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Assessing the performance of pāua (*Haliotis iris*) fisheries using GPS logger data

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The pāua *Haliotis iris* dive-logger data collection programme is an industry-led initiative aimed at achieving near real-time monitoring of the fishery. The dive loggers record the position, depth, and duration of individual dives, and allow the individual catch to be recorded. This detailed data recording is expected to allow the management of the fishery to be at finer spatial and temporal scales than is currently possible.

Here, we provide a first description of the dive-logger programme. We assessed the current coverage of the fishery by the logger programme by comparing dive-logger data with data reported on Pāua Catch Effort and Landing Return (PCELR) forms. To determine whether the dive-logger programme is relevant for fisheries management, we used Bayesian linear mixed models to gain an understanding of the relationship between logger-derived effort and catch data, both at large scales (using daily records from all Quota Management Areas (QMAs) and years) and small scales (catches and individual dives aggregated to 1-hectare (ha; 10 000 m^2) hexagons).

We found that an increasing number of divers participated in the data-logger programme in the period from the 2010–11 to the 2013–14 fishing year. The catch recorded on data loggers also covered an increasing percentage of the total catch of the pāua fishery, including more than 50% of the total catch in QMAs PAU 7 and PAU 3 in 2012–13 and 2013–14. Some limitations remain, both with reporting (erroneous diver identifiers or catch reported) and with the logger hardware (e.g., missing locations); however, the quality of the data are improving as the coverage increases.

The data provided insights into dive patterns within QMAs, which, although variable, showed some consistent trends towards longer and shallower dives. Models at both large and small scales suggested that dive variables, especially bottom time (the time spent diving relative to the total fishing time), were strongly related to catch. At equivalent total effort (total fishing time), increased bottom times thus predicted increased catches. From the modelling, we recommend bottom time (relative to total fishing time) as a useful indicator of fishery status.

Spatial patterns in the fishery were also investigated using areas and effort concentration measures calculated from kernel utilisation densities (KUDs). On large scales, patchy diving within the total area searched over the day was correlated with lower catches, whereas on the hexagon scale, patchy diving was correlated with higher catches, possibly due to diving on pāua aggregations. We suggest that daily area and concentration indices could serve as indicators of trends in the fishery if monitored over time.

Overall, the logger data provide considerable information about the fishery, and are likely to provide fishery-relevant data that can be used to gain an understanding of patterns and trends in the fishery. As both the quality of the data and the volume of data increase, the proposed metrics will become more useful, and more complex metrics such as spatial catch-per-unit-effort (CPUE) can be constructed to identify local depletion. To illustrate this potential, we estimated a CPUE index at both statistical-area and 1-ha hexagon scales. This estimation showed up to fourfold differences in CPUE among statistical areas within QMAs.

1. INTRODUCTION

Pāua (*Haliotis iris*) are one of New Zealand's most valuable seafood resources. Pāua fisheries are currently managed under the Quota Management System (QMS), involving the setting of a minimal legal size (MLS) and a Total Allowable Commercial Catch (TACC) as two of the management tools used within each Quota Management Area (QMA; Ministry for Primary Industries 2012). While QMAs are regional-scale areas (covering hundreds of kilometres of coastline), pāua populations may be spatially structured over much smaller spatial scales (kilometres or less) (Prince & Hilborn 1998, McShane et al.

1988) due to limited larval dispersal from local populations (McShane et al. 1988) and variation in pāua habitat. As a consequence, life-history parameters that are relevant to the fishery, such as growth and size-at-maturity, may also vary at kilometre scales (McShane & Naylor 1995).

In pāua stock assessments, the primary indicator of stock abundance hs been fishery-dependent catch-per-unit-effort (CPUE) data (Fu 2012, Fu et al. 2012, Breen & Smith 2008). Analysis of CPUE currently relies on Pāua Catch Effort Landing Return (PCELR) forms, which record daily fishing time and catch per diver. Data from these forms are recorded in pāua statistical areas, which generally encompass tens of kilometres of coastline. With catch and effort reporting at this scale, it is possible for changes in CPUE measures to be masked by hyper-stability (where there is a non-linear relationship between abundance and CPUE, so abundance may decrease without a proportional decrease in CPUE). Hyper-stability can result from aggregating behaviour of pāua, causing them to form high-density patches even at low numbers (Prince & Hilborn 1998). Serial depletion, where divers sweep reefs and successively deplete local populations, as well as advances in technology and harvesting techniques, may further contribute to a hyper-stable CPUE index.

Pāua are predominantly harvested by free diving. To provide catch and effort information at reef scales, data loggers were recently introduced to the fishery. These data loggers consist of two units, a boat unit, used to record catch, boat position and daily dive conditions, and a so-called “turtle logger”. The turtle loggers fit into a pouch on the diver’s back. When the diver is underwater, the logger records dive profiles with a pressure sensor, and when the diver is on the surface, it records the location with a Global Positioning System (GPS) sensor. Information about the catch is provided by the boat loggers, which are used to record the position of each landed catch bag of pāua, and also to capture information about the daily catch by each diver. The development of the dive loggers followed the introduction of similar units to the Tasmanian abalone fishery (Mundy 2012). The unprecedented resolution of the data allowed for a detailed spatial analysis of diver data that produced valuable information on “hotspots” of fishing activity and patterns of resource use. In the context of Tasmanian fisheries, management strategies incorporating such fine scale data are currently being developed.

In addition to providing an improved qualitative understanding of the fishery, recent reviews (McCluskey & Lewison 2008) and analyses of fishing data (e.g., Hanchet et al. 2005) suggest that using fishing data logged at fine spatial and temporal scales can substantially improve effort calculation and resulting CPUE indices. The temporal and spatial resolution of the dive loggers make it possible, in theory, to test the hypothesis that divers adjust their fishing behaviour to maintain high average catch rates when there are declines in the resource. This adjustment may involve increases in dive depth and bottom times, and changes in search patterns (e.g., surface intervals). These differences may be seen as additional effort being expended beyond the baseline effort of standard fishing, and are a form of effort creep that would not be detectable from fishing activity time measures alone (Marchal et al. 2001, 2006).

Dive loggers were first used in New Zealand in 2010, and a fish-down experiment to validate the utility of logger data to estimate local catch rates was conducted in the summer of 2011–12 (Abraham 2012). During the experiment, an area previously closed to fishing (Fighting Bay) was fished to deplete local biomass. Abraham (2012) found that CPUE calculated from boat and turtle unit data was strongly related to biomass throughout the experiment, and hyper-stability was not observed, thus suggesting a basis for the use of dive-logger derived CPUE data in the fishery. Catch rates during the experiment, however, were well above those experienced in adjacent fishing grounds, and the relationship of CPUE to biomass may not be as clear at lower abundance. Furthermore, fishing was conducted during several bouts of 2–3 consecutive days, over several months. It is possible, that there may not have been sufficient time between fishing bouts to allow the remaining animals to aggregate and cause hyper-stability. Nevertheless, the experiment provided promising initial results about the relationship of catch rates to biomass, and valuable detail about dive patterns throughout the fishing activity.

In addition to collecting data at the spatial scale of individual dive events, the dive logger programme is expected to allow for timely monitoring of the fishery. Currently, assessments of stock status are typically carried out every three years using a length-based stock-assessment model. The logger data may allow for monitoring and management of the fishery at much shorter time scales. To explore whether the logger data will be useful for this purpose, it is necessary to understand how the signals in the logger data relate to the pāua catch. In this report, we provide a characterisation of the logger programme, and a demonstration of the signals in the data that are predictive of catch.

Specifically, the purpose of this study was to identify potential indicators of fishery status and performance that could provide early warning signs of local depletion of the resource. To investigate this possibility, we first (i) described the dive logger program and data set, and (ii) assessed the uptake and coverage to date by comparing to PCELR records. We then (iii) used logger derived data to investigate the influence of dive parameters such as dive depth and bottom time on CPUE on both large scales (encompassing all QMAs) and within QMA scales. We lastly (iv) used fine-scale spatial data from the loggers to construct local metrics of spatial utilisation, and investigated their relationship to local catch rates and catch per unit area.

2. METHODS

2.1 Data loggers

Pāua dive loggers were developed by Zebra-Tech (Nelson, New Zealand) and were introduced into the New Zealand commercial pāua fishery in October 2010. The dive loggers consist of two units, a boat unit used to record catch, boat position and daily dive conditions, and so-called “turtle logger”. The turtle loggers are compact units that fit in a pocket on the back of a diver’s wetsuit. When the diver is at the surface they record depth and position, using a GPS (in 10 s intervals), whereas underwater the loggers record the diver’s depth at 1 s intervals. The switch between recording modes is automated with a depth sensor that initiates surface and dive modes. The boat unit is used to record the location and time of catch bags being brought onboard (Figure 1).

The two units together are referred to as pāua dive loggers, and records from both are needed to calculate CPUE. Divers enter their Seafood Industry Training Organisation number (“SITO ID”) in the boat unit along the with number of their turtle unit (the “turtle ID”). Turtle units are thus assigned to individual divers, although turtle loggers do change owners on occasion. The turtle ID then links the turtle logger data to the boat data, and the SITO ID attributes the boat and turtle data to the diver. Failure to enter the correct turtle ID thus leads to difficulties linking the two data types, whereas entering the wrong SITO ID makes it difficult to attribute catch and effort data to a particular diver.

The development and deployment of the loggers is being managed by the fishing industry, through the Paua Industry Council Limited (PICL), supported by Seafood Innovations Limited (SIL) and the Ministry for Primary Industries (MPI). The current intention is to work towards complete monitoring of all commercial pāua diving in New Zealand.

2.2 The dive-logger database

Data were downloaded from the turtle logger and boat units as separate text logfiles, which were uploaded to a PostgreSQL database. Turtle unit IDs and diver SITO numbers were entered into the boat unit at the start of each day’s fishing. All daily records from the boat unit were matched with the daily dive records (from the turtle unit), based on records meeting the following criteria:

- The turtle unit ID entered into the boat unit matched the turtle unit’s ID (see previous section).
- The SITO ID entered into the boat unit matched the SITO number that the turtle unit had been assigned to.
- The bounding box of all of a day’s dives was within 50 m of the bounding box of all the bag landings for the day, and the dive events and bag events were not more than 30 minutes apart. This criterion (at the day level) ensured that wrong turtle IDs entered into a boat unit did not lead to

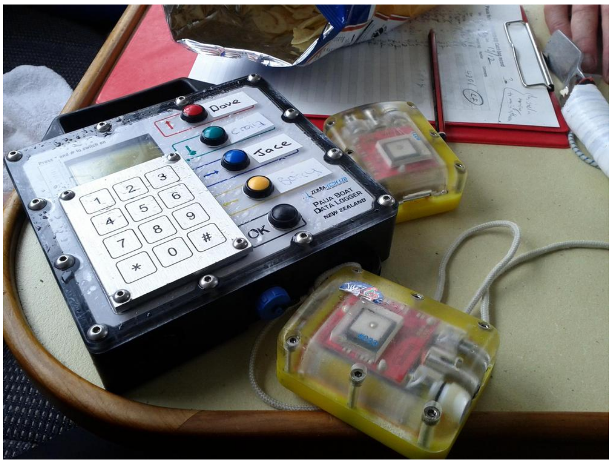


Figure 1: Pāua (*Haliotis iris*) dive loggers consisting of a larger boat unit (with buttons for recording catch bags and a key pad for entering catch weight and other data) and ”turtle loggers” carried by divers.

erroneous matches.

Once matched, the daily records (dive conditions, use of boat assistants), dive and bag events for each boat, diver, and day combination were aggregated into a diver-day, and the individual dive and bag events were stored as properties of the diver-day, through the following database tables:

- Individual dive table: bottom time, depth, start and end location and timestamps of individual dives. These records are linked to the diver-day, but can be linked to individual landed bags by attributing dives occurring prior to a bag being landed to that bag. The surface interval can be calculated as the interval between successive dives.
- Bag record table: location, weight (approximated as an equal fraction of the day’s total catch weight) and timestamp.
- Boat record table: boat locations, boat ID (linking boat units to owners).
- Fishing day table: diver (SITO) ID, turtle ID, boat assistant usage, swell, visibility.

To construct the dive table, we corrected occasional failures to switch from surface into dive mode by removing all records that indicated depths over 1 m, but where the dive sensor indicated that the diver was at the surface. Conversely, the turtle logger will occasionally switch into dive mode if the diver carrying the logger is immersed, even if the diver is not diving (i.e., are vertical in the water rather than swimming horizontally on the surface). To filter out such dive data, we defined a surface depth which was intended to represent the average immersion depth of the turtle logger at the surface. The surface depth was calculated using a moving window of 10-minute medians of depth records while the unit was in surface mode. Data recorded in dive mode were retained as actual dives if the dive depth was 20 cm below the corresponding 10-minute median surface depth.

A dive event was marked by a diver exceeding the depth threshold, and the bottom time was the period of time spent below this depth threshold (e.g., for a single dive, or summed within a spatial or temporal unit, such as over a day or within a hectare of the fishery; Table 1). We note here that any definition of a dive from depth data is somewhat arbitrary, as divers may be fishing at shallow depth, when they do not have to dive below the surface for extended periods of time.

2.3 Uptake and coverage of the logger programme

To be useful as a data source that can inform both voluntary management by the industry and, ultimately, to provide data to inform stock assessments, it is necessary that the logger data are representative of the fishery, both geographically and in terms of catch volume and fisher effort. We characterised the uptake and coverage of the dive loggers by i) investigating the number of divers participating in the programme, ii) the geographical coverage of the programme in terms of statistical areas visited by divers with turtle loggers, and iii) the proportion of catch that was taken by divers operating with data loggers.

We assessed the coverage of the logger programme using the PCELR records from MPI's *warehou* catch-effort database as a reference. Given that the information on diver identities was not identical between the PCELR records and the dive logger database, we matched turtle logger records to PCELR records using known diver names for logger units and diver initials on the PCELR forms. Both of these records contained errors (see Subsection 3.1 for a detailed discussion), and we applied heuristic matching rules to improve the overall matching of the data sources.

Data collected on PCELR forms are currently used to estimate CPUE indices of abundance, and these data are likely to remain the main dataset for informing stock assessments and formal management in the medium term. A potential immediate benefit of the turtle logger data is to give context to CPUE data from PCELR forms, as well as providing access to detailed spatial information. The latter can be used to refine sampling protocols for growth and maturation sampling, and provide information to spatially characterise the fishery. To investigate whether data recorded in the logger programme and data on PCELR forms are comparable for matching events, we compared effort and CPUE calculated from PCELR forms with corresponding metrics calculated from the dive-logger database.

Abraham (2012) used two measures of effort calculated from the turtle loggers: bottom time was calculated for each diver by assuming a surface depth (see above) and taking logger depth records below this depth to be dive events. The bottom times of individual dive events were then added up to an effort measure that was meant to reflect actual fishing activity. A second measure was derived by dividing the day into half-hour intervals and counting the intervals in which bags were landed (subsequently called boat activity time). This measure has the potential to account for differences in fishing styles (surface versus underwater search behaviour, for instance), that may lead to overly pronounced differences in effort from bottom time alone. It was found that CPUE calculated using this second approach to define effort most tightly corresponded with remaining biomass. In this project, we compared effort reported on PCELR forms (total time in water) to the two effort measures mentioned above, as well as to a third turtle logger-derived measure that was calculated by adding up half-hour intervals (as above) during which the turtle unit logged activity (the total fishing time; Table 1). We used this latter effort measure throughout as a proxy of the total time spent in the water over a day.

Table 1: Effort measures and their calculation used in the comparison of fishing effort reported on PCELR (Pāua Catch Effort Landing Return) forms (total time in water) and from dive-logger data.

Source	Effort measure	Calculation
PCELR	PCELR effort	Reported as total time in water per day (in h)
Data loggers	Bottom time	Sum of time spent diving (i.e., 20 cm below calculated surface depth) in a day or within a spatial unit (e.g., 1-hectare hexagon).
	Depth	Median dive depth for a day or within a spatial unit (e.g., 1-hectare hexagon).
	Surface interval standard deviation	Standard deviation of surface intervals between dives within a day or a spatial unit (e.g., 1-hectare hexagon).
	Boat effort	Sum of half-hour intervals within a day during which bags were landed (and reported on the boat unit).
	Total fishing time	Sum of half-hour intervals within a day during which the turtle logger was recording data.

2.4 Spatial and temporal patterns in dive parameters

2.4.1 Preparation of dive logger data

The data-logger database for the fishing years 2010–11 to 2013–14 consisted of nearly 1 million individual dive events as of 10 February 2014. An increasing number of dives have been recorded within all QMAs across years (Table 2), reflecting the increased uptake of the dive-logger programme within the pāua fishing industry.

Table 2: Number of individual dive event records (in thousands) by pāua Quota Management Area (QMA) and fishing year for the reporting period.

QMA	Fishing year					
	2009–10	2010–11	2011–12	2012–13	2013–14	Total
PAU 2	6.95	13.79	12.64	17.81	44.73	95.92
PAU 3	0.00	9.16	29.05	36.76	8.63	83.60
PAU 4	1.56	22.95	27.84	30.85	20.09	103.29
PAU 5A	0.00	3.90	5.96	10.53	8.69	29.08
PAU 5B	1.05	12.82	14.67	29.34	15.25	73.13
PAU 5D	0.00	4.65	6.65	16.12	2.89	30.31
PAU 6	0.00	0.25	0.62	0.24	0.00	1.11
PAU 7	2.94	85.24	153.13	188.34	99.98	529.63
Total	12.50	152.76	250.56	329.99	200.26	946.07

We also assessed the dive data based on dive durations and surface interval times since the initial definition of dives (see Subsection 2.2) produced both erroneously long dives (where the unit did not switch back into surface mode and remained below the depth threshold of 20 cm below surface depth) and dives of 0 seconds length. For this reason, we constrained dives to be at least 1 second long (potentially sufficient time to examine a boulder or similar), and at most 120 seconds long. Only very few dives were longer than this latter threshold, and most dives above this limit were obviously erroneous (e.g., longer than three minutes). We also constrained surface intervals to be between 1 second and 10 minutes. We considered that longer surface intervals were likely unrelated to the fishing activity. Last, median dive depths below 20 m were also considered errors (i.e., the average depth for any dive was unlikely to be below 20 m).

Some divers in PAU 4 (Chatham Islands) fish on SCUBA (self-contained underwater breathing apparatus), and we aimed to remove these data by restricting data in PAU 4 to days on which no dive records exceeded 3 minutes bottom time (in other QMAs, only individual dives with bottom times longer than 120 seconds were removed). We further removed dives in PAU 4 where the proportion of total fishing activity spent diving (i.e., calculating bottom time over total fishing time) was greater than the highest corresponding proportion of daily bottom time in all other QMAs (Figure 2). This approach was based on the assumption that the physical limit of time spent at depth per total fishing time is the maximum observed in other QMAs (and that the physical ability of divers in PAU 4 was not greater that that of divers elsewhere). The data preparation resulted in a total of 1020 matched diver-days across all QMAs and fishing years (Table 3).

Many of the spatial (GPS) records that were uploaded to the database prior to the 2012–13 fishing year were affected by a fault in the uploading software, that was only subsequently fixed (version 2.3 of the software). The fault caused leading zeros in the decimal places of GPS coordinates to be omitted from the record, causing frequent errors in recorded dive and boat locations. These records were discarded for all spatial analyses as a *post-hoc* correction of this data-recording error was beyond the scope of the current project.

For 40.37% of all dive records, location information was missing. Missing location data occurred for single dive events as well as longer periods of several consecutive missing dive locations (up to 494

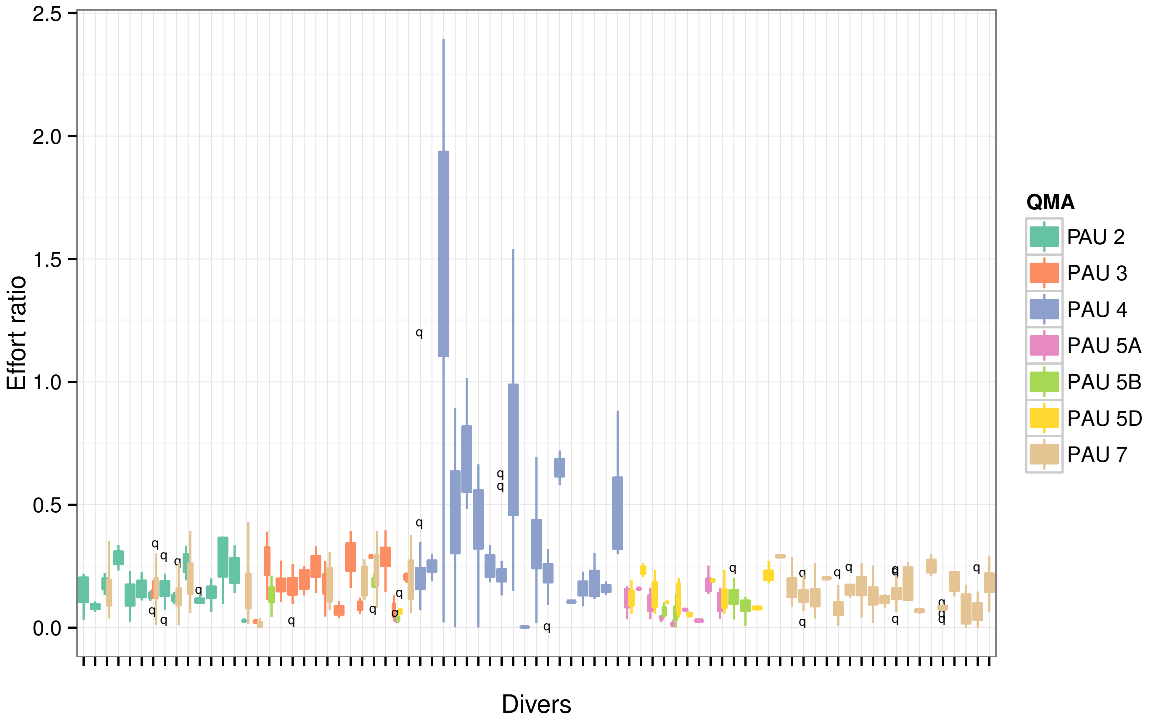


Figure 2: Effort ratio (diver bottom time divided by total fishing time) for all pāua divers with matched dive records by pāua Quota Management Area (QMA). Boxes indicate the interquartile range (IQR), and whiskers extend to data within 1.5 times the IQR; points are outliers beyond this range.

Table 3: Data set of the number of diver-days per pāua Quota Management Area (QMA) and fishing year following the data preparation.

	Fishing year				
QMA	2010–11	2011–12	2012–13	2013–14	Total
PAU 2	0	4	23	36	63
PAU 3	2	38	22	0	62
PAU 4	8	33	45	0	86
PAU 5A	1	9	25	1	36
PAU 5B	9	22	35	11	77
PAU 5D	2	13	37	2	54
PAU 7	117	197	265	63	642
Total	139	316	452	113	1020

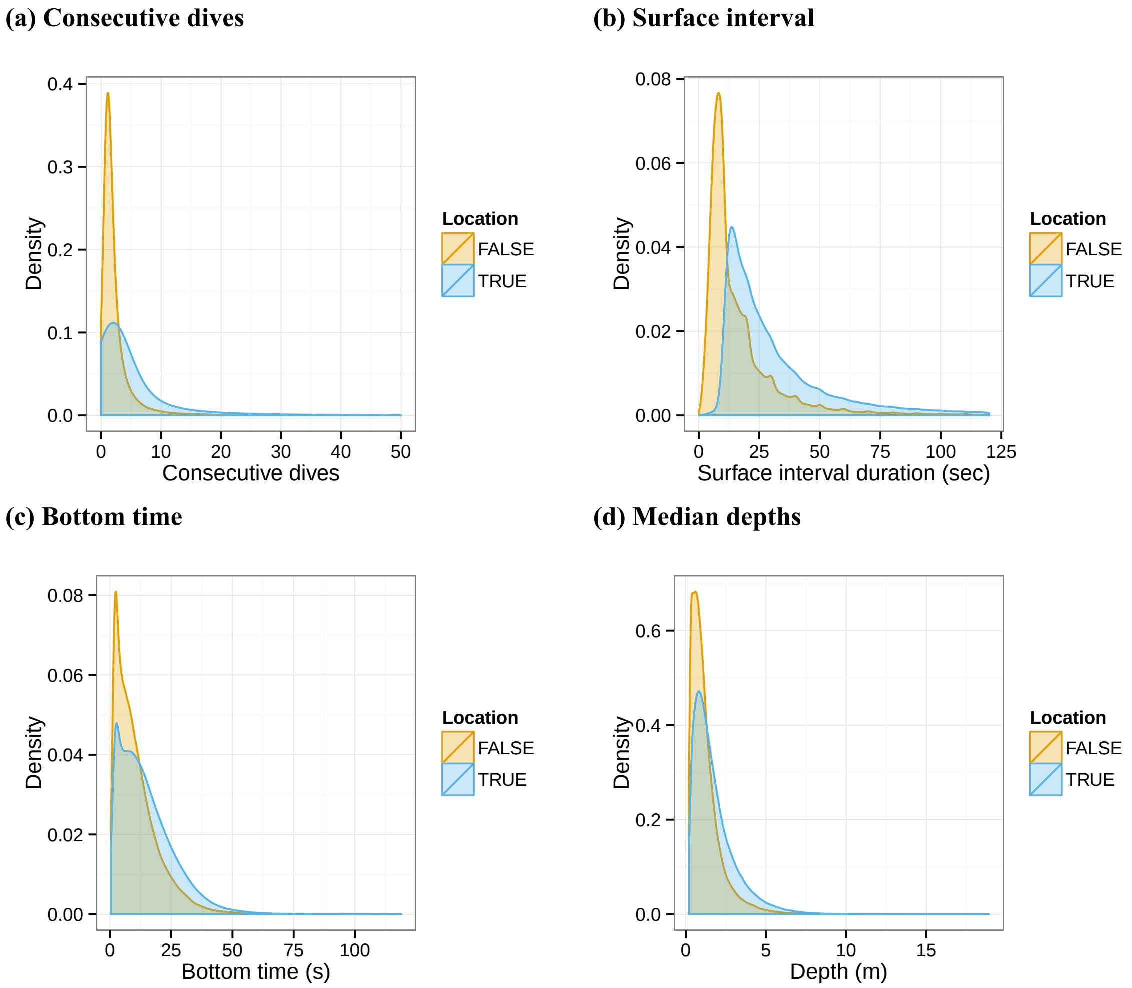


Figure 3: Distribution of a) the numbers of consecutive dives, b) surface interval duration, c) bottom times and d) median depths, for data with (TRUE) and without (FALSE) location information.

consecutive records), although short sequences of consecutive missing dives accounted for most of the missing data (95% of intervals with missing data were shorter than 15 dives). We found that the most likely explanation was that surface intervals between dives were too short to obtain a GPS position, or that the unit remained too deeply immersed to obtain a position. Furthermore, our definition of dive events effectively overwrites the GPS unit's own pressure threshold. This new definition led to data recorded in dive mode (without GPS positions) to be considered as surface intervals (i.e., dives that are above the 20 cm below-surface depth limit), thereby leading to surface intervals that do not have location positions.

A comparison of distributions of surface intervals suggested that surface intervals between dives with missing location data were shorter than those for dives with a recorded position (Figure 3). Comparing other dive parameters (depth and bottom time) between records with and without location did not suggest that these parameters were different between data with and without GPS positions.

2.4.2 Daily models of diver catch and effort

To gain an understanding of differences in fishing patterns among QMAs and years, we compared the distributions and summary statistics of dive parameters among QMAs and fishing years. To test whether these differences were associated with variation in catches, we used linear mixed models relating the log of daily catch to total fishing time, as well as dive variables (i.e., depth and bottom time) and external predictors, including co-variates for fishing-year within QMA, boat assistants and dive conditions (swell, visibility). All variables were centered and divided by twice their standard deviation to compare effect sizes relative to the standard deviation of the variable. A larger estimated effect for one variable relative to another can thus be interpreted in terms of a difference in effect size relative to the variability in the input (i.e., a larger estimated coefficient means a stronger effect per standard deviation in the input variable).

To examine the relationship between catch and different combinations of potential effort metrics (such as depth and bottom time), we tested a range of models and used model selection to compare model formulations. The rationale for this approach is further described below. The most complex models always used total fishing time (Table 1) as the base effort measure, and included dive conditions (swell, visibility), the use of boat assistants, fishing year within QMA effects (as covariates, fixed effect and random effect, respectively). Logger dive effort measures were added to the base effort as separate models for each dive effort variable; specifically, we added depth, bottom time or surface interval standard deviation (Table 1), hypothesising that the latter would decrease with increasing catches as dives become more regular. The data logger effort variables were introduced either as (fixed) effects (e.g., over all divers) or individual regression coefficients (random slope) to investigate how individual dive behaviour relates to catch (at equivalent total fishing times). Each model also included a random intercept to account for differences in average catch rates among divers. The full model was thus specified as:

$$
\begin{aligned}
\log(Y_{d,i,q,y}) &= \alpha_i Z_{d,i,q,y} + \beta X_{d,i,q,y} + A_y : Q_q + ID_i + \epsilon_d \\
\epsilon_d &\sim N(0, \sigma_d^2) \\
\begin{pmatrix} \alpha_i \\ ID_i \end{pmatrix} &\sim N\left(\begin{pmatrix} \mu_\alpha \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \rho\sigma_\alpha\sigma_{ID} \\ \rho\sigma_\alpha\sigma_{ID} & \sigma_{ID}^2 \end{pmatrix} \right) \\
A_y : Q_q &\sim N(0, \sigma_q^2),
\end{aligned}
$$

where $Y_{d,i,q,y}$ is the catch of diver i in QMA q on day d in year y, ID is a diver specific random effect and α_i is the effect of changes in the dive variable Z for diver i. Regression effects were included as $\beta = \beta_1 ... \beta_p$, for the p remaining covariates (effort and external variables) in the matrix X. For population level effects (over all divers) of the dive variable Z, the subscript on α_i is omitted (i.e., α can be included in the β vector as it is no longer a random slope, and Z can be specified as part of X). QMA Q_q and fishing-year (A_y) specific random intercepts were included in the model, drawn from a prior with QMA-specific population variance. The diver effects ID_i and α_i were modelled jointly using a multivariate normal distribution, which allowed us to explicitly model the correlation between the random slope and intercept parameters (Gelman et al. 2006).

Priors for β and μ_α were vague normal with mean 0 and variance of 1×10^6, (hyper-)priors for variances were vague gamma with shape s and rate r set to $s = r = 0.01$. For the diver identifier and fishing-year within QMA interaction, the hyper-prior for the population variances was formulated as a half-Cauchy distribution according to Gelman (2006), with a scale parameter of 0.05.

Our modelling strategy consisted of first building a base model that would incorporate covariates that would enter into model-based standardisation of PCELR CPUE data (i.e., total fishing time, dive conditions and diver effects; Fu et al. 2012). We then added effort variables from the logger data to investigate how much of the model fit would improve from the data-logger effort measures. We started with a mean model that did not include any covariates as a reference, and then sequentially added covariates, starting with total fishing time, then adding fishing-year within QMA effects, diver random effects, fishing conditions and the use of a boat assistant to build up to the base model. This approach allowed us to examine the importance of effects in the base model. To explore the effects of dive parameters on catch, dive effort measures (depth, bottom time, surface time standard deviation) were then added to the base model as covariates in either a fixed or random slope design. As dive depth was a significant contributor to bottom times, we included depth as a potential covariate for models with bottom time. Models were selected using the Deviance Information Criterion (DIC; Spiegelhalter et al. 2002).

All models converged to stationary posterior distributions (using three independent chains started at random starting values to verify convergence), and were run for 100 000 iterations with a thinning interval of

50 applied to each Markov Chain, resulting in 6000 samples from each chain being retained for analysis. Auto-correlation within chains was found to be negligible (using Gelman-Rubin and Raftery-Lewis diagnostics in the R package *coda* to confirm). We further used posterior predictive assessments (Gelman et al. 2004) to confirm that our models provided a reasonable fit to the data (see appendix, Figure A-1).

2.4.3 Investigating spatial metrics

To analyse spatial metrics relating to resource abundance, we restricted further analyses to data that were not affected by the turtle logger's geo-location fault (see Subsubsection 2.4.1). Specifically, we only used data with firmware versions greater than version number 2.3. This rule restricted the available data to the 2012–13 and 2013–14 fishing years and limited our ability to investigate temporal changes in the spatial data.

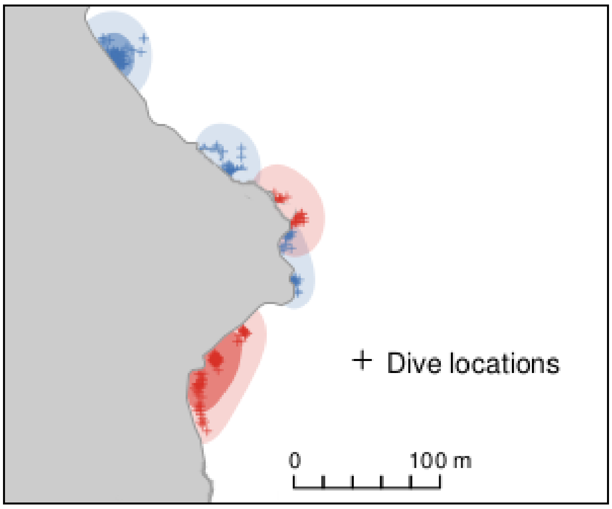


Figure 4: Example of estimated daily kernel utilisation densities for two divers (red, blue). Lighter shade of each colour corresponds to the 75% isopleth of the distribution, darker shade to the 25% isopleth. Crosses indicate individual dive locations, land mass appears in grey.

We initially calculated spatial metrics from dive data on a daily scale. Discussions with individual divers suggested that area searched per day should be sensitive to the density and overall abundance of the resource. To obtain a spatial index of daily fishing behaviour, we calculated isopleths of the daily kernel utilisation density (KUD), as suggested by Mundy (2012). The KUD is a spatial distribution that estimates the likelihood of finding a diver in a given place (see Figure 4 for an illustration). In our case, we calculated it on a daily basis for each diver. We used Brownian bridge kernel utilisation methods (Benhamou 2011, Benhamou & Riotte-Lambert 2012), which fit a spatial random process (an advection-diffusion model of movement) to the time and location data. To provide a measure of the spatial concentration of the diving, we calculated the ratio of areas of the 25% and 75% isopleths. We hypothesised that when the catch rates are high, the concentration index will be high (dive activity focused in a single area), and that when the catch rates are low, the concentration index will also be low (the dive activity would be dispersed, perhaps with patches of concentrated fishing).

The KUD can be calculated on various scales, and was included in finer scale models, where it was calculated on smaller spatial scales. At the largest scale, KUDs provide an estimate of the core area within QMAs, and provide a way to monitor the performance of these core areas by assessing the catch reported from these areas through time. Changes in these core areas could also allow monitoring for serial depletion. We illustrated this approach in PAU 7 and PAU 4, two QMAs with known differences in fishery status and catch rates. We estimated core areas from KUD isopleths within each QMA, and calculated the isopleth ratios and catch per ha within the core area. As an additional spatial metric, the distance swum during each day was calculated as the sum of distances between successive dives.

Spatial metrics calculated at the day scale were first introduced as covariates into the best model that was determined from all models (formulated in the previous section). We only used a smaller subset of the total data set (2012–13 and 2013–14 fishing years) due to errors in the spatial location of data in earlier fishing years. As we only had reliable spatial data over one complete fishing season, we did not include a year effect in this model. The latter could be considered in the future to build a spatio-temporal CPUE index.

Missing location data for many dives may introduce some error into the calculations. Nevertheless, the Brownian Bridge KUD method, being model based, interpolates between successive GPS positions. Furthermore, area fished and distance swum were strongly correlated (divers were searching in a narrow depth band along the coast). We thus only included the KUD 75% isopleth as a measure of search area, and the isopleth ratio as a measure of fishing concentration into our model.

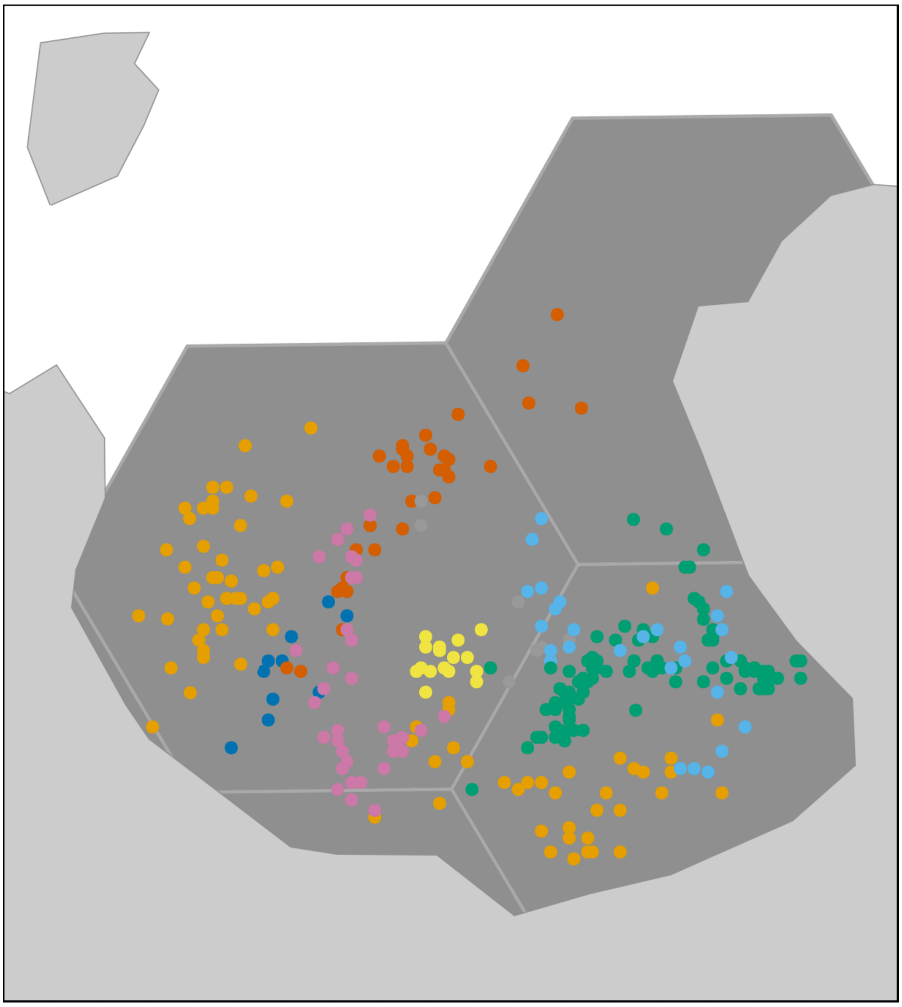


Figure 5: Dives by a single diver on a single day illustrating attribution of dives to catch bags and hexagons. Dives are colour coded corresponding to individual catch bags landed by that diver. For each bag, the catch was allocated to hexagons according to the proportion of dives within the hexagon.

2.4.4 Fine-scale spatial CPUE models

The model of daily catch detailed above may mask smaller scale patterns in abundance and fishing, and data from the turtle loggers should allow for a comparable analysis on finer scales. We split the analysis into finer spatial units with the aim of estimating a spatial index of CPUE. This split was achieved by applying a grid of 1-hectare (ha; 10 000 m^2) hexagons and attributing catch to these hexagons. Specifically, the day's catch was first divided evenly over the reported catch bags and the bag weight was then allocated to hexagons, according to the proportion of each bag's dives within the hexagons (see Figure 5 for an illustration). This process could not account for variability in weight between landed bags, but catch weights of individual bags were not reported. We lastly calculated diver behaviour (median dive depth, sum of bottom times for dives within a hexagon) as well as spatial (KUD) metrics within each hexagon. Some variables were only available at the day scale as the boat unit's firmware only recorded them as part of the unit's shut-down sequence (this feature was related to the firmware rather than the data treatment).

Table 4: Summary of data used for modelling of catch-per-unit-effort within pāua Quota Management Areas (QMAs). The dataset has a record for each hexagon-day (each day's fishing in each hexagon).

	Hexagon-days	No. hexagons	Statistical areas	Divers	Catch (t)
PAU 7	1598	887	28	15	46.1
PAU 4	321	193	21	8	36.5
PAU 5B	350	305	35	7	7.7
PAU 2	267	154	9	4	16.8

The model with data at the hexagon scale is mostly equivalent to the previous model at the daily scale. To avoid having small scale variability swamped by inter-QMA differences, we performed this finer analysis within QMAs. The QMA effect (and subscript) were replaced by random effects at both the statistical area and hexagon scale. These random effects provided a spatial CPUE index at those scales. We did not estimate random slopes for each diver (but retained a random intercept) within this model as the inclusion of random slopes led to model fitting problems. We restricted the analysis to PAU 2, PAU 4, PAU 5B and PAU 7 since other QMAs did not have sufficient data to reliably estimate model parameters. These data were further restricted to hexagons with more than ten dives and gross errors in catch reporting were eliminated (see Subsection 3.1; input data are summarised in Table 4).

3. RESULTS

3.1 Uptake and coverage of the logger programme

3.1.1 Programme uptake

On the date that we extracted the data for our analysis (March 2014), the logger database contained a total of 1612 diver-day fishing records classified as valid activity, meaning that there was a match between turtle and SITO IDs from the turtle logger and boat unit. A large number of records could, however, not be matched because either the turtle or SITO ID numbers did not match between turtle and boat unit, or because only data from one type of the dive loggers was uploaded (e.g., turtle loggers were uploaded but not the boat unit). It is not possible to determine what the exact numbers or proportions of these mismatches are, as there is no straightforward way of distinguishing an ID mismatch from a case where two non-matching units were uploaded independently and missed uploads from the other data source (e.g., data from a turtle unit without boat data may just be the result of a wrong turtle ID in the boat unit, or may not have any associated boat unit (and catch) data in the database).

The logger monitoring programme showed increasing uptake from the 2010–11 to the 2012–13 fishing year, with 56 and 79 fishers participating, respectively (Table 5, Figure 6). Nevertheless, turtle logger use did not necessarily carry over between years: 14 fishers who used turtle loggers in the 2010–11 fishing year did not carry loggers in 2012–13, despite a marked increase in the total number of divers using the loggers. There were 37 divers that fished with loggers in 2012–13, but have not yet reported data for the 2013–14 fishing year. As PAU 6 only accounts for 2 t of catch per year that are completely monitored, we do not report on patterns in this QMA in further analyses.

PAU 7 had the highest number of divers using dive loggers (Table 5, Figure 6), although 15 fewer divers

Table 5: Number of divers reporting data in the dive-logger programme by pāua Quota Management Area (QMA) between 2010–11 and 2013–14 (up to February 2014).

Year	QMA								Total
	2	3	4	5A	5B	5D	6	7	
2010–11	6	9	11	2	3	4	3	32	56
2011–12	8	16	13	9	8	13	3	35	75
2012–13	15	17	18	10	15	17	4	29	79
2013–14	19	8	11	5	7	11	0	14	61

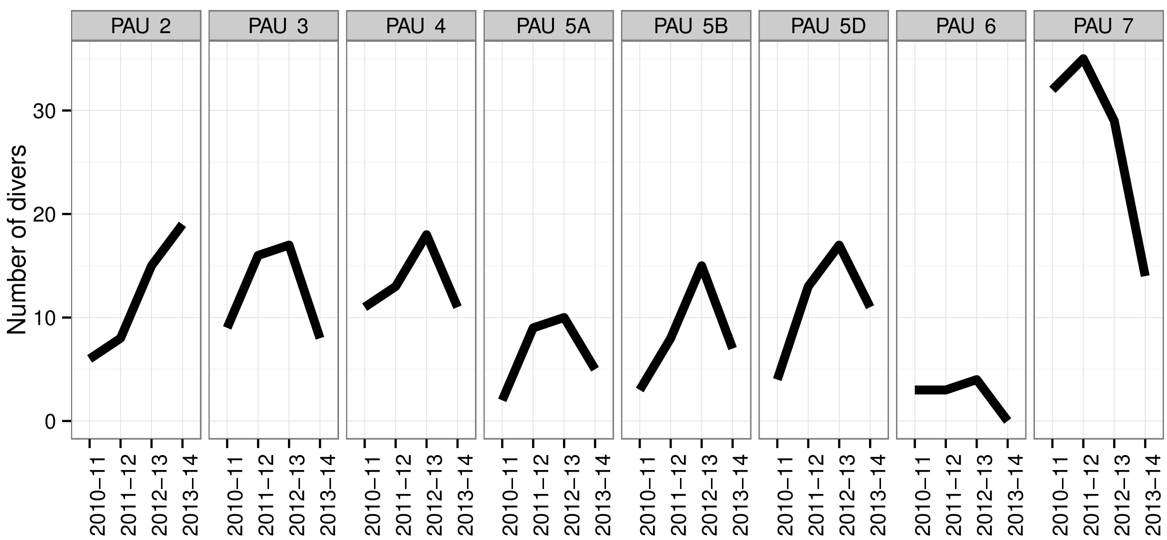


Figure 6: Number of divers using data ("turtle") loggers by pāua Quota Management Area (QMA) and fishing year. Lines on the graph indicate trends over time within each QMA. Data for the 2013–14 fishing year are up to February 2014 only.

Table 6: Comparison of pāua catch (t) reported on Pāua Catch Effort Landing Return (PCELR) forms and in the dive logger programme (Logger catch). Data are by fishing year and by Quota Management Area (QMA).

(a) Catch by fishing year

Year	PCELR landings	Logger catch	Proportion
2010–11	853	113	0.13
2011–12	834	249	0.30
2012–13	836	290	0.35
2013–14	448	139	0.31
Total	2971	791	0.27

(b) Catch by QMA

QMA	PCELR landings	Logger catch	Proportion
PAU 2	426	40	0.09
PAU 3	293	105	0.36
PAU 4	929	292	0.31
PAU 5A	300	38	0.13
PAU 5B	244	56	0.23
PAU 5D	292	36	0.12
PAU 7	480	223	0.46
Total	2971	791	0.27

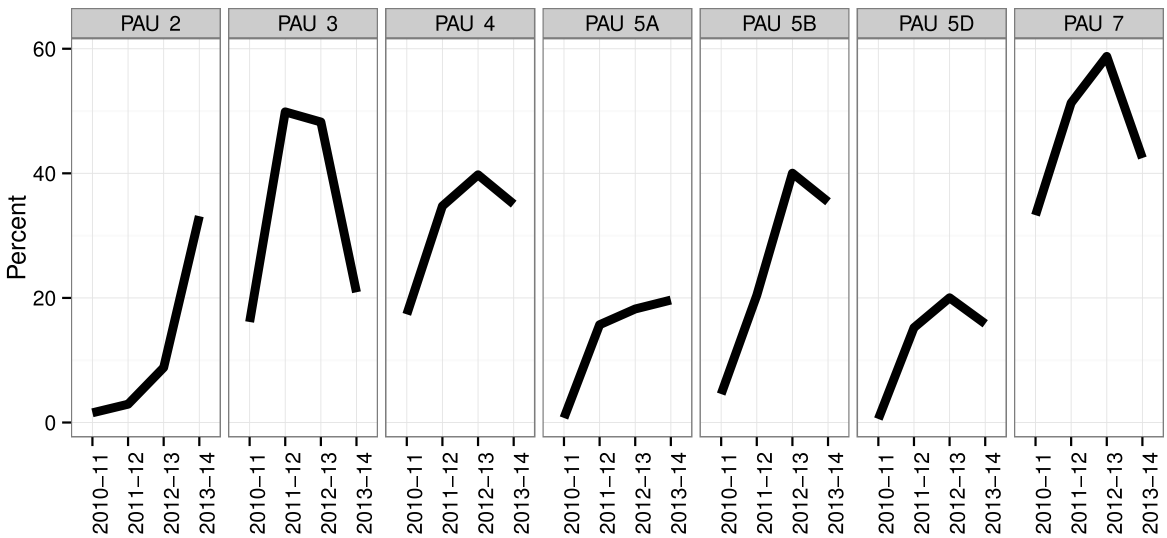


Figure 7: Percentage of total catch by QMA and fishing year recorded in the dive logger programme. Lines on the graph indicate trends over years within QMAs. Data for the 2013–14 fishing year is up to February 2014 only.

fished in PAU 7 in the 2012–13 fishing year than in previous years, with many (13) divers fishing in other QMAs in 2012–13. In other QMAs, the use of loggers generally increased up to the 2012–13 fishing year, while data for the 2013–14 fishing year were not complete at the time of reporting.

The amount of catch recorded by the logger programme increased overall and within individual QMAs (Table 6, Figure 7). When compared to PCELR data, more than half the catch in PAU 7, and close to 40% of the catch in PAU 4 was recorded in the logger programme in 2011–12 and 2012–13.

Geographically, the number of statistical areas covered by the dive logger programme increased markedly from the start of the programme in the 2010–11 fishing year (Table 7), with catch from a total of 87% of statistical areas recorded on PCELR forms covered in 2012–13. In PAU 7, where coverage was highest over all years (Table 7), the logger data from the 2011–12 fishing year included dives in statistical areas not noted in the PCELR forms (i.e., the number of statistical areas in the dive logger database for that year was larger than the number of statistical areas recorded from PCELR forms). This discrepancy may have been due to incomplete recording on PCELR forms, where lightly fished statistical areas may not be reported.

Table 7: Statistical areas (SAs) recorded on Pāua Catch Effort Landing Return (PCELR) forms, inferred from data-("turtle")-logger Global Positions System positions, and proportion of statistical areas recorded on PCELR covered by logger data, by fishing year and Quota Management Area (QMA). (Note that proportions covered <1 despite a larger number of statistical areas inferred from logger data indicated that the number of statistical areas differed between PCELR and dive loggers.)

(a) Statistical Area by Year

Year	PCELR SAs	Logger SAs	Proportion
2010–11	250	285	0.88
2011–12	248	280	0.89
2012–13	235	271	0.87
2013–14	200	219	0.91
Total	269	333	0.81

(b) Statistical Area coverage by QMA

QMA	PCELR SAs	Logger SAs	Proportion
PAU 2	18	27	0.67
PAU 3	25	29	0.86
PAU 4	49	54	0.91
PAU 5A	40	45	0.89
PAU 5B	63	79	0.80
PAU 5D	27	36	0.75
PAU 7	51	61	0.84
Total	269	333	0.81

3.1.2 Correspondence of PCELR and dive-logger records

Investigating the overlap of PCELR and dive-logger data in terms of boats and individual fishing days proved difficult due to several limitations:

- PCELR forms do not include names, but record initials, which may be prone to errors during data entry or due to multiple initials for any one diver. For example, any one diver may have a match in PCELR initials, but multiple potential matches that only require one letter to be substituted or deleted. Resolving this matter with certainty is made more difficult by family members diving together. An important point would, therefore, be to establish an explicit link between the dive-logger and PCELR data, possibly by entering the PCELR form numbers in the boat unit (although this linking would require a firmware update, and forms to be assigned prior to the day's fishing).
- Turtle loggers are usually registered to a diver, but the unit may be passed on to other divers (e.g., family members), which are then recorded on the PCELR forms.
- The submission of erroneous SITO ID numbers (pertaining to the dive-logger database only).

Notwithstanding these limitations, we matched turtle logger records to PCELR records where possible. Matching was initially based on both perfect matches between name records from dive loggers for fishing days in the dive-logger database (using both matched and unmatched days, i.e., days for which we only had boat-unit or turtle-logger data) and PCELR initials. This matching allowed us to determine the amount of matching to be expected if the matching in the data-logger database was perfect. The name-based matching accounted for 3004 matches for a total of 16 631 PCELR entries, corresponding to 18.06% of PCELR data and 63.64% of dive days in the logger database. To make further matches, we built a correspondence table that matched boat IDs in the dive-logger database to particular boats for all QMA/year combinations. We then attempted to match diver names based on boat ID and initials that allowed for one letter substitutions or deletions, which allowed us to match a further 244 diver-days.

Nevertheless, due to these limitations, some diver-days in the logger data set could not be matched to PCELR data. We matched a total of 3248 of diver-days in the dive-logger database, which corresponded to 73.53% of all recorded fishing days. Within QMAs (Table 8), the proportion of unambiguously matched dive-logger data matched to PCELR data increased from low levels in PAU 2 (20% in the 2011–12 fishing year) and PAU 5A (12% in 2010–11) to above 70% in both QMAs in 2012–13. For all other QMAs, the proportion of matched diver- -days remained reasonably high, although PAU 5B and PAU 3 had lower percentages of matched dive records in the 2012–13 fishing year.

Table 8: Proportion of diver-days in the logger database matched to Pāua Catch Effort Landing Return (PCELR) form records by Quota Management Area (QMA) and fishing year.

Year	QMA						
	2	3	4	5A	5B	5D	7
2010–11	0.33	0.90	0.52	0.12	0.67	0.77	0.72
2011–12	0.20	0.93	0.53	0.68	0.69	0.63	0.80
2012–13	0.70	0.81	0.76	0.73	0.55	0.76	0.80
2013–14	0.63	0.67	0.49	0.32	0.53	0.56	0.83

3.1.3 Comparing reported statistical areas within days

To assess if there was a systematic difference between the number of statistical areas reported by divers on PCELR forms and dives recorded in the dive-logger database, we compared matched records with reliable locations for the logger data (i.e., firmware versions with the location error fixed, Section 2.4.1). The comparison was based on 380 individual diver-days (i.e., matched data from the 2012–13 fishing year and the 2013–14 fishing year to February 2014).

Although the number of statistical areas coincided between both reporting methods for the majority of matched days (Figure 8a), there was a tendency to report fewer statistical areas on PCELR forms, meaning that the true spatial effort of fishing may often have been more spread out than reported on PCELR forms. In terms of actual dives, a combined 29% of dives were outside of statistical areas reported on PCELR forms. On a daily basis, the proportion of dives within statistical areas recorded on PCELR forms varied, with a substantial number of diver-days where the reported statistical areas was inaccurate (Figure 8b).

The increased number of areas reported by the dive loggers may be partly caused by GPS location errors. Although these errors were typically on the order of a few metres (and should, therefore, only have very minor impacts on analyses reported in this project), fishers diving near the boundary of a statistical area may occasionally be recorded as diving within adjacent statistical areas. Furthermore, missing location data on many dives (see Subsection 2.4.1) may lead to errors in the reported quantities if locations were not missing at random.

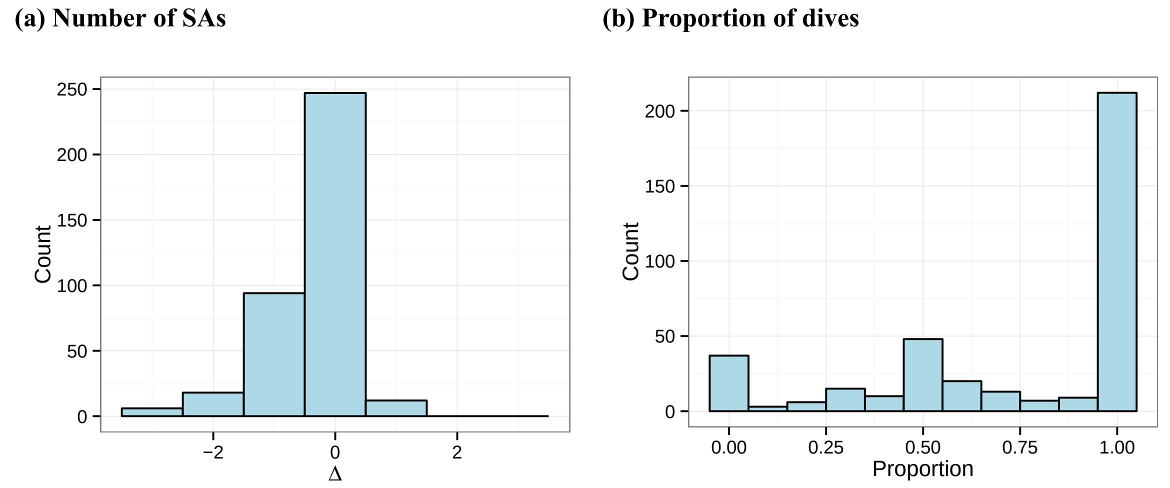


Figure 8: Comparison of statistical areas (SAs) reported on Pāua Catch Effort Landing Return (PCELR) forms and obtained from diver-logger data. (a) Difference between the number of SAs reported on PCELR forms and assessed from individual dive locations within a day (negative number indicates that fewer statistical areas were reported on PCELR forms). (b) Proportion of dives in SAs that were also recorded on PCELR forms (a value of one suggests that all dives on that day were within SAs reported on PCELR forms, a value of zero suggests that diving occurred exclusively in SAs not reported on PCELR forms).

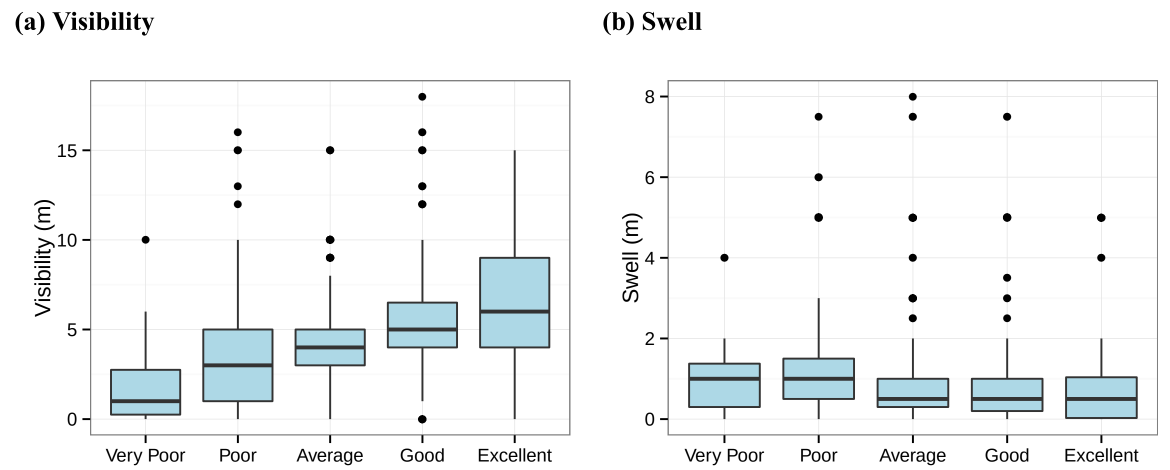


Figure 9: Distribution of swell and visibility records from the turtle logger database with matched condition indices reported on Pāua Catch Effort Landing Return (PCELR) forms.

3.1.4 Comparing reported dive condition

Dive conditions are reported on PCELR forms using a qualitative index with five categories, ranging from “Very Poor”, “Poor”, “Average”, and “Good” to “Excellent”. For the turtle loggers, divers recorded condition as swell height and visibility (both in metres). The condition index recorded on PCELR forms reflected both swell and visibility, with linear increases in the mean visibility and near linear decreases in swell height from Very Poor to Excellent (Figure 9).

3.1.5 Comparing reported catch and effort data

Catch and effort data were compared for diver-days with an exact match to PCELR data using both diver initials and names over all years, corresponding to 2608 of the 3004 diver-day records matched to PCELR data for which catch information was available (i.e., for which we had either matched boat and

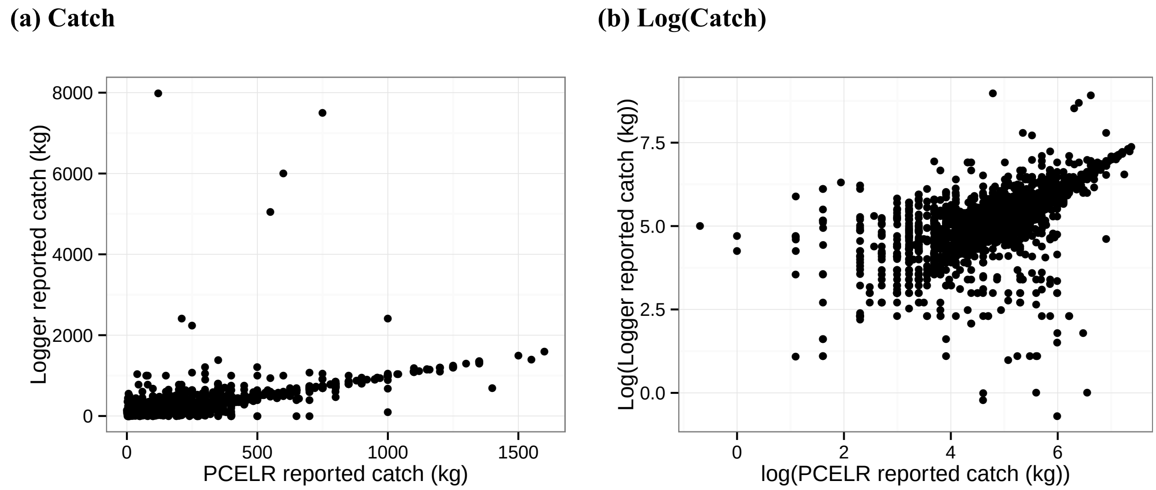


Figure 10: Comparison of recorded catches for matched dives from Pāua Catch Effort Landing Return (PCELR) forms and dive-logger databases.

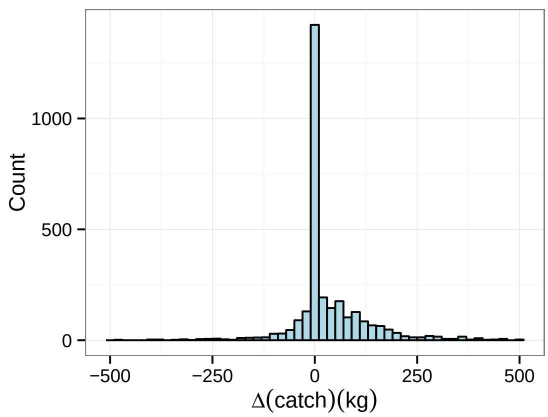


Figure 11: Difference in recorded catches for matched dives from Pāua Catch Effort Landing Return (PCELR) forms and the dive-logger database.

turtle logger records, or only the boat unit was uploaded for that day).

Reported catches coincided for 39% of matched records, while 62% of records had a difference of less than 50 kg. Comparing original and log scales, there were a few large errors that were likely to be due to data entry errors (such as accidentally repeated numbers that inflate actual catch, e.g., 250 kg 2250 kg) (see Figure 10). These obvious outliers were removed from all analyses relying on catch data (i.e., models for catch rate) to avoid biases or errors in inferences.

Most of the remaining discrepancies between matched catches in the two databases were evenly distributed around zero, with a slight bias towards inflated catches in the logger database (Figure 11). We found no indication that the discrepancy in reported catches improved with fishing years or within QMAs since the inception of the logger programme (multiple regression, $r^2 = 0.01$).

Comparisons among effort measures from logger and PCELR data showed that the total fishing time, measured by the sum of half-hour intervals with turtle logger activity (see Table 1), was most closely correlated to reported effort on PCELR forms (total time in water (in h); $r^2 = 0.34$, Figure 12). There was no evidence of systematic bias towards higher or lower reported effort in either measure. The two other effort measures calculated from logger data, the boat-effort measure and bottom time (see Table 1),

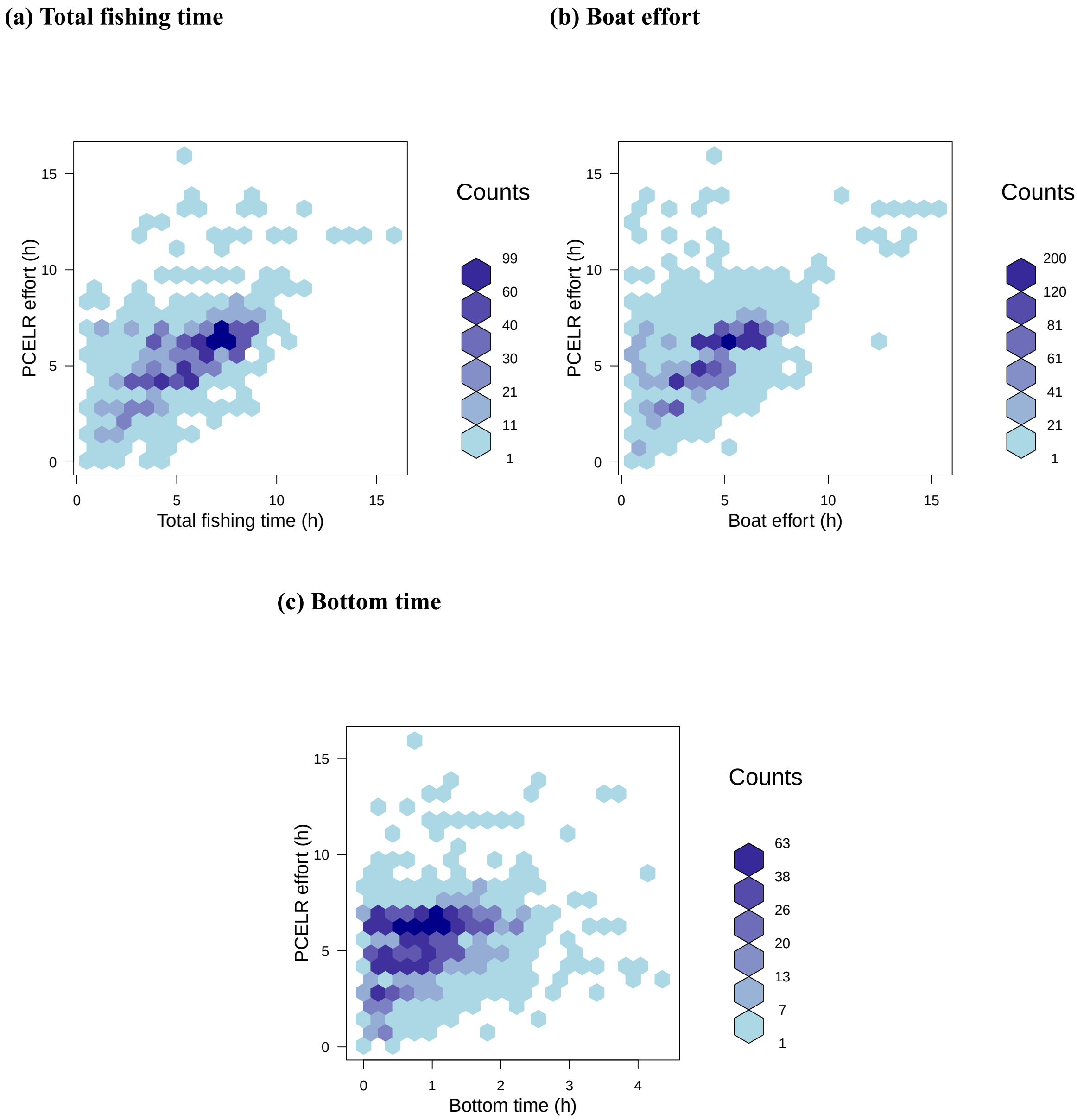


Figure 12: Comparison of effort measures for matched dives calculated from the dive-logger database (x-axis) and data from Pāua Catch Effort Landing Return (PCELR) forms (y-axis).

were less closely related to PCELR effort, with regression values of $r^2 = 0.26$ for the boat measure and $r^2 = 0.08$ for bottom-time effort. This finding suggests that the time in water reported on PCELR forms was, as expected, most closely related with the total time that loggers were active (the total fishing time effort), but did not reflect bag landings or bottom time.

3.2 Relating dive parameters to catch

3.2.1 Spatial and temporal patterns in dive patterns

Most pāua fishing happened on short and relatively shallow dives (Figure 13), with an average median depth of 1.2 m (interquartile range (IQR): 0.71 to 2 m) and median bottom time of 11 s (IQR: 5 to 18 s). Median surface intervals were 37 s long, with an IQR of 24 to 57 s. All dive parameters had long tailed-distributions with standard deviations of 10.63 s, 1.23 m and 48.58 s, for bottom times, median depths and surface interval duration, respectively.

Diving patterns were relatively consistent over fishing years, as the distributions of both bottom time and depths showed little variation among years and among most QMAs (Figure 13). Bottom times were more evenly distributed towards longer bottom times in PAU 4 and PAU 3 (Figure 13a), whereas the bulk of the fishing activity happened on short dives in all other QMAs. This finding is likely to reflect the greater average dive depth in these two QMAs, although PAU 3 showed a trend towards shallower, shorter dives over the years. In other QMAs, an opposing yearly trend towards more evenly distributed bottom times was apparent, suggesting a shift towards longer bottom times despite a slight decrease in dive depths. This shift towards shallower yet longer dives can be visualised as a shift in average dive parameters (Figure 14). Because of the progressive introduction of the loggers, it is unclear whether these changes are due to changes in the fishery, or are due to different divers using the loggers.

3.2.2 Modelling daily catch as a function of dive parameters

Starting with a mean model that initially only included an intercept term, other terms were sequentially added to build the base model (Table 9). The base model included total fishing time effort, dive conditions, diver and year in QMA random effects. This base model was the basis for developing more complex models, adding dive parameters as additional effort as either fixed effects or diver-specific random coefficients. The models developed from the base model did not build on each other, but were separate models for combinations of dive-effort measures.

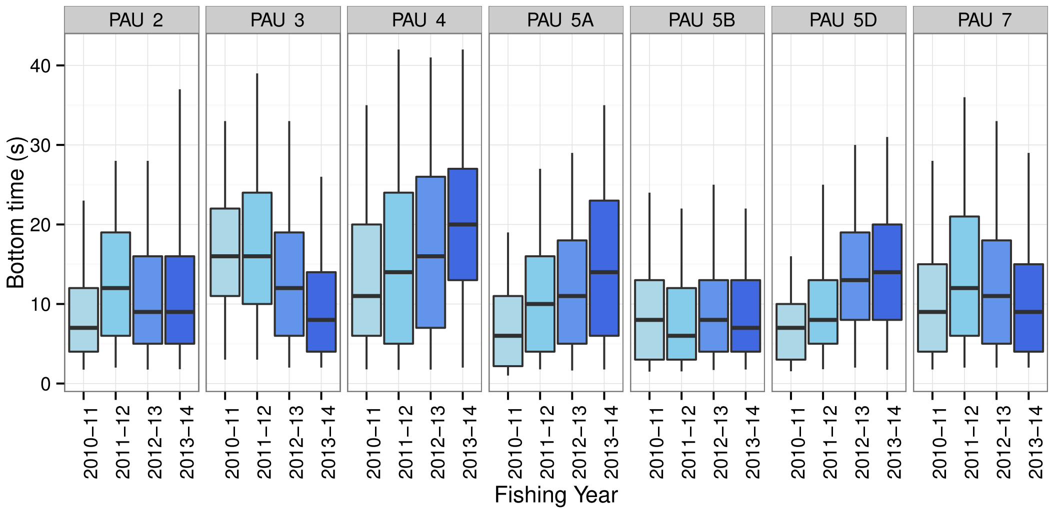
Selection between models for daily catch showed that a full model, including dive parameters and a random slope for the diver bottom-time effect, performed substantially better than all other models (Table 9). Compared with the simple mean model, including only total fishing time led to significant improvements in model fit. Including effects for fishing year within QMA and individual divers demonstrated the importance of differences in average catch rates among QMAs and individual divers by leading to progressively improved (i.e., lower) DIC values.

Table 9: Deviance Information Criterion (DIC) for models used to relate catch to effort and dive conditions in pāua fishing. The base model was developed by sequentially adding terms to the mean model that initially only included an intercept term. Models developed from the base model were separate models for combinations of dive effort measures (QMA, Quota Management Area; random, diver-specific random coefficient; SD, standard deviation).

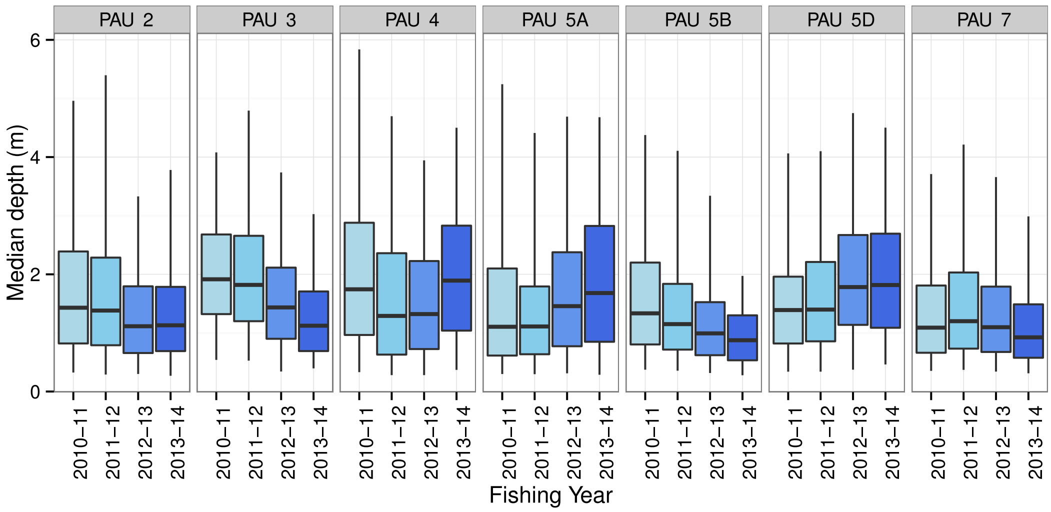
Model	DIC
Mean model	2037
+ total fishing time	1945
+ year:QMA	1551
+ diver ID	1208
+ condition	1192
Base model: + boat assistant	1178
+ depth	1178
+ bottom time	1177
+ surface interval SD	1176
+ depth + bottom time	1173
+ random depth	1157
+ random surface interval SD	1155
+ random depth +Bottom time	1151
+ random bottom time	1115
Best Model: + depth + random bottom time	1113

Models including dive condition provided a further improvement over models with only total activity time and QMA, year and diver differences (Tables 9 and 10, Figure 15). Increased swell and visibility were correlated with lower and higher CPUE, respectively. The presence of a boat assistant also improved

(a) Bottom time



(b) Median depths



(c) Surface intervals

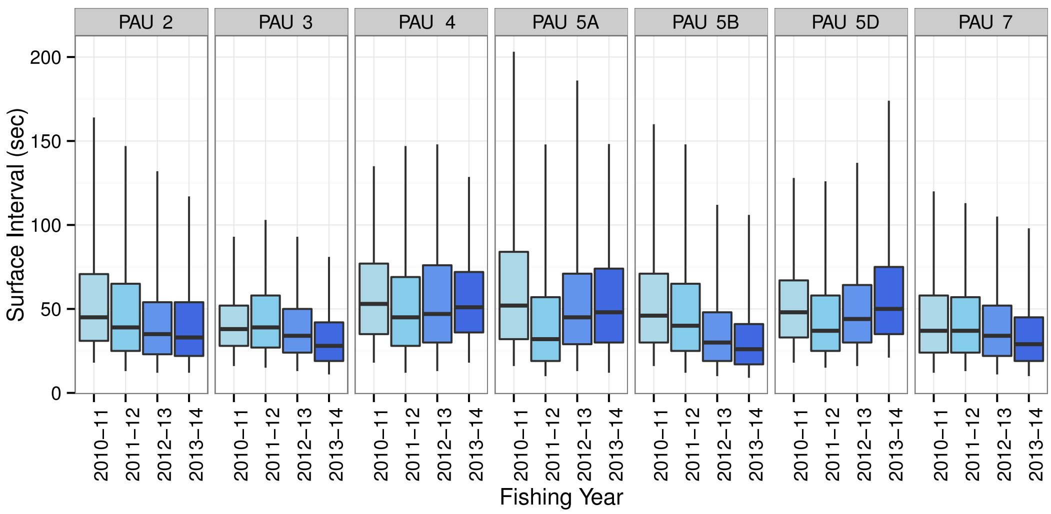
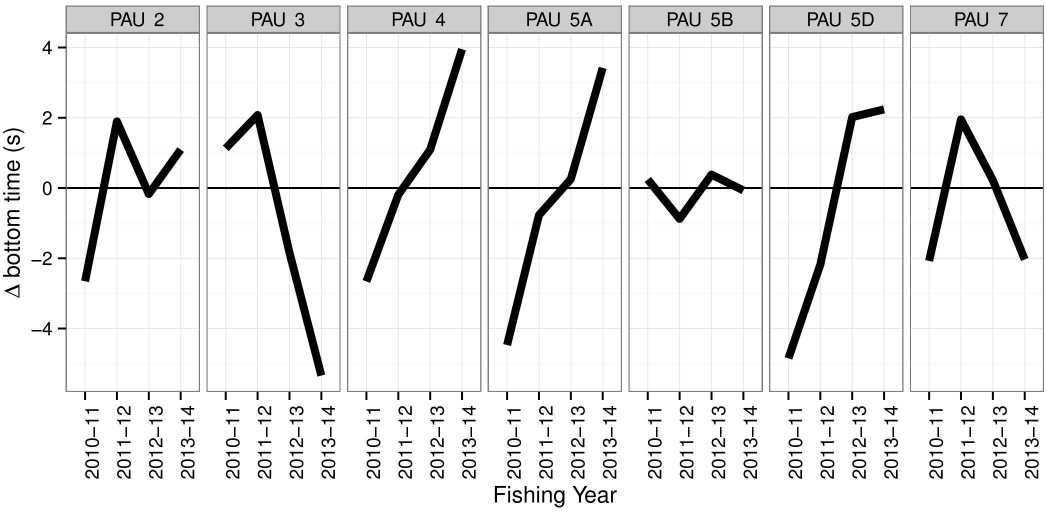


Figure 13: Distribution of a) bottom time, b) median dive depth and c) surface interval duration from dive-logger records by pāua Quota Management Area and fishing year. Boxes span the interquartile range, whiskers cover data within the 95% interpercentile range.

(a) Bottom time



(b) Median depths

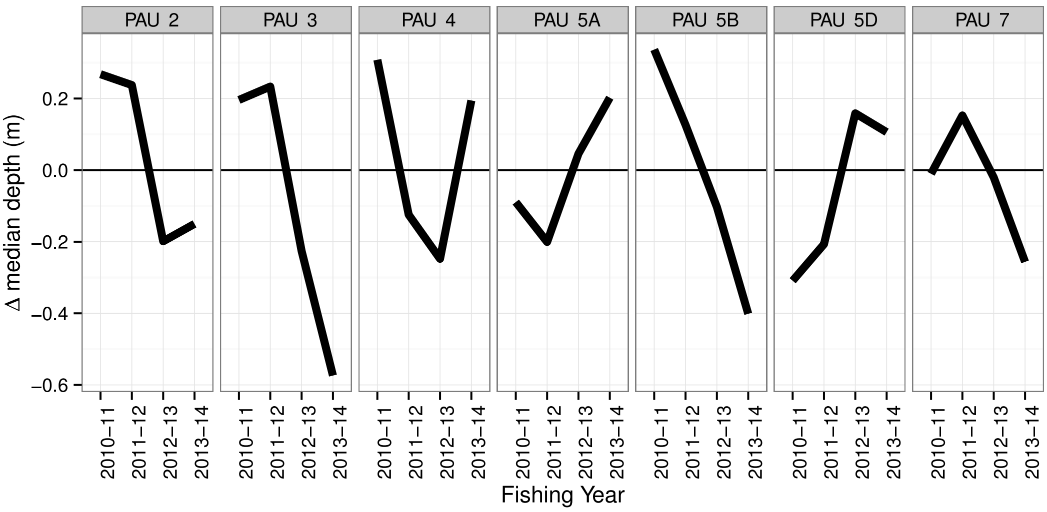


Figure 14: Deviation in mean bottom time and median depth among years relative to the mean bottom time and depth within pāua Quota Management Areas (QMAs) over the reporting period. Lines on graph indicate trends in bottom time and depth over years within individual QMAs.

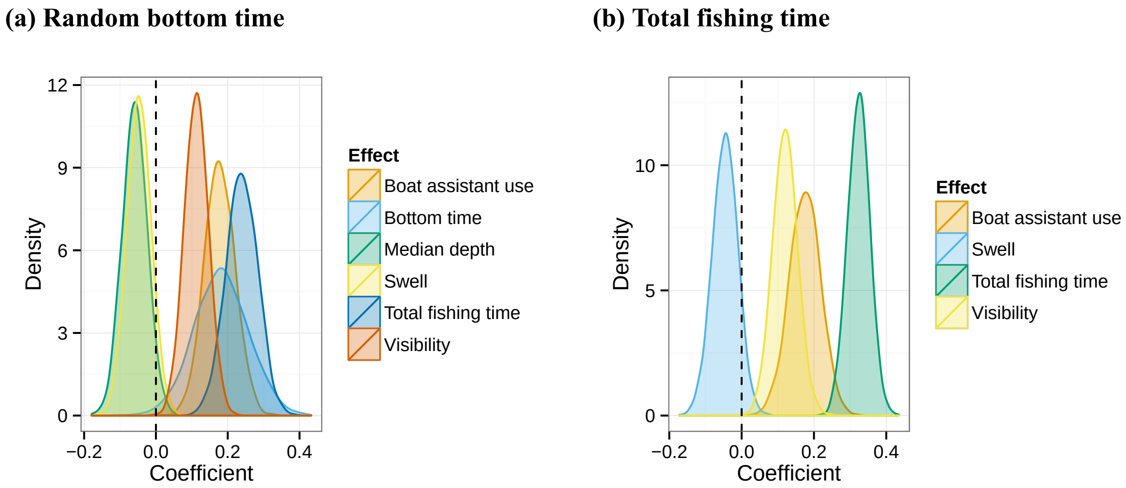


Figure 15: Posterior distributions for models with a) random bottom time (best model) and b) total activity time (and external variables). In a), the effect for bottom time is displayed at the population level. (A larger estimated coefficient (positively or negatively) indicates a stronger effect per standard deviation in the input.)

Table 10: Posterior means, 95% posterior quantiles and probability of being strictly positive for model parameters from the best model identified by Deviance Information Criterion model selection.

Parameter	mean(θ)	P($\theta > 0$)	2.5%	97.5%
Boat assistant use	0.18	1.00	0.10	0.26
Bottom time	0.18	0.99	0.03	0.33
Median depth	-0.06	0.05	-0.13	0.01
Swell	-0.05	0.08	-0.11	0.02
Total fishing time	0.24	1.00	0.15	0.32
Visibility	0.11	1.00	0.05	0.18

models for daily catch (Table 9), and the consistently positive coefficient of this factor suggested that crews using a boat assistant were able to achieve higher catch rates (Table 10, Figure 15).

For the best model, the estimated QMA effects were consistent with expectations of relative status of the fisheries in that PAU 4 consistently had the highest posterior CPUE index across years (Figure 16). Nevertheless, PAU 5A and PAU 5D had comparably high posterior CPUE indices in some years. PAU 7 had the consistently lowest year-within-QMA indices, showing a decreasing trend over the past four years. These estimates were based on data-logger data only, which was a subset of the total fishing activity in each QMA. For this reason, inter-annual changes may reflect changes in the uptake of the loggers. In the indices for QMA and year combinations (with comparably few data), there was large variability.

In the best model, total fishing time was the predictor with the largest coefficient (Table 10, Figure 15a), followed by bottom time and boat assistant use as predictors of catches. Both total activity time and bottom time were strongly positively related to catch. A comparison with a model that had total activity time as the only measure of effort (Figure 15b) suggested that bottom time diminished the estimated effect of total fishing time when added into the model: the effect for total fishing time in the base model was larger than the estimated effect in the best model. Despite this interaction, the correlation of coefficients for both parameters in the posterior distribution of the full model was reasonably low ($\rho \simeq -0.47$), and the posterior mean of the combined effect of bottom time and total activity time ($\bar{\beta}_{sum} = 0.42$) was substantially higher than the effect of total activity time in the base model without dive parameters ($\bar{\beta} = 0.31$).

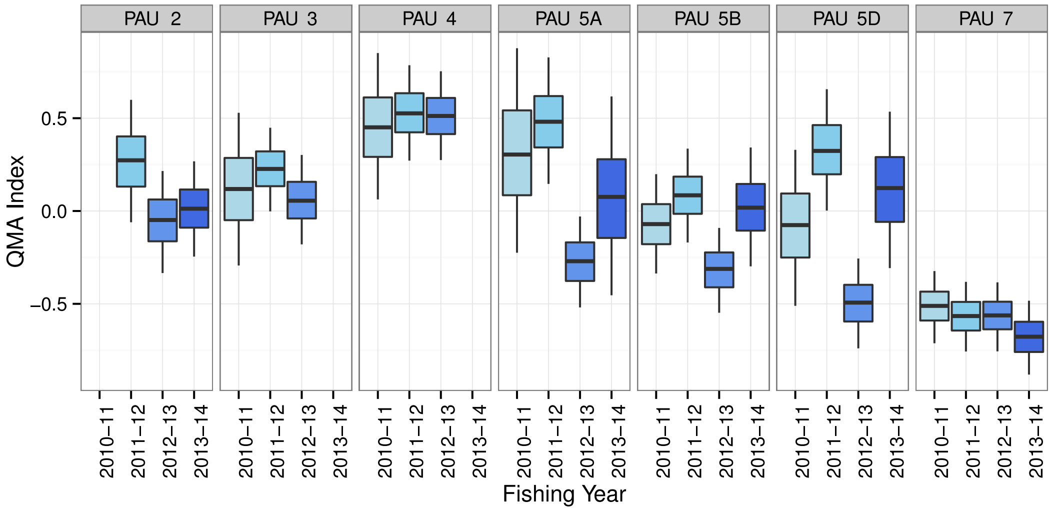


Figure 16: Posterior distributions for combinations of pāua Quota Management Area (QMA) and year-specific (interaction) random effects. Median values with boxes marking the 75% quantiles of the posterior distributions, whiskers enclose the 95% interval of the Markov Chain Monte Carlo draws from the posterior distribution.

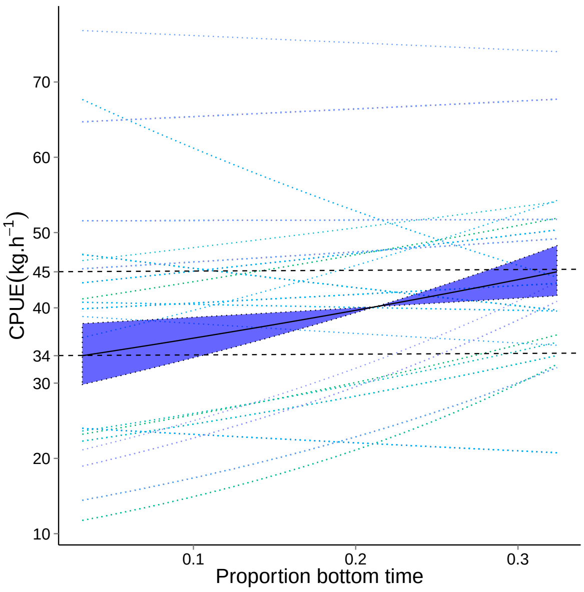


Figure 17: Predicted catch-per-unit-effort (CPUE) as a function of the proportion of bottom time for one hour of total fishing time, with all other covariates held at their mean value. The population level effect and regression uncertainty are plotted as the solid line and blue ribbon (95% posterior quantiles), respectively. Posterior means of individual divers as dotted lines, dashed lines indicate the range of predictions from the mean effect.

The response of catch to changes in bottom time was variable among divers (Figure 17); however, the population-level effect was significantly positive ($P < 0.01$). While few divers showed a strongly opposing response, there was a significant negative correlation between the response of catch to individual bottom times and diver-specific random intercepts, suggesting that divers who consistently had higher catches did not show trends in catch with changes in bottom times (Figure 17).

Depth was consistently negatively related to catch (Figure 15), although it only became a significant

Table 11: Posterior mean, probability of being strictly positive, and 95% credible interval for model parameters of the model for daily catches with spatial metrics. KUD 75% area refers to the kernel utilisation density area within the 75% KUD isopleth.

Parameter	mean(θ)	P($\theta > 0$)	2.5%	97.5%
Boat assistant use	0.12	0.95	-0.02	0.27
Bottom time	0.15	0.82	-0.17	0.46
KUD 75% area	-0.11	0.09	-0.26	0.05
KUD ratio	0.13	0.98	0.01	0.26
Median depth	0.13	0.97	-0.01	0.25
Swell	-0.09	0.10	-0.23	0.05
Total fishing time	0.61	1.00	0.39	0.83
Visibility	0.05	0.71	-0.12	0.23

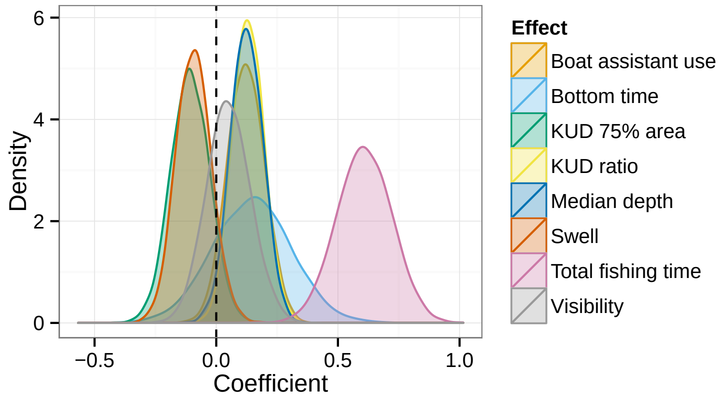


Figure 18: Posterior distributions for model coefficients in the model for daily catches with spatial predictors. KUD 75% area refers to the kernel utilisation density area within the 75% KUD isopleth. (A larger estimated coefficient (positively or negatively) indicates a stronger effect per standard deviation in the input.)

factor (in the sense of $P(x > 0)$) when bottom time was included in the model, and the effect size remained relatively small compared to fishing time and bottom time.

3.3 Investigating spatial performance metrics

3.3.1 Spatial effort metrics on large scales

The best model for daily catch, including bottom time and depth as predictors, was extended to include spatial metrics (see posterior distributions for model coefficients in Table 11, Figure 18). This model was restricted to data after the GPS position error was fixed (i.e., excluding many of the records before the 2012–13 fishing year). The model showed a similar pattern to the non-spatial analysis on the whole dataset. The overall estimated effects of dive metrics (bottom time and depth), however, were not as strong as total fishing time. Depth appeared as a significant predictor in this new model, whereas the population level effect of bottom time adjustments was less likely to be different from zero.

Spatial metric variables appeared as important predictors of catch on a daily scale, with catch increasing with the KUD ratio, which represents effort concentration. An increase of the ratio (and effort concentration) from 0.1 to 0.2 was associated with a 21% higher CPUE (Figure 19). Conversely, catch declined with the size of the 75% isopleth of the KUD. The overall effect was less strong, with CPUE decreasing 7% when the KUD area increased from 20% to 200% relative to the mean KUD area. (Note that after an initial run including distance travelled, we discarded the variable as it was highly correlated with area

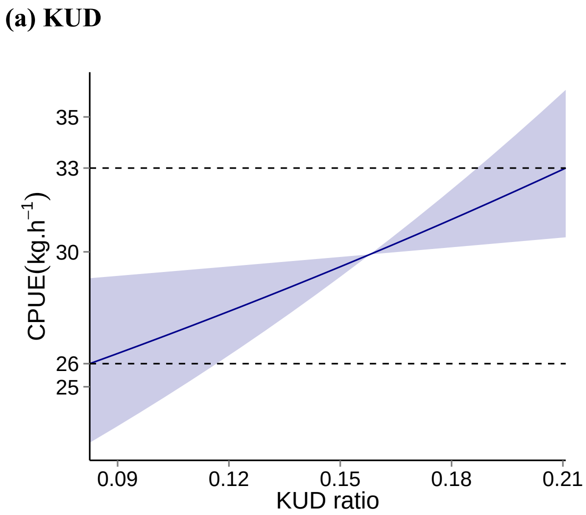


Figure 19: Predicted catch-per-unit-effort (CPUE) as a function of the proportion of a) the kernel utilisation density (KUD) ratio, and b) the area of the 75% isopleth of the KUD relative to the average area (integrated over random effects and with all other covariates held at their mean). Solid line shows the prediction and the posterior mean of the regression parameter; blue shading indicates predictions at parameter values within the 95% quantiles of the posterior distribution for regression parameters; dashed lines indicate the range of predictions.

fished, and led to highly correlated posterior distributions for both variables.)

As an illustration of the potential of KUD metrics to reflect status and changes in the fishery, we compared KUD areas within PAU 7 and PAU 4. This comparison between QMAs was chosen as the amount of data within a single QMA was insufficient to contrast spatial resource use through time (due to the short time since the inception of the data-logger programme). The two QMAs had similar TACCs, but catch rates were markedly higher in PAU 4, helping to clarify patterns in spatial resource use. Nevertheless, the logger data to the reporting date only represented a subset of divers in each QMA. For this reason, the current results are presented for illustrative purposes only as comparisons need to be made within QMAs and over time.

For a similar TACC, the 75% isopleth in PAU 7 was large and covered much of outer Marlborough Sounds facing Cook Strait (Figure 20), whereas in PAU 4, the 75% isopleth was patchier, broken into distinct spots on the coastline (Figure 21). Although more data were available to estimate core areas in PAU 7 (about 40 000 dives compared with about 12 000 dives in PAU 4), this pattern suggested that most of the potential fishing ground within PAU 7 was visited regularly, whereas only a few spots in PAU 4 were fished (based on the subset of divers participating in the data-logger programme). Accordingly, the area inscribed by the 75% isopleth contours in PAU 4 was only 8% of the size of the corresponding area in PAU 7, and the 25% KUD area in PAU 4 was only 2% of the size of the corresponding area in PAU 7. Furthermore, over the entire reporting period, the catch from the 25% KUD area in PAU 7 was approximately 11 kg ha^{-1}, whereas the catch in the 25% KUD area in PAU 4 was 133 kg ha^{-1}.

3.3.2 Within QMA models of spatial CPUE

Models on the hexagon scale (i.e., on a rasterised coastline) within QMAs showed a reasonable fit (see appendix, Figure A-2), and gave consistent results for both spatial metrics and dive effort metrics (ie., bottom time and depth effort). Bottom time in particular was found to be the most important predictor of catch, and was consistently more important than total fishing time (Table 12, Figure 22). At equivalent total fishing times, increasing bottom times over the observed range led to an increase of over 300% in predicted CPUE within QMAs (Figure 23). This effect was an order of magnitude stronger when

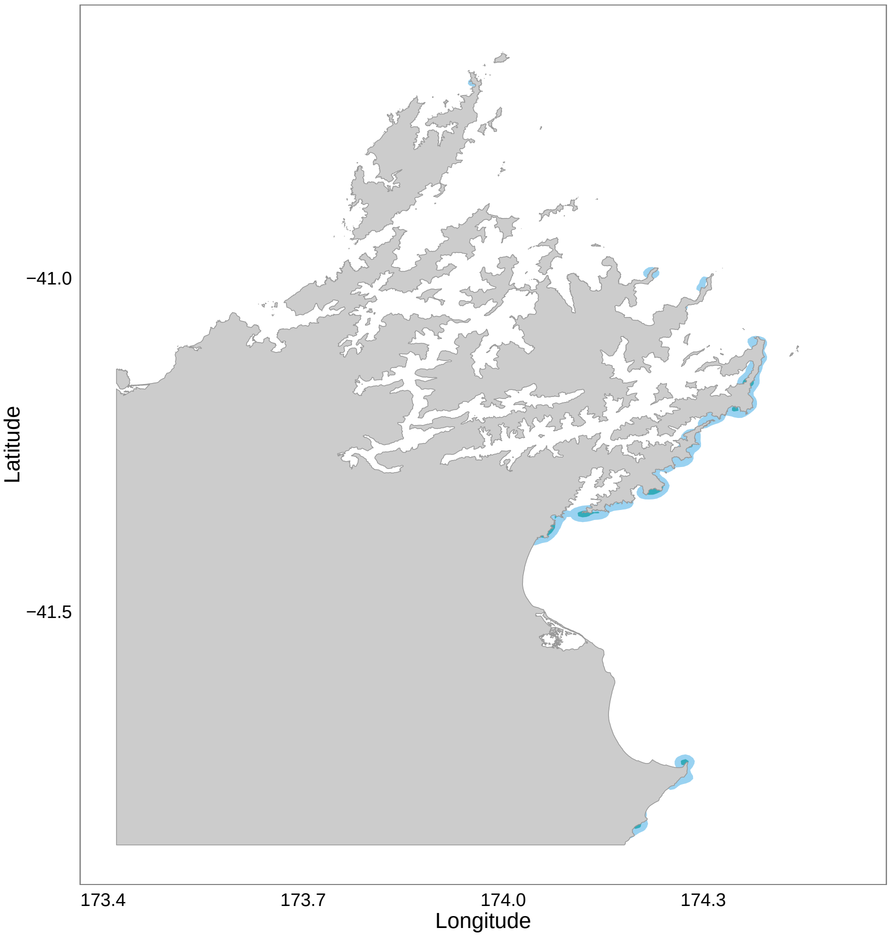


Figure 20: Kernel utilisation densities (KUDs) estimated over all dives in pāua Quota Management Area PAU 7, Marlborough Sounds. Lighter and darker shades indicate estimated 75% and 25% isopleths, respectively.

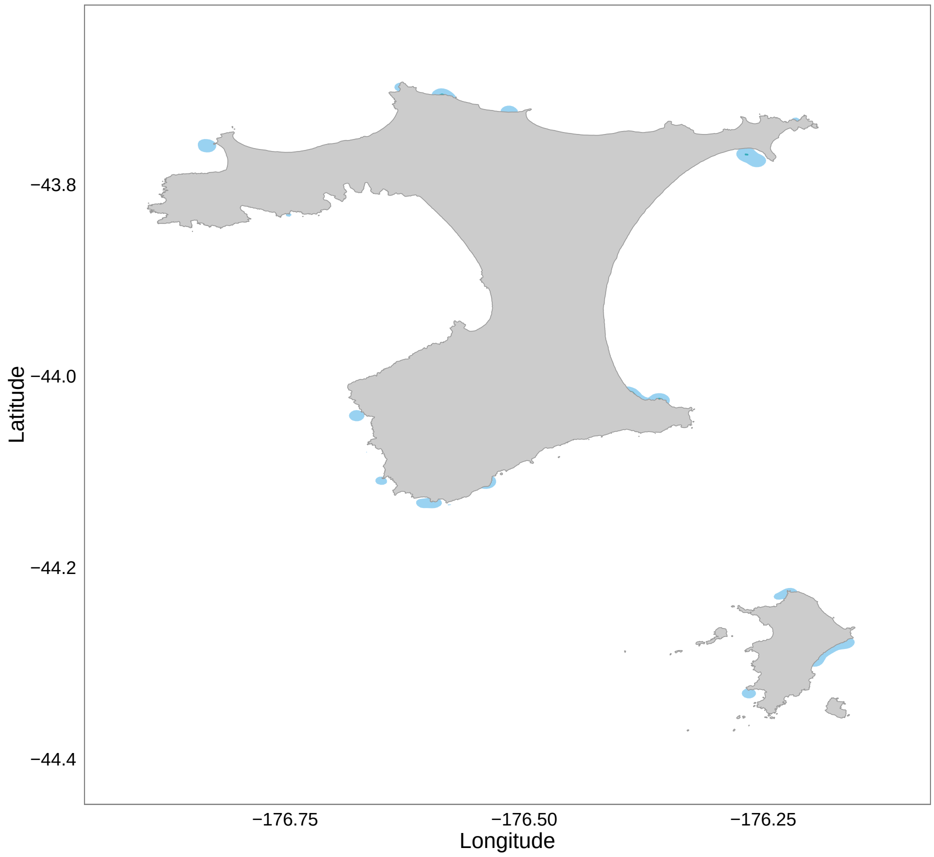


Figure 21: Kernel utilisation densities (KUDs) estimated over all dives in pāua Quota Management Area PAU 4, Chatham Islands. Lighter and darker shades indicate estimated 75% and 25% isopleths, respectively.

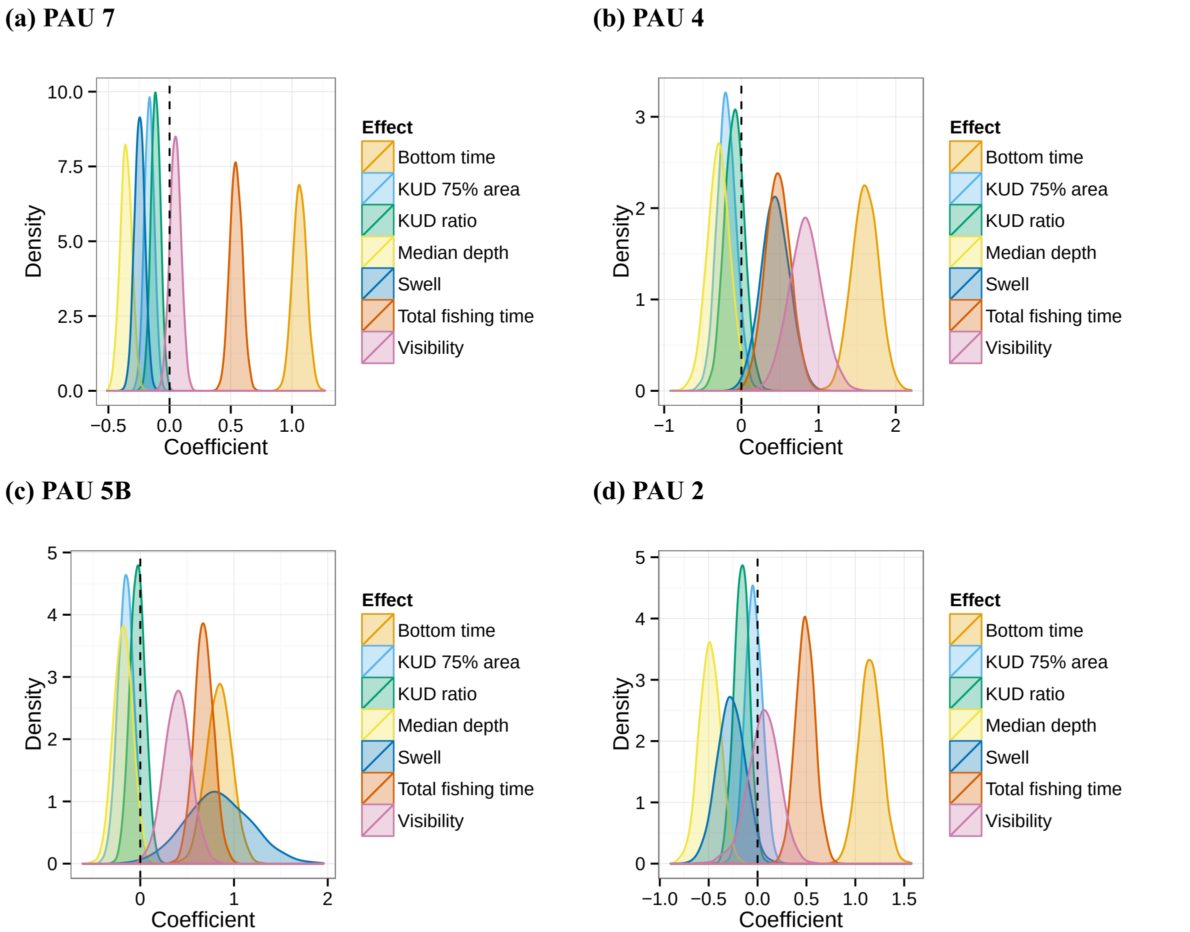


Figure 22: Posterior distributions for model coefficients in models at the hexagon scale within pāua Quota Management Areas with spatial predictors. KUD 75% area refers to the kernel utilisation density area within the 75% KUD isopleth. (A larger estimated coefficient (positively or negatively) indicates a stronger effect per standard deviation in the input.)

estimated within QMAs on small spatial scales, compared with estimates across QMA models on the daily scale. Catch was also negatively related to median depth in all QMAs, although it was only in PAU 4 that the effect was on the same order of magnitude as the effort metrics bottom time and total fishing time.

At average bottom and fishing times within hexagons, PAU 7 and PAU 5B had low Catch Per Unit Area (CPUA, measured by catch per 1-ha hexagon) compared with PAU 2 and PAU 4 (Figure 23, see also Table 4). Nevertheless, given that for PAU 5B, PAU 4 and PAU 2, there were only limited amounts of data available for fine-scale models, these estimates should be regarded as initial indications only. Absolute values within QMAs are likely to change once more data become available.

Spatial metrics (KUD ratio and KUD area) were inversely related to catch in PAU 7 and PAU 2; in PAU 5B, only KUD area was negatively related to catch. The KUD ratio thus showed an inverse pattern (as compared to the daily scale) for both PAU 2 and PAU 7 (Figure 23). The effect of both KUD ratio and area fished was not nearly as large as the effect of dive-related variables, but still showed a consistent pattern across QMAs.

The response of catch rates to dive conditions showed consistent patterns in terms of visibility, with higher visibility leading to increased catch rates (Table 12). The response to swell was variable, with catch rates in PAU 7 and PAU 2 being negatively related to swell, whereas catch rates in PAU 4 and PAU 5B showed a strong positive correlation with swell height.

Table 12: Posterior means, probability of being strictly positive, and 95% credible interval for model parameters of models on a scale of individual hexagons within pāua Quota Management Areas. KUD 75% area refers to the kernel utilisation density area within the 75% KUD isopleth.

(a) PAU 7

Parameter	mean(θ)	P($\theta > 0$)	2.5%	97.5%
Bottom time	1.06	1.00	0.95	1.17
KUD 75% area	-0.17	0.00	-0.24	-0.09
KUD ratio	-0.11	0.00	-0.19	-0.04
Median depth	-0.36	0.00	-0.45	-0.27
Swell	-0.24	0.00	-0.33	-0.16
Total fishing time	0.54	1.00	0.45	0.64
Visibility	0.05	0.86	-0.04	0.14

(b) PAU 4

Parameter	mean(θ)	P($\theta > 0$)	2.5%	97.5%
Bottom time	1.60	1.00	1.27	1.93
KUD 75% area	-0.19	0.06	-0.43	0.05
KUD ratio	-0.09	0.24	-0.33	0.16
Median depth	-0.29	0.03	-0.59	0.00
Swell	0.44	0.99	0.08	0.80
Total fishing time	0.47	1.00	0.15	0.79
Visibility	0.83	1.00	0.41	1.26

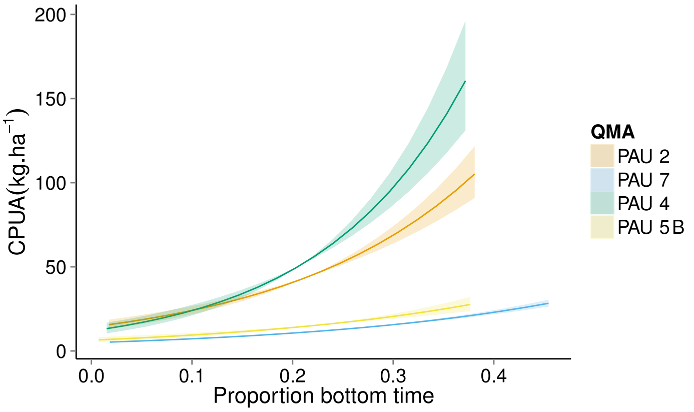
(c) PAU 5B

Parameter	mean(θ)	P($\theta > 0$)	2.5%	97.5%
Bottom time	0.84	1.00	0.58	1.10
KUD 75% area	-0.15	0.03	-0.32	0.01
KUD ratio	-0.03	0.36	-0.18	0.13
Median depth	-0.18	0.04	-0.38	0.02
Swell	0.83	0.99	0.17	1.52
Total fishing time	0.68	1.00	0.48	0.88
Visibility	0.40	1.00	0.12	0.68

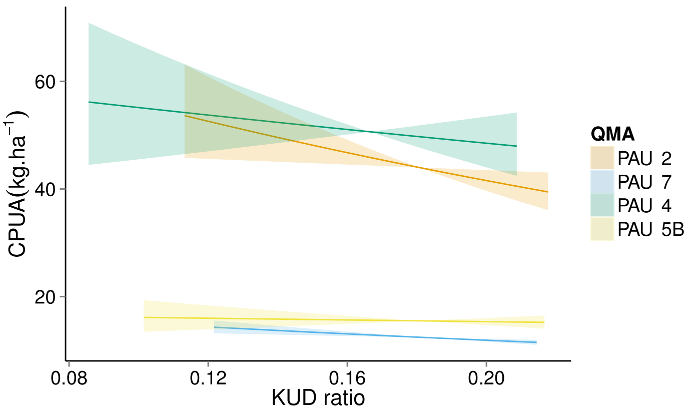
(d) PAU 2

Parameter	mean(θ)	P($\theta > 0$)	2.5%	97.5%
Bottom time	1.15	1.00	0.92	1.38
KUD 75% area	-0.04	0.33	-0.21	0.13
KUD ratio	-0.16	0.02	-0.32	-0.01
Median depth	-0.49	0.00	-0.70	-0.28
Swell	-0.27	0.03	-0.55	0.01
Total fishing time	0.49	1.00	0.30	0.69
Visibility	0.06	0.66	-0.30	0.36

(a) Bottom time



(b) KUD ratio



(c) KUD 75% Area

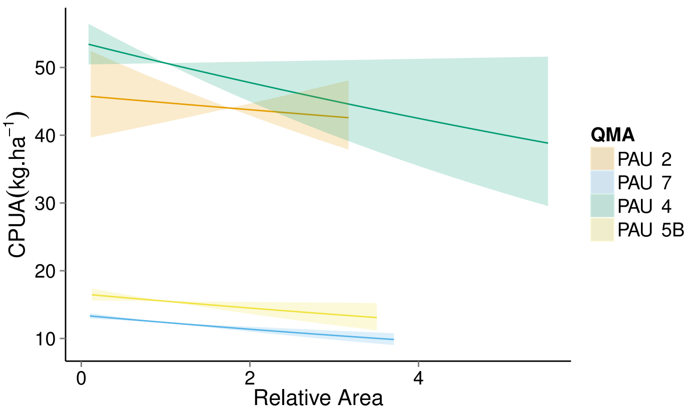


Figure 23: Posterior mean of predicted Catch Per Unit Area (CPUA) as a function of a) proportion bottom time (relative to average fishing time within hexagons), b) kernel utilisation density (KUD) ratio, and c) KUD area relative to the average KUD area fished. All predictions are plotted over ranges of predictors observed within pāua Quota Management Areas (QMAs).

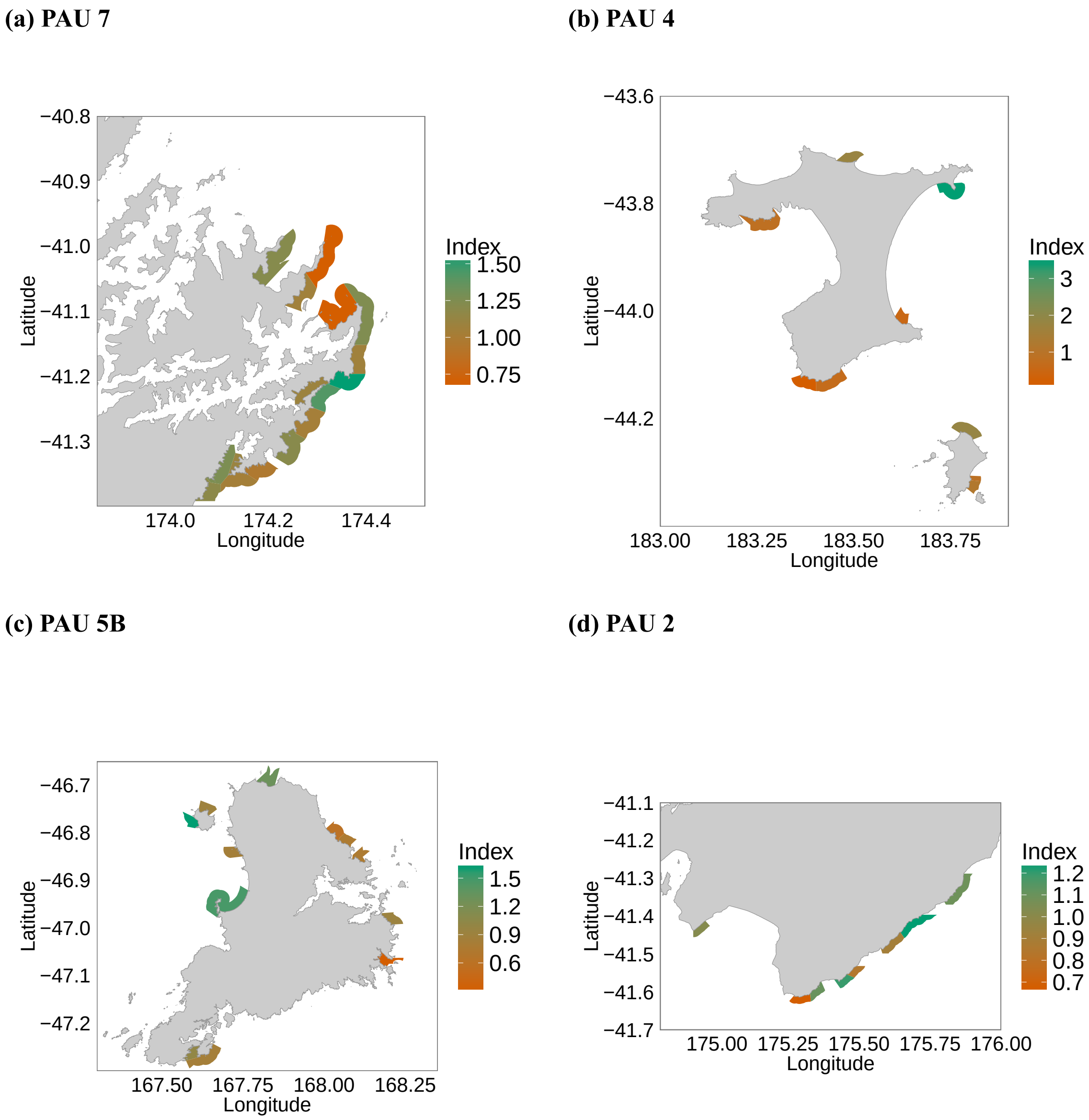


Figure 24: Spatial index of catch-per-unit-effort (CPUE), with maps showing statistical areas dived by pāua crews corresponding to at least three Annual Catch Entitlement holders. Land is indicated in grey and statistical areas are coloured according to the posterior mean of the CPUE index as estimated from Quota Management Area specific standardisations at the hexagon scale.

Table 13: Posterior means of estimated random effect variances within individual pāua Quota Management Areas.

Effect	PAU 7	PAU 4	PAU 5B	PAU 2
Diver	0.79	1.43	0.97	0.17
Statistical Area	0.11	0.17	0.48	0.10
Hexagon	0.41	0.85	0.45	0.29

The model at hexagon scale allowed us to estimate both statistical area and hexagon-specific random effects. For PAU 7 and PAU 4, there was a hierarchy of effect sizes for random effects (Table 13). Diver effects showed the highest population level variance, while the statistical area effect variance was on the order of half the diver effect. Hexagon-specific effects were the smallest by nearly an order of magnitude, meaning that most of the detectable variability in catch rates was on spatial scales larger than 1-ha hexagons. This pattern was the same in PAU 5B for diver and statistical area effects. The hexagon effect, however, was on the same order of magnitude as the statistical area effect, suggesting small scale variability within statistical areas. In PAU 2, the estimated effects were all small relative to other QMAs, and the statistical area effect variance was nearly twice as large as the diver effect variance. The hexagon-specific effects were again the smallest.

The spatial random effects can be visualised on a map as a spatial index of CPUE (Figure 24). On the statistical area scale, estimated differences between individual areas were large (up to 400%) in PAU 4 and PAU 5B, and approached 100% in PAU 7 and PAU 2. A geographical pattern of higher CPUE within Cook Strait compared with outer Marlborough Sounds was evident in PAU 7, whereas in other QMAs such large-scale patterns were less evident. In PAU 4, a single exceptional fishing spot accounted for much of the difference between statistical areas.

4. DISCUSSION

This study provides a first quantitative assessment of the dive-logger programme. The data contain a substantial amount of information that can be used to calculate relevant metrics to monitor catch on small spatial and temporal scales. Although many of the benefits may not become apparent until a time series of logger-derived metrics can be established, the consistent relationships between dive parameters, spatial metrics and CPUE found in our models provide a strong basis for monitoring.

4.1 Programme uptake: limitations and considerations

Our analyses suggest that the dive loggers have the potential to provide automated reporting that has several benefits over the current reporting practice (i.e., PCELR forms). Dive conditions reported as Good on PCELR forms, for example, were negatively related to swell, and positively correlated with visibility. Our spatial models for logger data within QMAs (at hexagon scales), however, suggest that in some areas (e.g., PAU 4, PAU 5B) both swell and visibility can positively influence catches, most likely because the most productive fishing grounds consistently receive high swells, but yield high catches at good visibility. The combined condition index currently used on the PCELR forms would not allow for this possibility.

The modelling also suggested that the use of a boat assistant leads to increased catch rates, and the logger programme allows for monitoring of their use. The positive effect of dive assistants on catch rates (see Figure 15) does suggest that the widespread introduction of this practice is a form of effort creep that may have masked declines in CPUE. This effect has not been included in pāua stock assessments. Nevertheless, it is possible that the crews that do not use boat assistants are generally less efficient, and that the boat-assistant effect is a general marker for more efficient crews. The diver effect should account for this potential difference in efficiency.

Additionally, the data loggers provide a way to increase the accuracy of spatial reporting. Although only a subset of divers are currently participating in the programme, it is apparent that spatial reporting on PCELR forms is often inaccurate. This finding is not surprising, as filling in PCELR forms is a manual process, and it may not always be straightforward for divers to correctly identify all statistical areas from which a day's catch originated. With turtle loggers, the statistical areas can be automatically inferred from the GPS position of the diver.

Inconsistencies with the data collection and reporting remain, and currently restrict some analyses of dive-logger data. In some cases, divers did not record catch bags until the end of the fishing day. This data recording makes it impossible to spatially disaggregate the catch, as any dive on that day could have been associated with any landed catch bag. Consistent reporting of catch bags when they are landed on the boat by divers will improve the information from the dive-logger programme.

Furthermore, the catch weight is only reported at the end of the day, which also prevents an accurate disaggregation the day's catch. We addressed this limitation by evenly dividing the day's catch among dive bags. This approach introduces a spatial smoothing that will increase the difficulty of estimating a spatial CPUE. A recent firmware change makes it possible for divers to report estimated catch weight for each bag. This reporting practise could further improve the accuracy of inferences made from the logger data. Nevertheless, conversations with divers made it clear that they consider this reporting practice as additional effort, and that they are reluctant to adopt it. Meanwhile, aggregating data at the 1-ha hexagon scale provides a way to address this limitation to some extent, depending on how much the fishers move between hexagons during the day.

Missing dive location data further complicated some of our analyses, and introduced unknown (although probably small) errors in inferences made here. As most missing data intervals were relatively short, it is unlikely that they introduced large errors or biases in our inferences. Missing GPS position data seemed to be largely due to short surface intervals. We also suggest that the proportion of GPS positions lost will further depend on the way divers position the loggers on their wetsuit (e.g., whether the loggers are worn on the belt or back, in a casing or not), and on the spatial location of the dives themselves. When dives occur close to high coastal features such as cliffs, the latter may block the signal from the satellites, leading to failed GPS records on the turtle logger units.

Lastly, the location-reporting error in the hardware led us to discard a large amount of dive data that were recorded before the correction for the fine-scale analysis was implemented. We attempted to correct these incomplete dive data using both heuristic and machine-learning techniques, both of which failed to provide satisfactory results. In many cases, erroneous locations could not be differentiated from divers changing location. A related problem with the data loggers was that some of the units did not turn on or off at the appropriate time. The water switch on dive units is prone to turn on and record dives in locations that are unlikely to correspond to actual dive locations. Given the large amount of dive data from the programme (more than a million lines of dive data to date), it is difficult to filter out these locations manually. In addition, automated corrections based on heuristics were not always successful at discarding erroneous dive data. We did, however, only include hexagons with more than ten dives in our analysis of fine-scale spatial data in an attempt to reduce these shortfalls. Any dive positions recorded on land were also discarded.

Despite some remaining limitations with the data logger data, consistent patterns can be inferred from the data collected since the start of the programme. Addressing the reporting and hardware issues outlined above will increase confidence in the inferences made from the logger data, and ensure that the maximum benefit is gained from the data collection.

4.2 Dive metrics

The dive data collected as part of the logger programme provided indications of temporal trends in the fishery. Most noticeably, there was a trend towards longer bottom times yet slightly shallower average depths in some QMAs over the four years of the logger programme. Despite the small magnitude of the changes (less than 10 s and less than 1 m, respectively), these adjustments may reflect a response by divers to changing catch rates. An increase in bottom time in particular may be indicative of a change in the resource. Nevertheless, dive parameters also varied strongly among divers of different fitness, habits and preferences. For this reason, changes in the mean values of dive parameters may reflect an increased uptake of the logger programme by divers with different dive styles. Additionally, dives are likely to reflect the resource density and distribution, which in turn may change due to fishing, biotic (e.g., abundance of algal food sources for pāua) and abiotic (e.g, wave climate) factors.

Our modelling results consistently found that bottom time and depth were strong predictors of catch, both on daily scales and within individual 1-ha hexagon blocks. The results were consistent among QMAs, and extend patterns first reported by Abraham (2012) from a pāua fish-down experiment in Fighting Bay, Marlborough Sounds. Although the overall distributions of dive duration and surface swimming distance did not change markedly during the fish-down experiment, it was evident that an increasing proportion of daily catches came from deeper dives as abundance in the area declined.

We found that the variation in the effect of bottom time depended on the diver. Divers that generally achieved high CPUE did not consistently increase their catches by spending more time at depth, whereas divers with lower average catch rates did (Figure 17). Divers fishing at low CPUE could thus potentially increase their bottom time to increase their fishing power, potentially leading to hyper-stable CPUE indices. In PAU 7, for example, the model at the daily scale suggested that catch rates within this QMA had been declining, despite increasing bottom times. This finding could be interpreted as a potential warning sign that divers spend increasing time at depth to offset lower catches. (Note, however, that data for the 2013–14 fishing year was incomplete and inferred patterns may change with more complete data.)

Our results suggest that a model including both total fishing time and bottom time provides higher predictive power (i.e., lower DIC) than a model including only the total fishing time. Although a comparison of our best model on the daily scale and the base model suggested that there is some redundancy in these two effort measures, their combined effect was clearly larger than the effect of total fishing time alone. This result indicates that traditional CPUE based on total daily fishing effort may miss patterns related to bottom time. For example, stable catches at stable total fishing times may mask a decline in the resource if bottom times increase over the same period. Estimating temporal and spatial (e.g., at the statistical area level) CPUE indices from logger-derived data could considerably improve the robustness of these indices in the future.

The strength of dive effects varied with the geographical scale of the analysis. Some small scale spatial variation was smoothed out over the day, such that effects on a daily scale were not as strong as inferred effects on the hexagon scale. Despite this smoothing, median depths and bottom times of divers could provide an index of performance on both small (reef level) scales and large (day level) scales. For example, consistent increases in bottom time that coincide with stable or decreasing CPUE may be indicative of a decline in the resource. Nevertheless, given that the effect of bottom time is strongly dependent on individual divers, a model framework that accounts for individual diver effects would be needed to infer such a change.

4.3 Spatial metrics

Estimates of core areas, using the KUD, illustrate how the spatial data from the logger programme can be used to construct metrics that relate to catch rates at both daily and hexagon scales. Both the area fished and the concentration index measured by KUD isopleth ratios were consistently related to catch, although the KUD ratio showed opposing patterns at daily and hexagon scales. A likely explanation for this outcome is related to the scale itself. At large spatial scales such as the area covered in a day, patchy core areas for the day relative to a large search area should indicate that the overall abundance is low and the distribution is patchy. On a reef scale, however, the size of the hexagon constrains the maximum size of the search area, and a more patchy distribution of the dives may indicate that the diver found aggregations of pāua that led to higher catches within a given hexagon.

The overall effect size of these spatial metrics on CPUE at the fine scale, however, was comparatively low (see Figure 23), so that monitoring these metrics at a fine scale may be of limited use for predicting the performance of individual reefs. On a day scale, the patterns were more pronounced, and monitoring daily areas and KUD ratios may be used as an indicator of changes in the resource.

Furthermore, KUD area can be monitored at various isopleth percentages to give an indication of whether core areas are expanding, moving or contracting. For example, in PAU 4, the 25% isopleth contained a very small area. An expansion or shift of this area could indicate that divers are moving from a few very productive reefs to new areas, which could be taken as a warning sign for serial depletion (Mundy 2012).

The KUD ratios and areas may be useful spatial metrics of fishery performance at both the day level and QMA level. In particular, they provide a means of estimating relative fishing pressure in a given area while being able to account for missing dive locations. This reporting is more resource oriented than reporting by statistical areas, and would be more likely to detect serial depletion as patterns are not smoothed out by the arbitrary division of effort into statistical areas.

4.4 Towards spatial CPUE

Within our models, we showed that data from the logger programme can be used to construct a spatial (or non-spatial) index of CPUE. Such a CPUE index could be monitored on different spatial scales and over time. Over short timescales (e.g., between months), this monitoring would require large amounts of data. To allow detection of a spatial signal, data would need to provide near-complete coverage of the fishery to ensure sufficient overlap among fishing operations. Nevertheless, the present analysis suggested that with the current, relatively small dataset spanning two years, strong spatial variability in CPUE can be estimated within a model to provide baseline information about spatial patterns in the fishery.

As diver effects in our models were consistently estimated to be larger than spatial effects (except in the model that was specific to PAU 2), accounting for diver effects is crucial to make inferences about spatial patterns that may otherwise be obscured by the dominant diver effects. The relative strength of random effects in our models suggests that raw spatial CPUE alone will only reveal limited information about true spatial patterns in the resource itself, and that model-based inference of spatial patterns will be essential for spatial management.

In the short term, indirect performance metrics such as KUD related metrics (e.g., catch within core area, KUD ratio) may provide immediate means to detect potential changes in the fishery. These changes can then be more thoroughly investigated using a model-based approach. In the present study, the limited amount of data with reliable locations (only one full fishing year), and the corresponding lack of a timeseries with reliable spatial data makes it difficult to assess which spatial indicators will prove most useful at this stage. Nevertheless, this study suggests that the information and performance measures that can be gained from the logger programme will be valuable in time for allowing the effective management of the pāua fishery on smaller spatial and temporal scales than is currently possible.

5. ACKNOWLEDGMENTS

We are especially grateful to Jeremy Cooper and Storm Stanley of the Paua Industry Council (PIC) for their far-sighted support of the data-logger programme, and to Julie Hills of the Ministry for Primary Industries for her focus on ensuring that the programme delivers actionable results. We are also grateful to Tom McCowan (PIC) for valuable comments and discussions throughout the course of this project. We also thank the divers who commented on potential metrics to include in the analysis, and John Radford at Zebra-Tech for discussions about pāua data logger issues.

The statistical analysis was carried out using the software JAGS; supplementary analysis was conducted with R; data were stored in a PostgreSQL database; report writing used the LaTeX document preparation system. We are extremely grateful to the many people who contribute to these key open source software

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APPENDIX A: Posterior predictive model assessments

Figure A-1: Posterior predictive assessment of the Bayesian mixed model considered the best model for predicting daily pāua catch (see subsubsection 3.2.2). Green band indicates the 95% credible interval for predictions at each point.

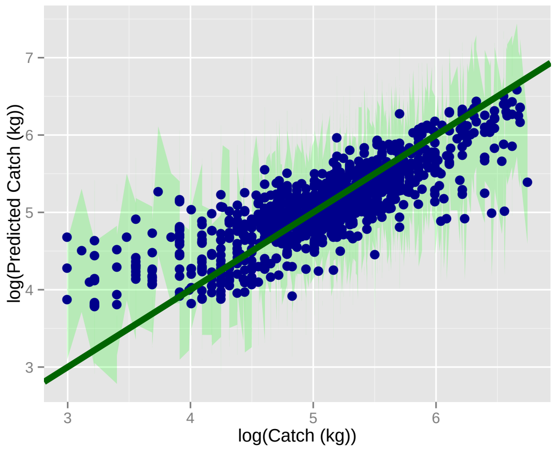

Figure A-2: Posterior predictive assessment of Bayesian mixed models for predicting daily pāua catch at the hexagon scale for different Quota Management Areas. Green bands indicate the 95% credible interval for predictions at each point