruitment and were removed by natural mortality and fishing mortality.

The model simulates the population from 1965 to 2018. Catches were available for 1974–2018 although catches before 1995 must be estimated from the combined PAU 5 catch, and were assumed to increase linearly between 1965 and 1973 from 0 to the 1974 catch level. Catches included commercial, recreational, customary, and illegal catch, and all catches occurred within the same time step.

Recruitment was assumed to take place at the beginning of the annual cycle, and length at recruitment was defined by a uniform distribution with a range between 70 and 80 mm. The stock-recruitment relationship is unknown for pāua. However, the Shellfish Working Group agreed to use a Beverton-Holt stock-recruitment relationship, with steepness (h) estimated for this assessment.

Growth, maturation and natural mortality were also estimated within the model, although no fitting to raw data was performed, and all inputs were provided as priors with mean and observation error. The model estimated the commercial fishing selectivity, which was assumed to follow a logistic curve and to reach an asymptote.

The assessment proceeded iteratively by first replacing the previous growth formulation (i.e. fitting to growth data from PAU 5D only within the model) with an informed prior on mean growth and growth variability. Previous assessments noted that growth collected from a limited number of sites may not represent mean growth and true growth variability across the QMA. It was noted in the current assessment that PAU 5D growth data was almost exclusively from sites with very fast growth, and that alternative assumptions about growth lead to radically different estimates of stock status. To reflect uncertainty about true growth, a prior formulated from a South Island-wide meta-analysis was used in the model.

Providing less information about growth to the model meant that more weight was placed on CPUE and CSLF data, and it was found that data weights were now the most influential uncertainty in the model. Previous methods to weight datasets give more weight to CPUE data by default because CPUE has a more direct link to abundance than CSLF data, and one can argue a lower potential for process error. However, for pāua in particular, CPUE is often seen as a risky index of abundance (see qualifications below). The current assessment therefore does not favour either dataset *a priori*, but rather attempts to explore scenarios where either dataset has high weight relative to the other. To more accurately quantify model fit and information loss from each data source, a new procedure was developed based on the log scoring rule (a scoring rule quantifies the predictive quality of a model). The log score provides a base to weight datasets (i.e. to penalise deviation from any dataset) and to measure information loss from data (e.g. the estimated CPUE and observation error) to model quantities. Models with various divergence penalty configurations for CPUE and CSLF were introduced and the resulting model fit and divergence between model and input were noted until a set of models with satisfactory fits and deviations was found.

The reference model (model 0) excluded the RDSI and RDLF data, fitted the combined CPUE series and the mean CSLF and observation error, estimated process error for CPUE and CSLF, updated growth estimates within the model, and estimated M and steepness within the model. The data weights in this model led to slightly increased information loss from CSLF data relative to CPUE data, with satisfactory fits to both datasets.

The sensitivity trials carried out used lower weight for the CPUE indices and a more restrictive prior for M as opposed to the base-case.

The assessment calculates the following quantities from the marginal posterior distributions of various partitions of the biomass: the equilibrium (unfished) spawning stock biomass (SSB_0) assuming that recruitment is equal to the average recruitment, and the relative spawning and available biomass for 2018 (SSB_{2018} and B_{2018}^{Avail}) and for the projection (*Proj*) period (SSB_{Proj} and B_{proj}^{Avail}. This assessment also reports the following fishery indictors:

Relative SSB	Estimated spawning stock biomass in the final year relative to unfished spawning stock biomass
Relative B^{Avail}	Estimated available biomass in the final year relative to unfished available stock biomass

P(SSB_{2018} > 40% SSB_0)	Probability that the spawning stock biomass in 2018 was greater than 40% of the unfished spawning stock
P(SSB_{2018} > 20% SSB_0)	Probability that the spawning stock biomass in 2018 was greater than 20% of the unfished spawning stock (soft limit)
P(SSB_{Proj} > 40% SSB_0)	Probability that projected future spawning stock biomass will be greater than 40% of the unfished spawning stock given assumed future catches
P(SSB_{Proj} > 20% SSB_0)	Probability that projected future spawning stock biomass will be greater than 20% of the unfished spawning stock given assumed future catches
P(B_{Proj} > B_{2018})	Probability that projected future biomass (spawning stock or available biomass) is greater than estimated biomass for the 2018 fishing year given assumed future catches

4.3 Stock assessment results

The base case model suggested a relatively flat trend in spawning stock biomass over the past seven years, following a slow downwards trend from 2005 to 2011 (Figure 4). The base case also indicated a high probability that the stock is currently near the target spawning stock biomass (Table 6), with little to no probability that it is below the soft limit of 20% *SSB*. This inference was supported by all sensitivity runs (Table 6). Nevertheless, relative available biomass was markedly lower than the spawning stock biomass, meaning that a considerable part of the spawning biomass was below the minimum harvest size, and is therefore not accessible to the fishery.

Projections suggested relatively stable SSB for scenarios of current catch and 10% or 20% increased or decreased catch (Table 7). For all catch scenarios, available biomass was projected to slowly increase, although this increase is somewhat uncertain (there was a 60% likelihood of an increase in three years over current available biomass at current catch).

Two sensitivity scenarios were agreed as the main sensitivity scenarios that bracketed estimated stock status in the base-case run. The first scenario was the base case with a more restrictive prior for M (log-normal SD of 0.1 instead of 0.2) which forced M to a lower point in the assessment; it also led to lower recent stock status, all else being equal (Table 6; Figure 4). Nevertheless, this scenario also suggested a recent upturn in the fishery with increasing available biomass, despite a lower stock status estimate. This model run suggested a potentially stronger impact from recent shelving measures than the base case. Projections from this scenario largely agreed with those from the base-case.

Table 6: Model runs for the stock assessment of pāua in management area PAU 5D. Posterior quantities for data fits in terms of the Kullback-Leibler divergence (KLD) for catch-per-unit-effort (CPUE) and catch sampling length frequency (CSLF), stock status (relative spawning stock biomass), relative available biomass and probability of the stock status being above the soft limit (P(SSBproj > 20% SSB0). Numbers are posterior medians, with the 0.025 and 0.975 posterior quantiles in parentheses.

Run	KLD CPUE	KLD CSLF	Stock status	Available	P(SSB_{proj} > 20% SSB_0)
Base	0.67 (0.53;0.82)	0.73 (0.66;0.84)	0.40 (0.25;0.65)	0.25 (0.17;0.39)	1.00
Constrain M	0.68 (0.53;0.92)	0.74 (0.66;0.84)	0.36 (0.24;0.56)	0.23 (0.16;0.35)	1.00
Lower CPUE weight	0.84 (0.70;1.05)	0.73 (0.65;0.83)	0.44 (0.28;0.71)	0.29 (0.19;0.46)	1.00

The second main sensitivity scenario did not up-weight the CPUE and, therefore, only down-weighted CSLF data. This sensitivity scenario resulted in declining recent spawning stock biomass trends (Figure 4), despite resulting in slightly higher estimates for current stock status (Table 6). The declining trend continued for projections in this scenario regardless of the applied catch. For both main sensitivity scenarios, the probability of stock status being at or falling below the soft limit was close to zero over the timeframe of projections.

For a number of reasons (outlined below) reference points based on deterministic MSY or B_{MSY} are not currently used for managing pāua stocks and were therefore not calculated.

There are several reasons why deterministic B_{MSY} is not considered a suitable target for management of the pāua fishery. First, it assumes a harvest strategy that is unrealistic in that it involves perfect knowledge of catch and biology and perfect stock assessments (because current biomass must be known exactly in order to calculate target catch), a constant-exploitation management strategy with annual changes in TACC (which are unlikely to happen in New Zealand and not desirable for most stakeholders), and perfect management implementation of the TACC and catch splits with no under- or over-runs. Second, it assumes perfect knowledge of the stock-recruit relationship, which is actually very poorly known. Third, deterministic MSY is commonly much higher than realised catch for pāua stocks (e.g. Marsh & Fu 2017) and deterministic B_{MSY} is estimated at biomass levels corresponding to very low available biomass levels. Management based on deterministic MSY-based reference points would likely lead to biomass occasionally falling below 20% B_0, the default soft limit according to the Harvest Strategy Standard. Thus, the actual target needs to be above this theoretical deterministic biomass, but the extent to which it needs to be above has not been determined.

In the meantime, an interim target of 40% B_0 is used as a proxy for a more realistic interpretation of B_{MSY}.

Table 7: Projections for key fishery indicators from the base case model: probabilities of being above 40% and 20% of unfished spawning biomass (SSB) [P(SSB_{Proj} > 40% SSB_0) and P(SSB_{Proj} > 20% SSB_0)], the probability that SSB in the projection year is above current SSB, the posterior median relative to SSB, the posterior median relative available spawning biomass B_{Proj}^{Avail}, and the probability that the exploitation rate (U) in the projection year is above $U_{40\%\ SSB0}$, the exploitation rate that leads to 40% SSB_0. The total commercial catch (TCC) marked with * corresponds to current commercial catch under 35% shelving of the current TACC (89 t). Other TACC scenarios show 50% shelving (44.5 t), 20% shelving (71.2 t) and fishing at the current TACC. Simulation to equilibrium (assumed to have been reached after 50 projection years) are indicated with Eq. in the year column.

TACC (t)	Year	P(SSB_{Proj} > 40% SSB_0)	P(SSB_{Proj} > 20% SSB_0)	P(SSB_{Proj} > SSB_{2018})	Median rel. SSB_{Proj}	Median rel. B_{Proj}^{Avail}	P(U > $U_{40\%\ SSB0}$)
44.5	2018	0.52	1	0	0.41	0.46	0.46
	2019	0.51	1	0.39	0.42	0.48	0.31
	2020	0.52	1	0.45	0.43	0.5	0.26
	2021	0.53	0.99	0.49	0.44	0.52	0.23
	Eq.	0.63	0.87	0.61	0.52	0.53	0.24
57.85	2018	0.52	1	0	0.41	0.46	0.46
	2019	0.51	1	0.39	0.42	0.48	0.44
	2020	0.5	0.99	0.42	0.42	0.5	0.42
	2021	0.5	0.98	0.44	0.42	0.51	0.4
	Eq.	0.53	0.81	0.52	0.47	0.48	0.4
71.2	2018	0.52	1	0	0.41	0.46	0.46
	2019	0.51	1	0.39	0.42	0.48	0.54
	2020	0.48	0.99	0.39	0.41	0.49	0.53
	2021	0.46	0.96	0.41	0.41	0.5	0.53
	Eq.	0.46	0.75	0.44	0.42	0.42	0.57
89	2018	0.52	1	0	0.41	0.46	0.46
	2019	0.51	1	0.39	0.42	0.48	0.64
	2020	0.45	0.99	0.36	0.4	0.48	0.66
	2021	0.42	0.94	0.37	0.4	0.48	0.68
	Eq.	0.37	0.68	0.34	0.36	0.37	0.73

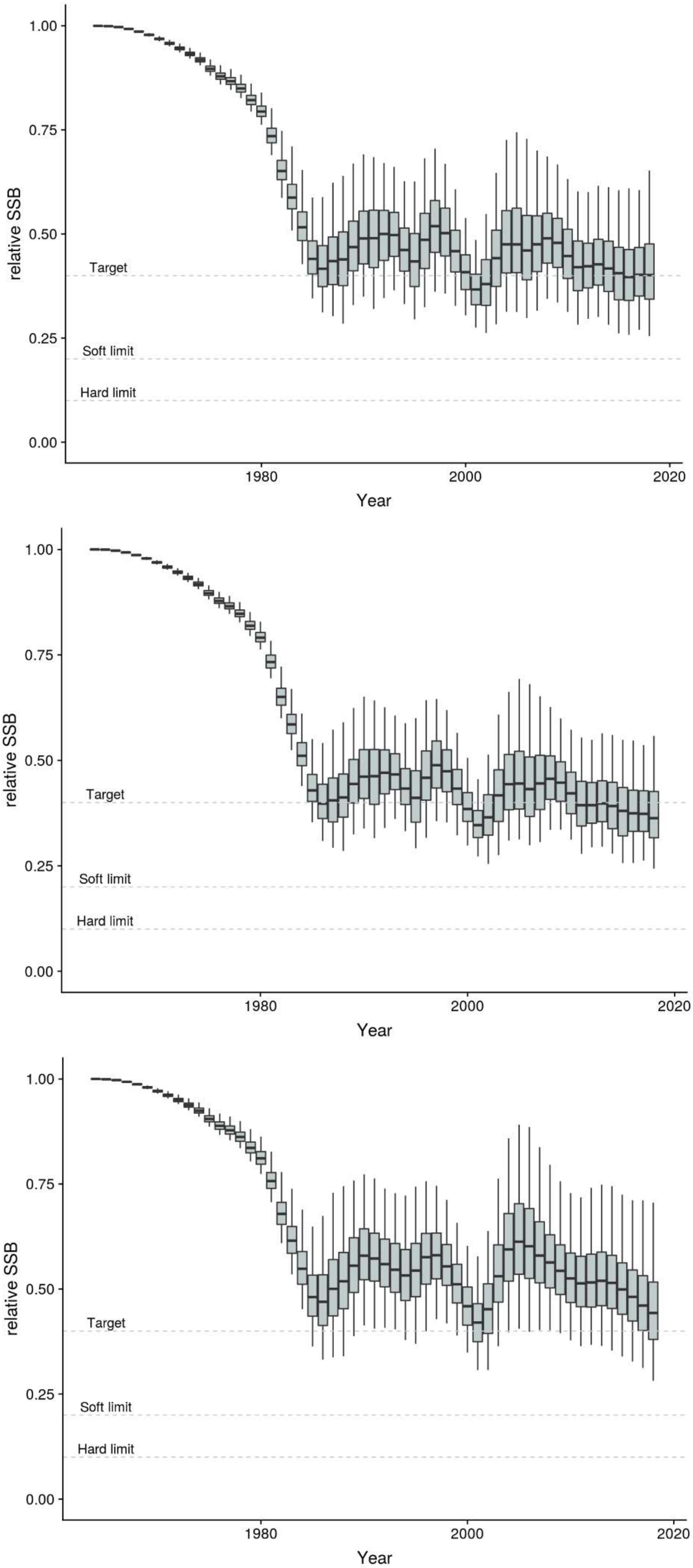


Figure 4: Posterior distributions of spawning stock biomass from the base case model, the sensitivity scenario with a more constrained prior on natural mortality (M), and the sensitivity scenario with lower weight on CPUE. The box shows the median of the posterior distribution (horizontal bar), the 25th and 75th percentiles (box), with the whiskers representing the 95% confidence range of the distribution.

4.4 Other factors

To run the stock assessment model a number of assumptions must be made, one of these being that CPUE is a reliable index of abundance. The literature on abalone fisheries suggests that this assumption is questionable and that CPUE is difficult to use in abalone stock assessments due to the serial depletion behaviour of fishers along with the aggregating behaviour of abalone. Serial depletion is when fishers consecutively fish-down beds of pāua but maintain their catch rates by moving to new unfished beds; thus CPUE stays high while the overall population biomass is actually decreasing. The aggregating behaviour of pāua results in the timely re-colonisation of areas that have been fished down, as the cryptic pāua, that were unavailable at the first fishing event, move to and aggregate within the recently depleted area. Both serial depletion and aggregation behaviour cause CPUE to have a hyperstable relationship with abundance (i.e. abundance is decreasing at a faster rate than CPUE) thus making CPUE a poor proxy for abundance. The strength of the effect that serial depletion and aggregating behaviour have on the relationship between CPUE and abundance in PAU 5D is difficult to determine. However, because fishing has been consistent in PAU 5D for a number of years and effort has been reasonably well spread, it could be assumed that CPUE is not as strongly influenced by these factors, relative to the early CPUE series.

The assumption of CPUE being a reliable index of abundance in PAU 5D can also be upset by exploitation of spatially segregated populations of differing productivity. This can conversely cause non-linearity and hyper-depletion in the CPUE-abundance relationship, making it difficult to track changes in abundance by using changes in CPUE as a proxy.

Another source of uncertainty is the data. The commercial catch is unknown before 1974 and is estimated with uncertainty before 1995. Major differences may exist between the catches we assume and what was actually taken. Non-commercial catch estimates, including illegal catch, are also poorly determined and could be substantially different from what was assumed.

The model treats the whole of the assessed area of PAU 5D as if it were a single stock with homogeneous biology, habitat and fishing pressure. The model assumes homogeneity in recruitment and natural mortality.

Heterogeneity in growth can be a problem for this kind of model (Punt 2003). Variation in growth is addressed to some extent by having a stochastic growth transition matrix based on increments observed in several different places; similarly the length frequency data are integrated across samples from many places. Thus, length frequency data collected from the commercial catch may not represent the available biomass represented in the model with high precision.

The effect of these factors is likely to make model results optimistic. For instance, if some local stocks are fished very hard and others not fished, recruitment failure can result because of the depletion of spawners, as spawners must breed close to each other, and the dispersal of larvae is unknown and may be limited. Recruitment failure is a common observation in overseas abalone fisheries, so local processes may decrease recruitment, an effect that the current model does not account for.

Another source of uncertainty is that fishing may cause spatial contraction of populations (Shepherd & Partington 1995), or that it may result in some populations becoming relatively unproductive after initial fishing (Gorfine & Dixon 2000). If this happens, the model will overestimate productivity in the population as a whole. Past recruitments estimated by the model might instead have been the result of serial depletion.

5. FUTURE RESEARCH CONSIDERATIONS

- Revisit PAU 5 catch reconstructions.
- Examine the effects of removing historical catches from areas that are now closed.
- Re-examine the diver surveys and length frequencies to determine their utility.
- Further investigate method for representing potential increases in catchability over time; e.g. a linear trend.

- Consider the need for more tagging in certain areas to fill gaps in growth data; e.g. Colac Bay and Moeraki.
- Further investigate data weighting procedures for pāua stocks. The prior on R_0 previously used in the PAU 5D assessment implied a prior on stock status that may have biased assessments of pāua stock status high. Check this further and determine whether it may also be an issue for other pāua stocks.

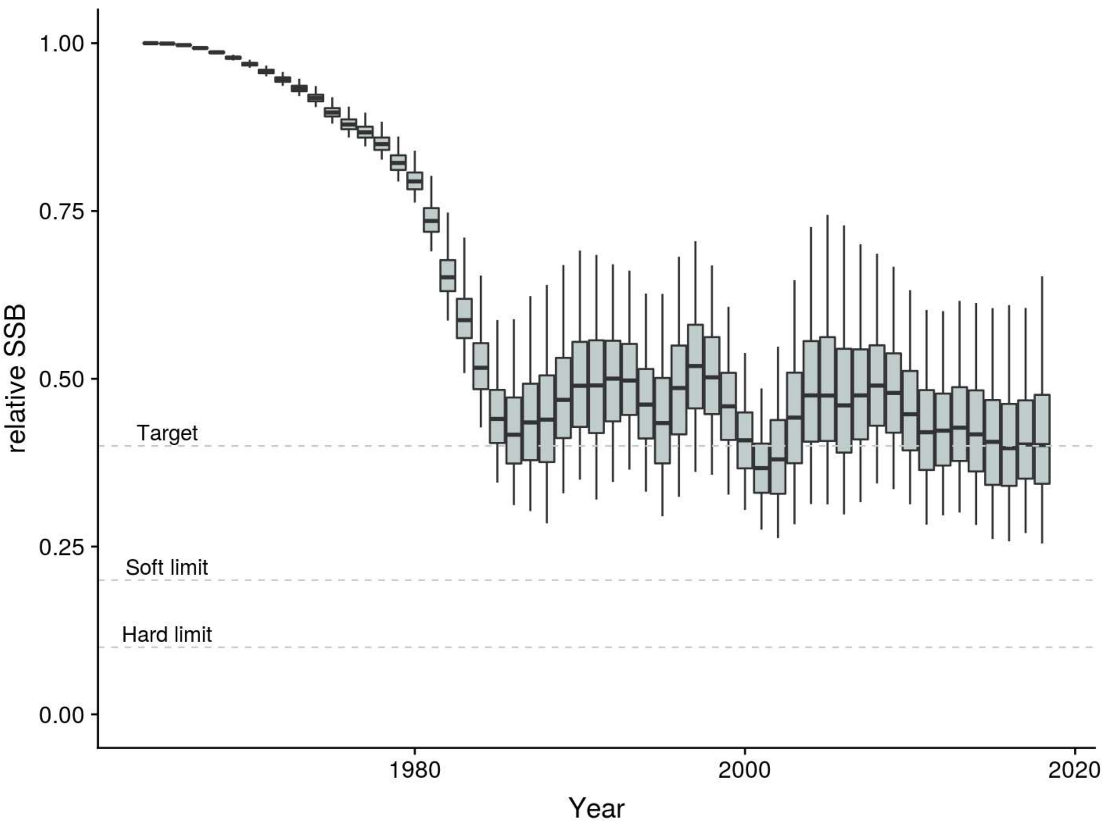
6. STATUS OF THE STOCK

Stock Structure Assumptions
PAU 5D is assumed in the model to be a discrete and homogenous stock

- **PAU 5D - *Haliotis iris***

Stock Status	
Year of Most Recent Assessment	2019
Assessment Runs Presented	Reference case MCMC
Reference Points	Interim Target: 40% B_0 Soft Limit: 20% B_0 Hard Limit: 10% B_0 Overfishing threshold: $U_{40\%B0}$
Status in relation to Target	B_{2018} was estimated to be 42% B_0. About as Likely as Not (40–60%) to be at or above the target
Status in relation to Limits	Very Unlikely (< 10%) to be below the soft limit and Very Unlikely (< 10%) to be below the hard limit.
Status in Relation to Overfishing	Overfishing is About as Likely as Not (40–60%) to be occurring.

Historical Stock Status Trajectory and Current Status



Posterior distributions of spawning stock biomass from the base case model. The box shows the median of the posterior distribution (horizontal bar), the 25th and 75th percentiles (box), with the whiskers representing the 95% confidence range of the distribution.

Fishery and Stock Trends	
Recent Trend in Biomass or Proxy	Biomass decreased up to about 1984 and has been fluctuating moderately around the target subsequently.
Recent Trend in Fishing Mortality or Proxy	Exploitation rate peaked in 2002 and has since declined.
Other Abundance Indices	Standardised CPUE generally declined until the early 2000s, recovered in the mid-2000s, and gradually decreased to a recent stable but below average level.
Trends in Other Relevant Indicators or Variables	Recruitment appears to pulse in approximately five year intervals, with two larger than average pulses in the mid-1990s and 2000. Increases in pāua areas closed to commercial fishing and voluntary increases in MHS both create buffers to fishing.

Projections and Prognosis	
Stock Projections or Prognosis	At the current catch level biomass is About as Likely as Not (40–60%) to remain at current levels. Under the current TACC, biomass is likely to decline in the short term.
Probability of Current Catch or TACC causing Biomass to remain below or to decline below Limits	Results from all model assessment runs presented suggest it is Very Unlikely (< 10%) that current levels of catch will cause a decline below the soft or hard limits.
Probability of Current Catch or TACC causing Overfishing to continue or to commence	About as Likely as Not (40–60%) for current catch; Very Likely (> 90%) for current TACC

Assessment Methodology and Evaluation		
Assessment Type	1- Full Quantitative Stock Assessment	
Assessment Method	Length based Bayesian model	
Assessment Dates	Latest: 2019	Next: 2022
Overall assessment quality (rank)	1 – High Quality	
Main data inputs (rank)	- Catch History - CPUE Indices early series - CPUE Indices later series - Commercial sampling length frequencies - Tag recapture data - Maturity at length data	2 – Medium or Mixed Quality: not believed to be fully representative of catch in the QMA 2 – Medium or Mixed Quality: not believed to be fully representative of CPUE in the QMA 1– High Quality 1 – High Quality 2 – Medium or Mixed Quality: not believed to be representative of the whole QMA 1 – High Quality
Data not used (rank)	- Research Dive survey indices - Research Dive length frequencies	3 – Low Quality: not believed to be a reliable indicator of abundance in the whole QMA 3 – Low Quality: not believed to be a reliable indicator of length frequency in the whole QMA
Changes to Model Structure and Assumptions	- Both CPUE series combined to form a single index - Calculations for the CPUE likelihood were reverted to predicting CPUE from beginning of year biomass since the previous change to mid-year predictions did not affect the	

	assessment and caused potential for error and increased computational burden. - A Bayesian statistical framework across all data inputs and assessments (i.e. MPD runs were not performed, all exploration was performed using full Markov Chain Monte Carlo). - The assessment model framework was moved to the Bayesian statistical inference engine Stan (Stan Development Team 2018), including all data input models (the assessment model was previously coded in ADMB). - Changed CSLF data handling to model-based estimation of observation error and partitioning between observation and process error for CSLF and CPUE, with use of a multivariate normal model for centred-log-ratio-transformed mean CSLF and observation error. - Changed data weighting procedure to use scoring rule (log score) and associated divergence measure (Kullbach-Liebler divergence) to measure information loss and goodness of fit for CPUE and CSLF. - Growth and maturation were fit to data across all QMAs outside of the assessment model, and the resulting mean growth and estimate of proportions mature at age were supplied as an informed prior on growth to the model; no growth or maturation data was explicitly fitted in the model.
Major Sources of Uncertainty	- Growth data were limited and may not be representative of growth within the entire QMA. This was mitigated by formulating a weakly informative prior about growth based on meta-analysis for all South Island pāua stocks. - Assuming CPUE is a reliable index of abundance for pāua - Sensitivity of the model to data weighting assumptions - Potential increases in q

Qualifying Comments
Uncertainties in the input data and model structure necessitate caution in the interpretation of the assessed status of the stock. However, the high MHS relative to length-at-maturity (along with closed areas) means that a relatively large proportion of the spawning stock is not available to the fishery and provides a buffer from the effects of fishing for the stock.

Fishery Interactions
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6. FOR FURTHER INFORMATION

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