Spatial structure for the south Pacific albacore assessment including regional weights

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1 Executive summary

"Regional weights" are empirical estimates of the proportion of the population in each region of the assessment area, vulnerable to a specified fishing gear, and help constrain the stock assessment to estimate sensible values for movement and population size among regions. This report presents the analyses that estimate regional weights for South Pacific Albacore for the 2015 stock assessment, using an extensive operational-level longline CPUE database. Several scenarios are explored that use data from different time periods and use different methods of imputing CPUE values for unfished cells. Regional weights were estimated to be highest for regions 5, 6 and 8, though the relative weights among regions showed moderate variation depending on the scenario assumed. This can largely be attributed to the different methods of imputing values for unfished cells at the southern extent of fishing activity. Due to this uncertainty, we not only make recommendations about regional weights to use in reference case stock assessment models, but also weights to use in the uncertainty grid. Avenues for further improvement of regional weights for albacore and other species in the WCPO are discussed.

2 Introduction

Many of the stock assessments of pelagic fish in the West and Central Pacific Ocean (WCPO) are spatially disaggregated, which permits subregional population dynamics and movement of fish among subregions. This additional model complexity comes at the cost of greater difficulty in the estimation of parameters, particularly if the data available provide only limited information about some parts of the model. The so-called "regional weights" (McKechnie et al., 2014) are empirical estimates of the proportion of the population in each region of the assessment area, vulnerable to a specified fishing gear (typically longline, LL).

Without regional weights, these models often have too much flexibility in where they assign recruits and move individuals among regions, leading to unrealistic exchange rates and population size among regions. Regional weights are therefore used to adjust the standardised catch-per-unit-effort (CPUE; numbers of fish per hundred hooks) indices used in the assessment, which in conjunction with the assumption of shared catchability among these fisheries, and the effort deviation penalties, provide constraints on the relative abundance among regions over the time-period that the regional weights were calculated.

Several considerations need to be taken into account when calculating regional weights. The approach relies not only on the assumption that catchability can be shared among the focal fisheries in each region, but also that the regional weights accurately reflect the underlying population size of fish vulnerable to the gear among regions. Processes such as changing targeting practices over space and time, and spatial variation in catchability introduced by the distribution of fleets, or variation in environmental conditions such as thermocline depth, must be accounted for to meet this latter assumption.

Regional weights have been utilised in the stock assessments of bigeye and yellowfin tuna for some time (Langley et al., 2011; Harley et al., 2009, 2014; Davies et al., 2014), and the recent methodology (McKechnie et al., 2014) can be briefly summarised as; aggregate-level relative abundance (CPUE) data is collated over a period of time where spatial differences in catchability (due to targeting etc.) are thought to be minimised and spatial coverage of data is adequate, spatial surfaces of relative

abundance are estimated for the entire Pacific Ocean in each year-quarter over a defined period using generalised additive models (GAMs), the predictions of this spatial surface are used to sum abundance over all cells in a region (including imputed values for cells with missing data) and the region-specific values are scaled to sum to 1, and finally, the regional weights used in the stock assessment are calculated as the region-specific means over the time period.

Previous stock assessments of South Pacific Albacore (SP-ALB) have used a model with a single region, with subregional structure introduced using spatially restricted fisheries definitions (Hoyle et al., 2012), which does not require the use of regional weights. The 2015 stock assessment of South Pacific Albacore (Harley et al., 2015a) is the first for this stock with spatial disaggregation, and so this report details the process of estimating regional weights for the 8 regions. For these analyses we utilise the extensive operational-level LL CPUE database previously used by Tremblay-Boyer et al. (2015); McKechnie et al. (2015).

There are several issues unique to SP-ALB that need to be addressed when calculating regional weights; 1) SP-ALB are thought to undergo more pronounced seasonal migration than the tropical tunas and so seasonality must be considered when estimating abundance surfaces, 2) if operational-level data are analysed to address targeting behaviour, spatial gaps in CPUE data are more prevalent than for aggregate-level data used for other species, and so assumptions about fishing activity in missing cells and imputation methods need careful consideration, 3) in contrast to the tropical tunas where relative abundance declines relatively uniformly with increasing latitude, SP-ALB abundance appears to be high near the southern boundary of fishing activity, which makes decisions about abundance in unfished cells in southern areas very important. Below we outline our attempts to overcome these issues and produce robust estimates of regional weights for use in the 2015 SP-ALB stock assessment.

Our general approach to estimate regional weights involved; identifying ALB targeting using cluster analyses of the operational-level LL dataset and removing non-target data, modelling ALB CPUE using GAMs with covariates such as fleets and thermocline depth to estimate a spatial surface of relative ALB abundance across the assessment area, developing rules to determine how predictions of CPUE should be applied to cells with no records of fishing activity, and finally, summing relative abundance across cells within regions to give a single regional weight for each region, which can then be used in the assessment to adjust standardised effort for the LL fisheries. We present regional weights estimated under several scenarios and make recommendations on which we believe are most suitable for use in the 2015 SP-ALB stock assessment.

3 Methods

3.1 Changes to stock assessment regional structure

The 2012 stock assessment of SP-ALB consisted of one region extending from 50° S to the equator, and from 140° E (Australia) to 70° W (the Americas landmass). For the 2015 stock assessment it was decided that the assessment would be restricted to the WCPFC convention area (including overlap area) as this is the unit at which management decisions are made, and that a spatially explicit regional structure would be investigated to allow for more explicit non-homogeneous population and fisheries dynamics across the assessment area.

Several factors were considered in the development of the 2015 regional structure shown in Figure

1. The boundary at 10° S that separates the equatorial regions (regions 1 and 4), and those to the south was established to be consistent with the tropical tuna assessments, and separates fishing activity mostly targeting the tropical species, from the temperate areas where there is a mixture of ALB and tropical tuna targeting. The boundary at 25° S is consistent with the 2012 assessment and was originally established based on differences in length-compositions of fish caught by LL vessels north and south of this latitude. The longitudinal divisions at 170° E and 150° W were established to be consistent with the tropical tuna assessments and allow more robust development of bioeconomic models (Kirchner et al., 2010).

Within a stock assessment region there can be multiple fisheries defined, with model input data allocated to these fisheries on the basis that they have relatively stable selectivity and catchability characteristics over time. Our approach to the fisheries definitions in the 2015 SP-ALB stock assessment has been to begin with relatively simple definitions and let the assessment model diagnostics guide any further division of fishing activity into separate fisheries. The 14 fisheries defined for 2015 are shown in the appendix (Figures 18–31) and consist of 1 LL fishery for each of the 8 regions, 3 troll fisheries (regions 3, 6 and 8) and 3 driftnet fisheries (regions 3, 6 and 8) which operated over a short time-frame in the late 1980s. No fisheries have been split on the basis of flag, as has previously been done.

3.2 Datasets to estimate regional weights and focal fisheries

The geographical extent and regional boundaries of the 2015 SP-ALB stock assessment are shown in Figure 1. Each region has one LL fishery which encompasses all vessels fishing with that gear (summaries of these fisheries are shown in the appendix, section 7), and the standardised CPUE indices estimated by Tremblay-Boyer et al. (2015) are used to standardise the effort of these fisheries for input to Multifan-CL (MFCL; Harley et al., 2015b). The regional weights we estimate below are therefore incorporated into the effort standardisation for these 8 fisheries.

The datasets used in these analyses are those presented in detail by Tremblay-Boyer et al. (2015) when estimating standardised CPUE indices for SP-ALB. Their report outlines the rules for data grooming and the cluster analyses undertaken to identify discrete groups of targeting activity in the data. They only retained those sets classified as ALB-targeted for analyses and we follow this approach in an attempt to ensure that the effects of spatial variation in the species being tageted by vessels on our estimated spatial abundance surface is minimised.

We impose two further restrictions on the dataset. We removed sets with zero catches of ALB as we would expect sets that target albacore to capture at least one individual, and by removing these sets we are able to fit the CPUE data with GLMs that assume normality on the log scale. These sets represented a very small proportion of overall set counts ($< 2\%$). We restricted the dataset to one of two time-periods; (1) 1975 to 2008 (hereafter "full"), and (2) 2008 to 2014 ("truncated"). The former represents the time-period when we have widely available data, while the latter period was chosen because it represents a period where the albacore stock was fully exploited across its geographic range.

3.3 Model CPUE data as a function of thermocline, flag and quarter

Albacore CPUE was modelled over space as a function of quarter, fleet and the depth of the thermocline (see Table 1). The modelling was done in two steps to ensure that the effect of

thermocline was remodelled from the 2D lon-lat surface. We elected to use a two-step approach because thermocline data are highly correlated in space, and it would have been challenging to distinguish the effects of thermocline on the CPUE from that of the lon-lat surface if they had been fitted together in the same model. The thermocline predictions were obtained from GODAS and matched to cells based on lon-lat coordinates www.cdc.noaa.gov/data/gridded/data.godas.html.

We used `gam` models from the package `mcgv` in R, (R Core Team, 2013; Wood, 2006), and all models were fitted separately on the full and truncated datasets. In the first step, the logarithm of CPUE (number of fish per hundred hooks) was modelled against a smooth of thermocline and categorical variable with a Gaussian error distribution and an identity link, i.e.

$$\log(CPUE_i) = \beta_0 + \beta_{flag_i} + f(thermocline_i) + \epsilon_i \tag{1}$$

where the errors are normally distributed with mean 0 and estimated variance σ^2, i.e. $\epsilon_i \sim N(0, \sigma^2)$. The residuals from that model were extracted, left in log-space, and fitted to a 2D spline of longitude and latitude at a one degree resolution, with a normal error distribution and an identity link. The spline was a thin plate smoother from the function `s()` in `mcgv`.

$$\epsilon_i = \beta_0 + f(lon_i, lat_i) + qtr_i + \xi_i \tag{2}$$

where the errors are again normally distributed $\xi_i \sim N(0, \tau^2)$. Note that in this two-step model the spatial surface is fitted to all data aggregated over the time-period, which differs from the approach in previous years, but makes imputation of abundance in unfished cell more robust (section 3.4).

At this stage, because of strong monthly patterns in fleet activity, we defined three scenarios for the inclusion of quarters in the model: (1) quarters included as categorical variable; (2) quarters included as an interaction with the lon-lat surface; (3) lon-lat surface fit to each quarter independently. We only present results for scenarios (1) and (3) (and refer to (3) as the 'interaction' model since the shape of the lon-lat surface is allowed to change between quarters).

Table 1: Description of explanatory variables used in model for regional weights.

Variable	Symbol	Explanation
Quarter	β_{Qi}	Quarter during which the set occurs; captures seasonality in catch rates
Flag	β_{flag_i}	Fleet nationality of vessel; captures variations in vessel efficiency and species targeting
lon-lat, 1×1 degree cell	lon_i, lat_i	lon-lat coordinates of set assigned to 1×1 degree cell
Depth of the thermocline	–	Impacts catchability by constraining the size of the vertical habitat

3.4 Estimating regional weights from model output

Regional weights are calculated by summing the model-predicted CPUE (back-transformed from the log-scale) for each 1×1 degree cell in the set of cells considered to have ALB population in each

region. There are choices to be made however on what constitutes this set, and how predictions of relative CPUE in cells with missing data are made (an imputation situation).

In order to estimate total abundance by region we had to define how abundance in unfished cells relates to model-predicted abundance in fished cells. This is an imputation problem as we need methods and rules to predict abundance in all cells in the region where ALB population size is considered to be non-trivial. We differentiate between two types of unfished cells. Some cells had no records of fishing in our dataset over the entire time-period and we assume that these cells had trivial abundance and zero abundance is assumed. This mainly applies to cells at the southern extent of regions 3, 6 and 8. The second type were cells that were not fished for a quarter over the whole time period (but were fished at least once during another quarter). Two methods of imputing relative abundance for these cells were explored, either:

i. we assume they have an abundance of zero during that quarter only – this assumes that cells are only occupied seasonally by albacore, or

ii. we predict abundance based on imputation from the spatial abundance surface estimated for that quarter – this assumes that cell abundance is similar to that of neighbour fished cells but factors other than abundance have prevented fishing from occurring there.

For each time-period (full and truncated), relative abundance in each cell was imputed for these two scenarios. The relative abundances in fished cells were estimated by predicting abundance using the fitted model where the prediction was made for each 1×1 degree cell, for each quarter. The regional weights for a quarter were then constructed by summing over the relative abundance of all fished cells in a region, for each quarter, and over all unfished cells in the region-quarter using the imputation rules above, resulting in four sets of regional weights that could potentially be used in the stock assessment. Annual weights by region were the average of quarterly regional weights. Regional weights were then normalised across regions to ensure they summed to one.

3.5   Use of regional weights by Multifan-CL

The regional weights estimated in the sections above are used to adjust the standardised effort that is input to MFCL for the fisheries for which the standardised CPUE indices are calculated. In conjunction with the assumption of shared catchability among these fisheries, and the effort deviation penalties, these regional weights provide constraints on the relative abundance among regions over the time-period that the regional weights were calculated. The process of adjusting nominal effort is as follows. If $C_{f,t}$ and $E_{f,t}$ are the observed total catch and total effort, and I_t is the standardised CPUE index (typically normalised such that it has a mean of 1, but this is not essential), all for fishery f in year-quarter t, then initially we adjust the CPUE indices by

$$\acute{I}_{f,t} = \frac{w_f}{\dfrac{1}{n} \sum_{t \in T} I_t} \tag{3}$$

where w_f is the normalised regional weight for region f, and $T = \{t_a, t_{a+1}, ..., t_b\}$ where t_a and t_b are the first and last year-quarter over which the regional weights were calculated, and n is the number of time periods in T. Note that any year-quarters within this range for which a CPUE estimate is not available are excluded from the set T. The total effort, $E_{f,t}$ input to MFCL is then adjusted by ensuring the ratio of observed total catch $C_{f,t}$ to standardised effort, $\acute{E}_{f,t}$, is equivalent

to $\acute{I}_{f,t}$, i.e.

$$\acute{E}_{f,t} = \frac{C_{f,t}}{\acute{I}_{f,t}} \quad . \tag{4}$$

Thus the mean ratios of $(C_{1,t}/\acute{E}_{1,t}) : (C_{2,t}/\acute{E}_{2,t}) :, ..., : (C_{8,t}/\acute{E}_{8,t})$ over the time-periods in T will be the same as the ratios of $w_1 : w_2 :, ..., : w_8$. The likelihood of these "observed" effort values, given the models predictions of effort, are then added as a component of the overall objective function of the stock assessment model.

4 Results

4.1 CPUE for albacore targeting sets

The overall spatial distribution of records and the observed CPUE for the full and truncated datasets are shown in Figure 2. There is significant spatial variation in CPUE with some general patterns being; very low CPUE close to the equator (north of 8° S), moderate CPUE in middle latitudes with several discrete patches of low CPUE in these regions, very high CPUE between about 25° S and 42° S with a discrete area east of New Zealand with anomalous low CPUE, very few operational-level records available south of 42° S despite high CPUE immediately to the north.

There are significant monthly differences in the spatial distribution of records of albacore targeted fishing in the dataset, within the stock assessment area (Figure 3), with the highest spatial coverage observed between April and August (quarters 2 and 3). Outside of these months the proportion of cells for which we have records of fishing activity in northern regions were relatively stable, but there were a substantially higher proportion of cells in southern regions (3, 6, and 8) for which there are no records of fishing in the dataset. There is also some evidence of higher CPUE in these southern regions during April–August period of high spatial coverage (Figure 4).

Spatial coverage of the dataset was highest in the 1970s and has been contracting towards specific locations since then, leaving large areas of the stock assessment area where we have no operational-level records of fishing (Figure 4). The two main distant-water fishing fleets in the dataset, Chinese Taipei and Korea, show distinctive temporal changes in the spatial extent of fishing records available (Figures 5–6). Records for the Korean fleet have high to moderate spatial coverage over 1960s–1980s, but nearly all subsequent records are restricted to the equatorial regions (Figures 5), while the dataset for the Chinese Taipei fleet contracts steadily over the decades into well defined patches including specific exclusive economic zones (Figures 6).

4.2 Depth of the thermocline

Thermocline depth shows relative stability over the seasons near the equator but there are substantial seasonal changes further south (Figure 7). The thermocline depth in the southern-most 6 regions was shallowest in the Austral summer and increased through the year, reaching its deepest values over most of the area in about August (Austral winter), before decreasing again. The relative spatial distribution of thermocline depth remains broadly similar among most months throughout these seasonal changes.

4.3 Model of relative abundance

The model of the relationship between CPUE and the predictor variables fleet and thermocline explained about 7% of the variation in the data. This model was fitted with all quarters within the specified temporal span. The spatial surface fitted individually to the residuals by quarters explained an additional ~15%. Fitting quarters individually vs. adding them as a categorical factor shifts the distribution of abundance between regions during the year. For instance, the relative distribution of abundance shifts between regions 5 and 6 during the year, which not be seen if quarters were not fit separately. Adding this quarter interaction also explains more of the variation in CPUE in quarters 2, 3 and 4.

The full models for the period 1976–2008 estimated that regions 5 and 6 should receive the highest weightings (Table 2), followed by region 8, with the other regions estimated to have populations of albacore of vulnerable sizess approximately half or less those in regions 5 and 6. The two imputation methods produced slightly different regional weights, with method ii giving more weight to southern regions 6, 8 and to a lesser extent 3, and less to the other regions.

The truncated model did not produce substantially different estimates of relative abundance than the full model (compare Figure 8 to Figure 13) but it does reduce the spatial extent of the fishery, especially in region 6. This results in more cells having an unfished status and thus being assigned an abundance of zero under imputation scenario i (see Methods section 3.4), modifying the distribution of abundance among regions.

5   Discussion

Regional weights are a key model input for multi-region stock assessments in the WCPO, as they constrain predictions of fish movement and population distribution among regions to a realistic parameter space during model fitting. Here, we improved on several aspects of previous work, notably by attempting to remove the effects of targeting and thermocline depth on catchability over the spatial range, by removing non-target clusters and including theromoline depth in the standardisation model, respectively. Furthermore, we account for seasonal shifts in the distribution of abundance over the assessment area, and have compared methods of imputation for unfished cells.

We estimate that regional weights are highest for regions 5, 6 and 8, although there is moderate variation between the sets of weights using the different models and different imputation methods. It was particularly the case that models for the truncated dataset shifted the weightings away from the southern regions where there was more missing data for this time periods. We recommend using the regional weights estimated using the full dataset (1975-2014) and imputation method i, because we believe that it provides are more parsimonious approach to predicting abundance in these sourthern regions. However, because of the uncertainty in our estimates between scenarios, we recommend using the truncated dataset (2008-2014) and imputation method i in the uncertainty grid in the stock assessment, as this set estimates among the most different weights from the set that we recommend for use in the reference case stock assessment.

There are several avenues of research that could improve on our approach. The GAM models we utilise are often unstable near the geographical boundaries of available data, such as the southern boundaries of regions 3, 6 and 8. This can make obtaining sensible predictions at the edges of

a species range difficult. Geostatistical approaches appear to be more robust in these situations (Cressie, 1993) as the spatial variation is modelled in the error structure of the model rather than the deterministic component, and so greater restraints are placed on predictions through the components of error (co)variance. Another issure that requires further work is the investigation of why fleets are not fishing in some quarters, so that we can refine our hypothesis for the imputation of cells unfished in specific quarters, for example region 6 has high biomass but also seasonal fishery. Lastly, we recommend a formal examination of the sensitivity of multifan to regional weight estimates as this would provide guidance for estimation of regional weights for albacore and other species in the future.

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Table 2: Estimated regional weights for the 8 regions in the 2015 SP-ALB stock assessment. Values are shown for the full (1976–) and truncated (2008–) datasets, and for the raw, observed CPUE values, and the two imputation methods (i and ii; see section 3.4).

Time	Method	1	2	3	4	5	6	7	8
1976–	Raw	0.02	0.14	0.09	0.07	0.20	0.26	0.09	0.13
	Imputation i	0.02	0.12	0.08	0.09	0.21	0.23	0.12	0.13
	Imputation ii	0.02	0.11	0.10	0.07	0.16	0.27	0.10	0.16
2008–	Raw	0.03	0.19	0.08	0.08	0.25	0.16	0.09	0.11
	Imputation i	0.03	0.16	0.07	0.12	0.26	0.15	0.12	0.10
	Imputation ii	0.03	0.12	0.09	0.10	0.19	0.18	0.11	0.17

6 Figures
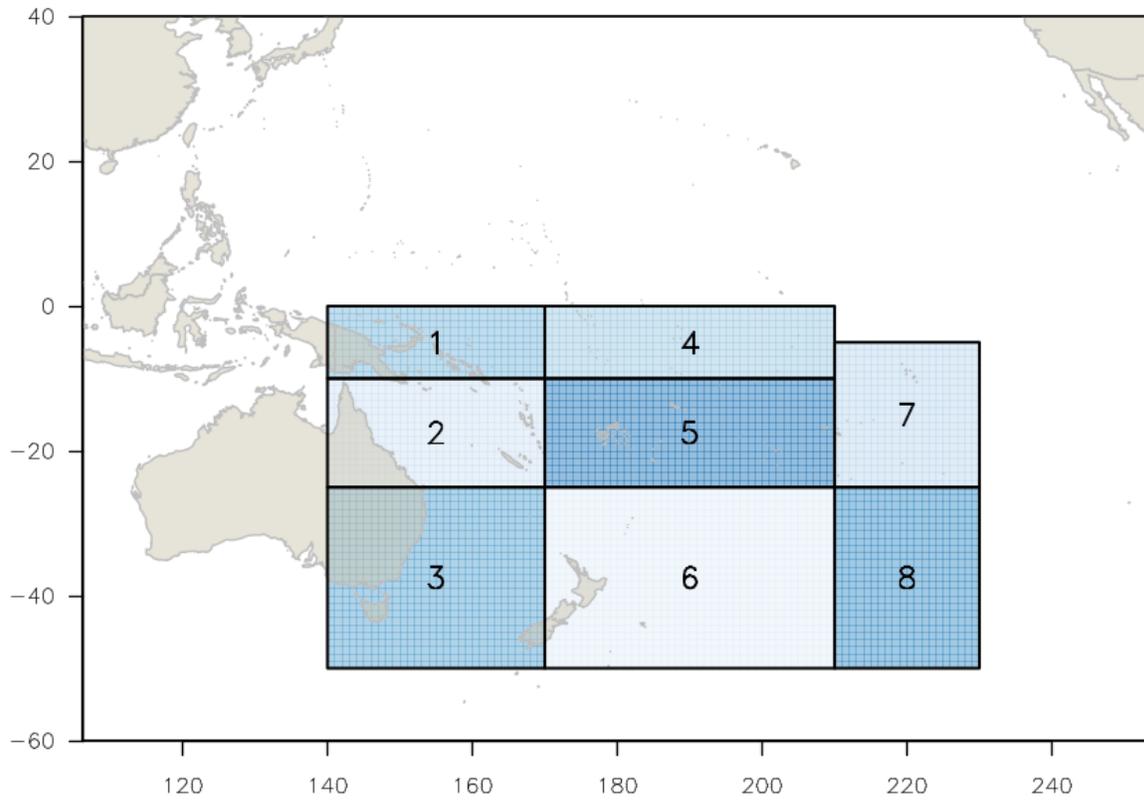
Figure 1: Map of the regional boundaries used in the 2015 stock assessment of SP-ALB.
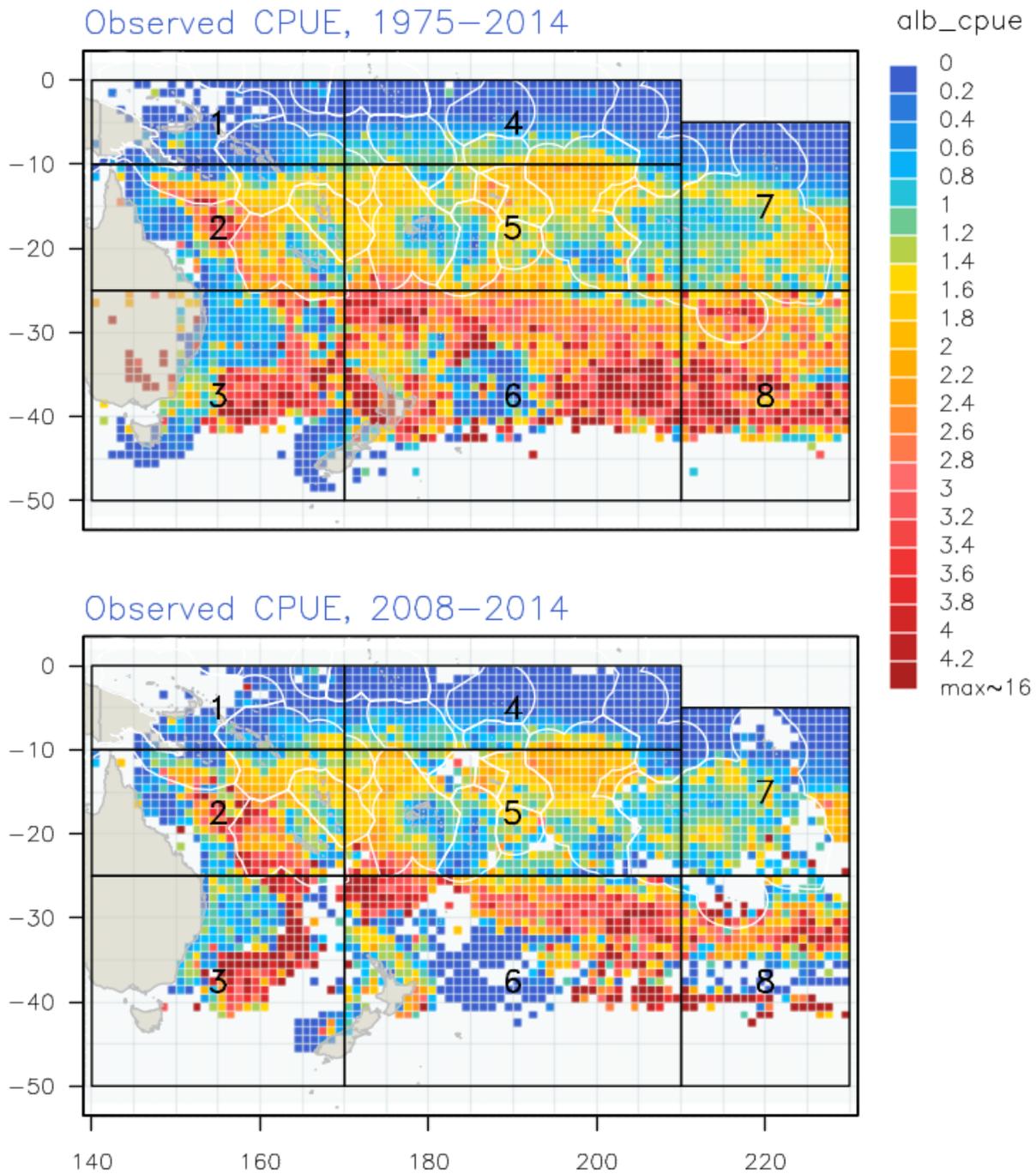
Figure 2: Observed CPUE for albacore targeting sets, averaged over 1975–2014 (top) and 2008–2014 (bottom).
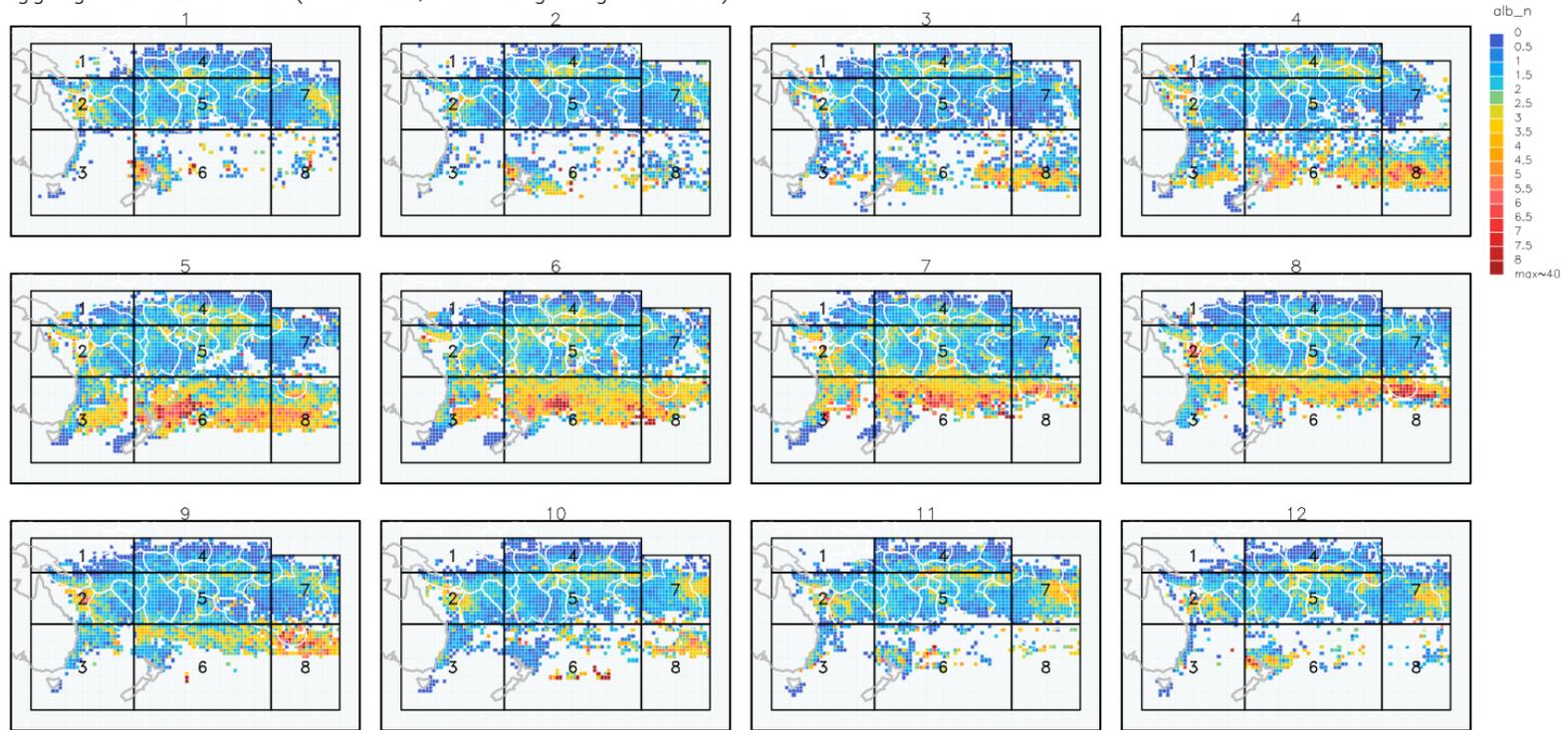
Figure 3: Observed CPUE (Number of fish/hundred hooks) for albacore targeting sets by month, for all fleets, for the period 1960-2014.
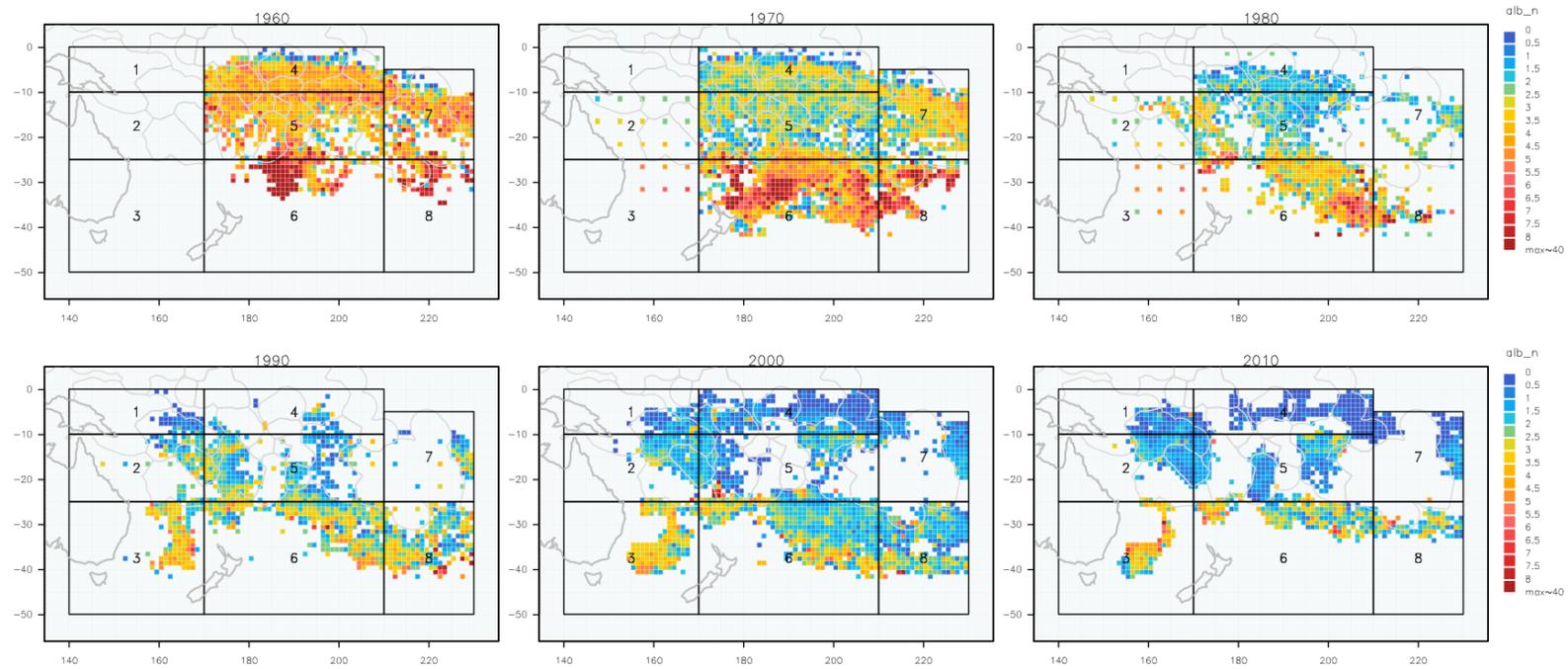
Figure 4: Observed CPUE (Number of fish/hundred hooks) for albacore targeting sets for all fleets, from the dataset used to standardize indices of abundance. The lack of records in regions 1–3 in the 1960s relates to the absence of ALB targeting sets identified by cluster analyses during this period
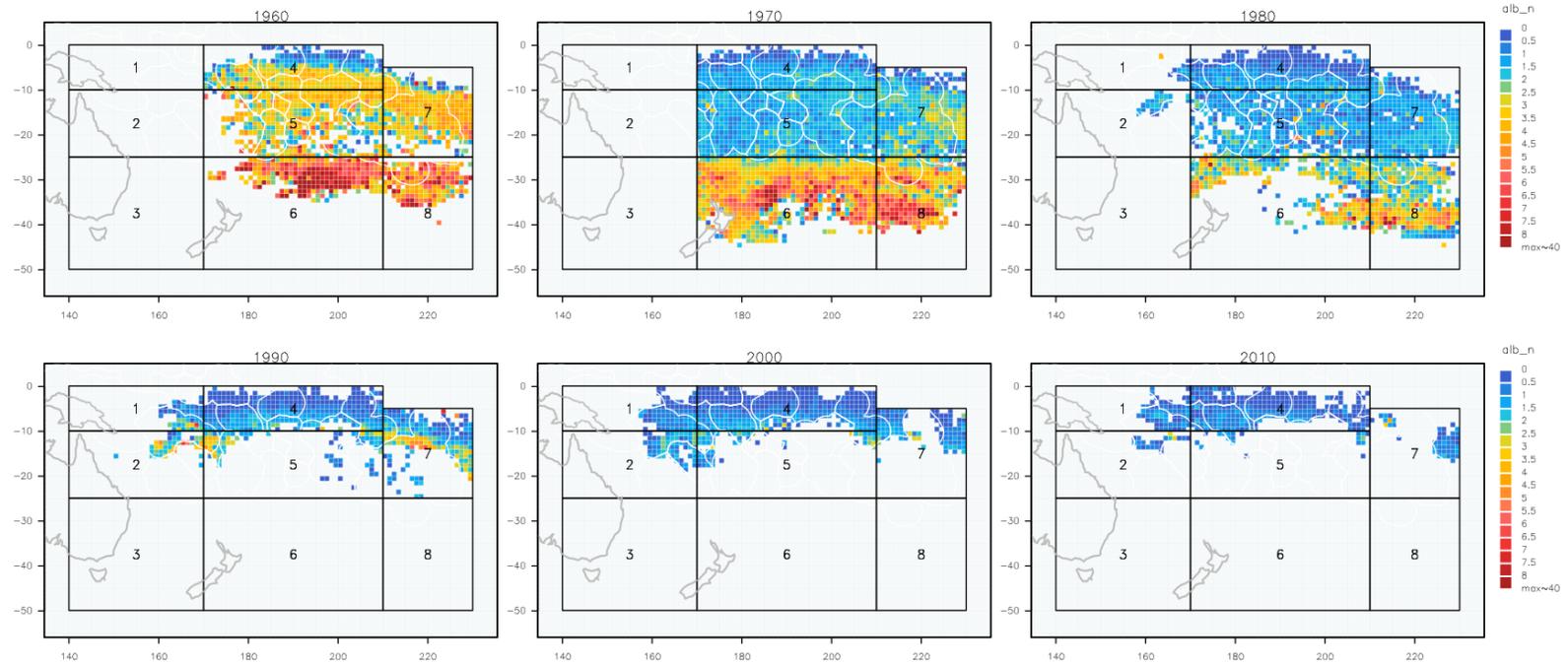
Figure 5: Observed CPUE (Number of fish/hundred hooks) for albacore targeting sets from the Korean fleet, from the dataset used to standardize indices of abundance. The lack of records in regions 1–3 in the 1960s and 70s relates to the absence of ALB targeting sets identified by cluster analyses during this period
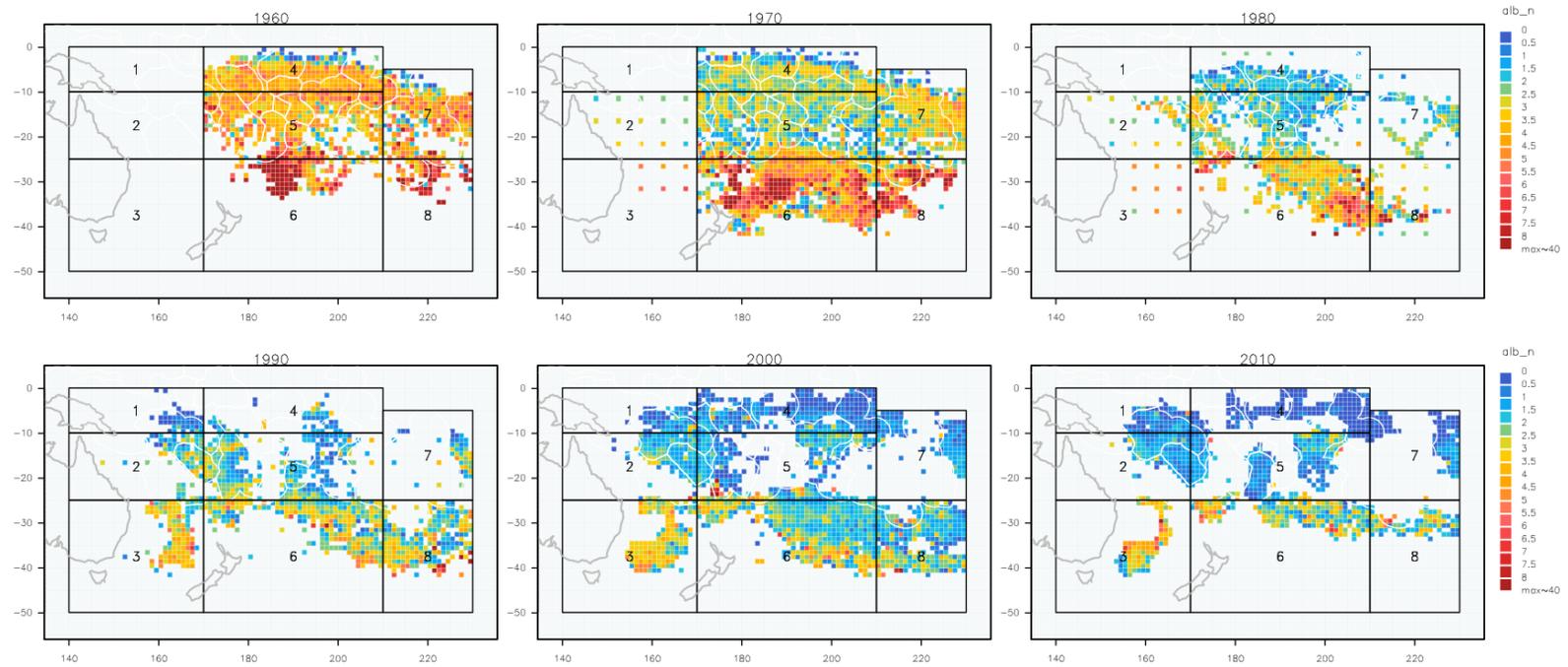
Figure 6: Observed CPUE (Number of fish/hundred hooks) for albacore targeting sets from the Chinese Taipei fleet, from the dataset used to standardize indices of abundance. The lack of records in regions 1–3 in the 1960s relates to the absence of ALB targeting sets identified by cluster analyses during this period
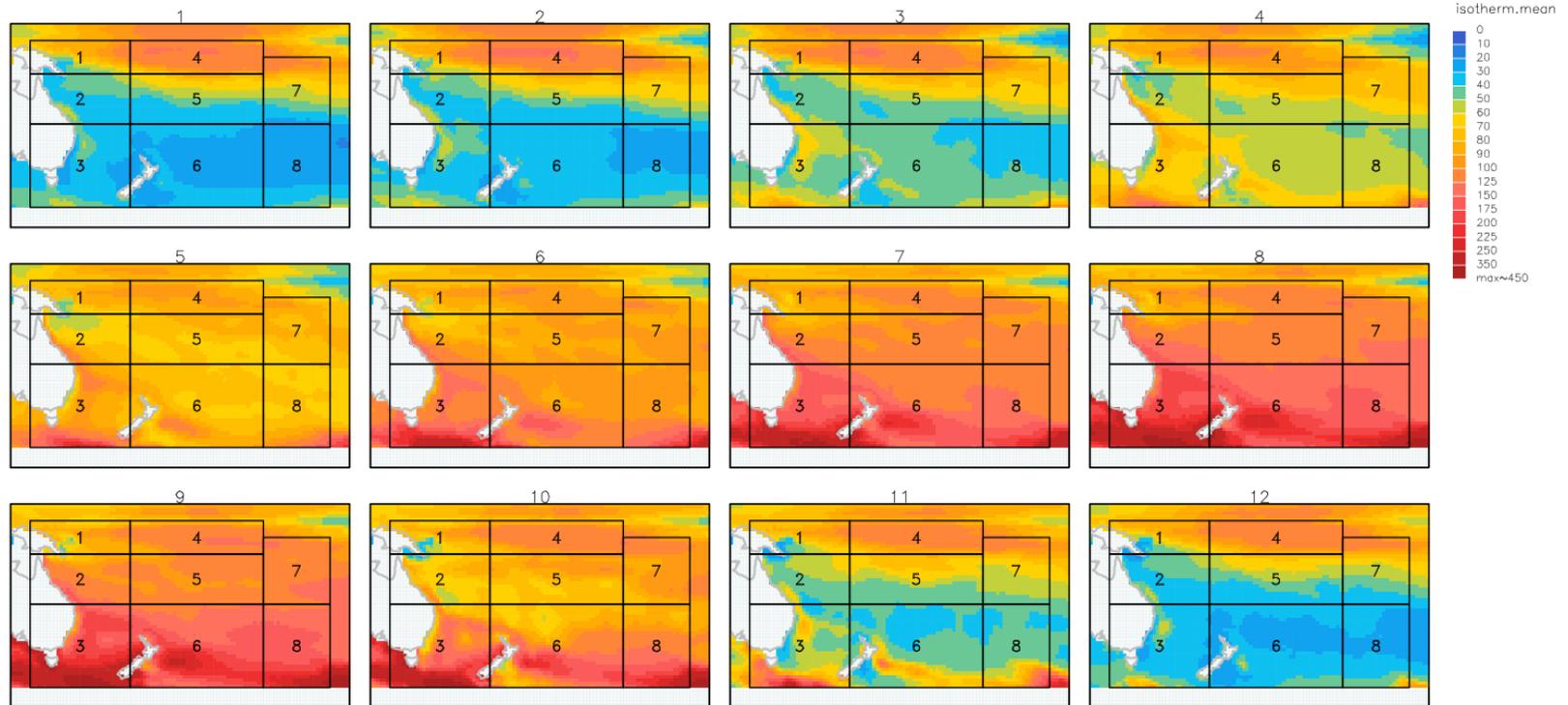
Figure 7: Depth of the thermocline (in meters) per month, averaged by one degree cell over the period available from the GODAS model (1980-2014; data obtained from www.esrl.noaa.gov/psd/data/gridded/data.godas.html)
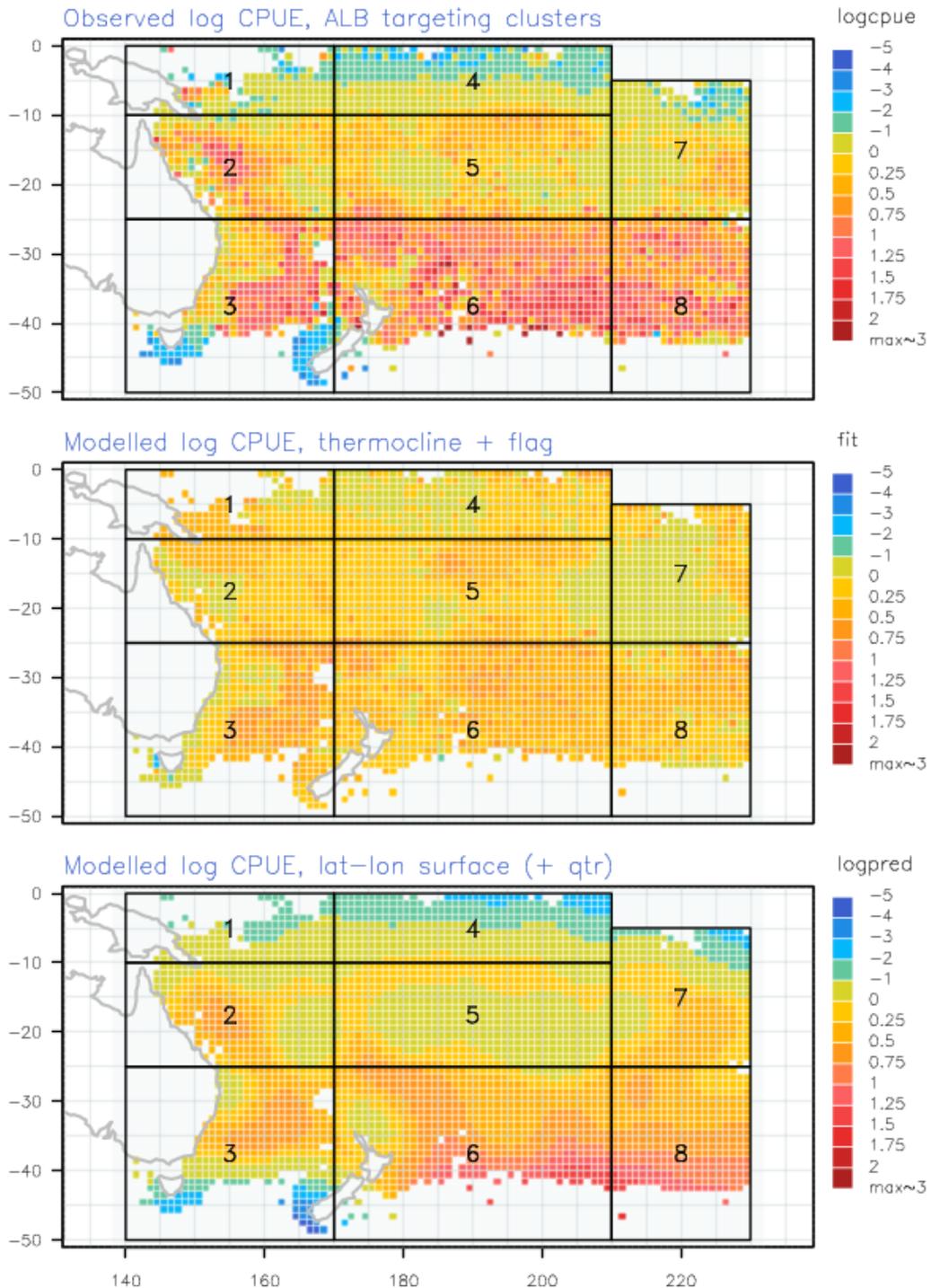
Figure 8: Observed log CPUE (Number of fish/hundred hooks) for 1975-2014 for albacore targeting sets (top); fitted model for the effect of thermocline and fleet (middle); and fitted model of relative abundance once thermocline and fleet have been accounted for, with all quarters included in the response variable and no quarter interaction in the shape of the lon-lat surface.
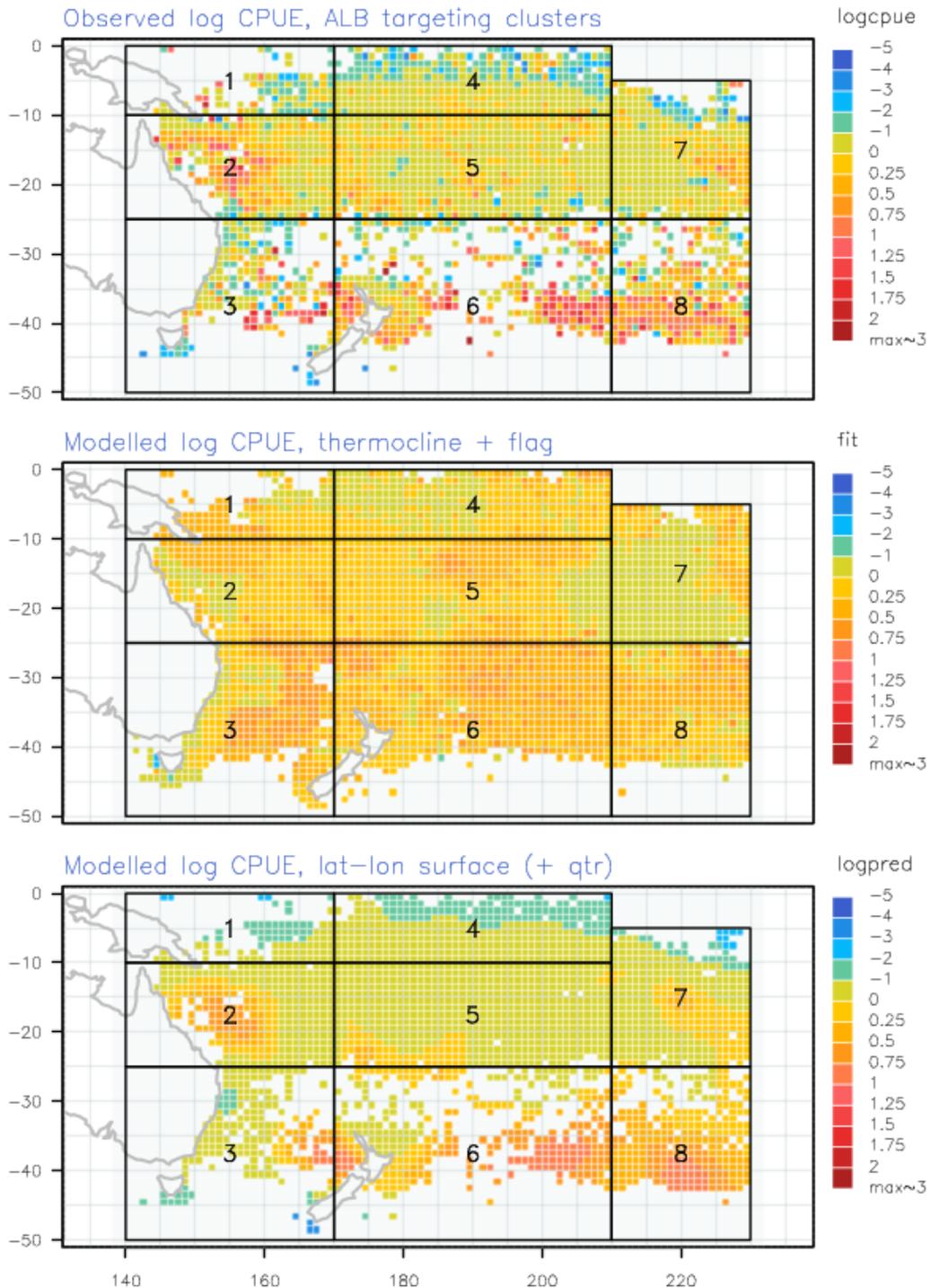
Figure 9: Observed log CPUE (Number of fish/hundred hooks) for quarter 1 (January-March) over 1975-2014 for albacore targeting sets (top); fitted model for this quarter only for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance once thermocline and fleet have been accounted for.
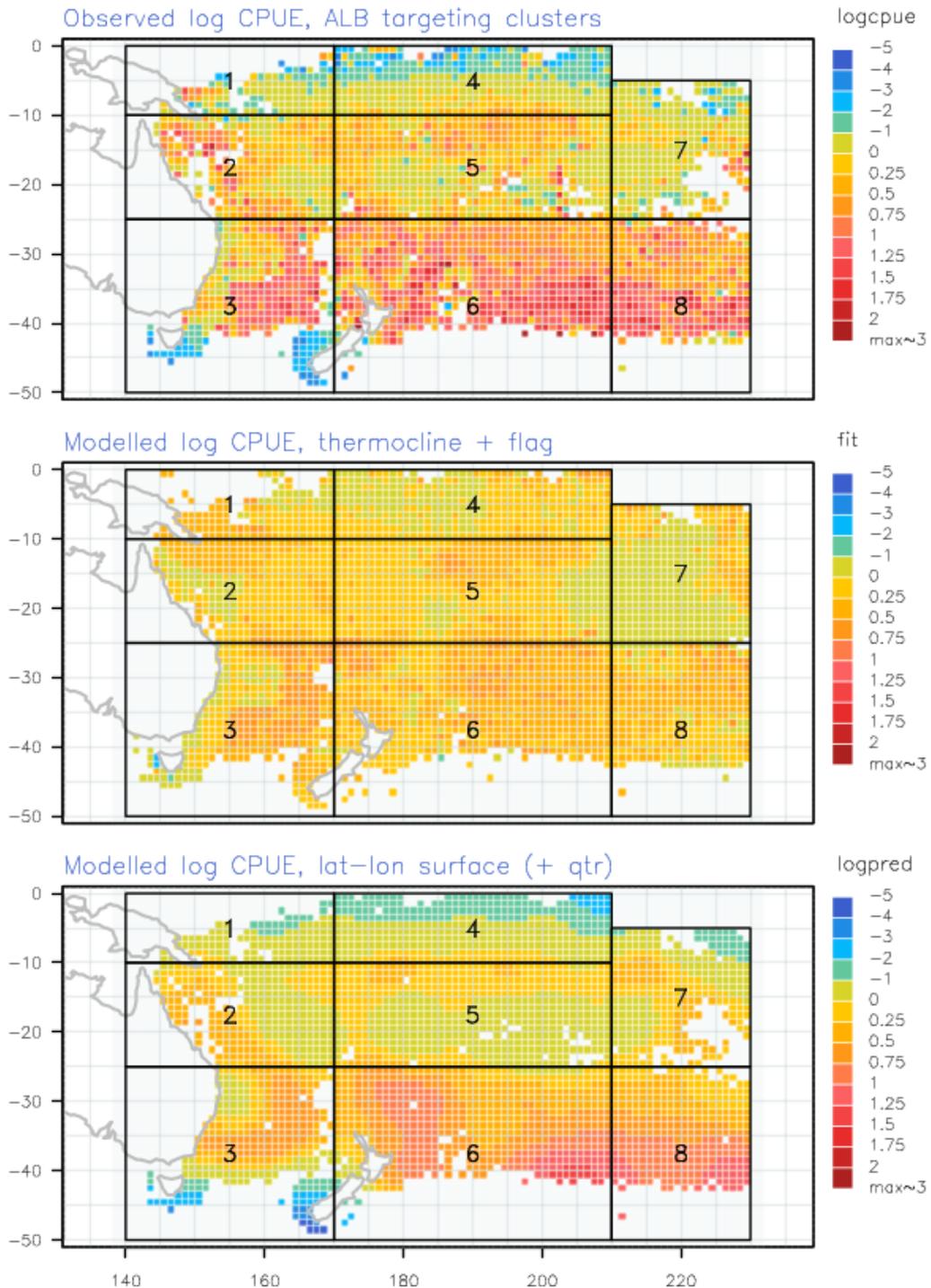
Figure 10: Observed log CPUE (Number of fish/hundred hooks) for quarter 2 (April-June) over 1975-2014 for albacore targeting sets (top); fitted model, for this quarter only, for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance once thermocline and fleet have been accounted for.

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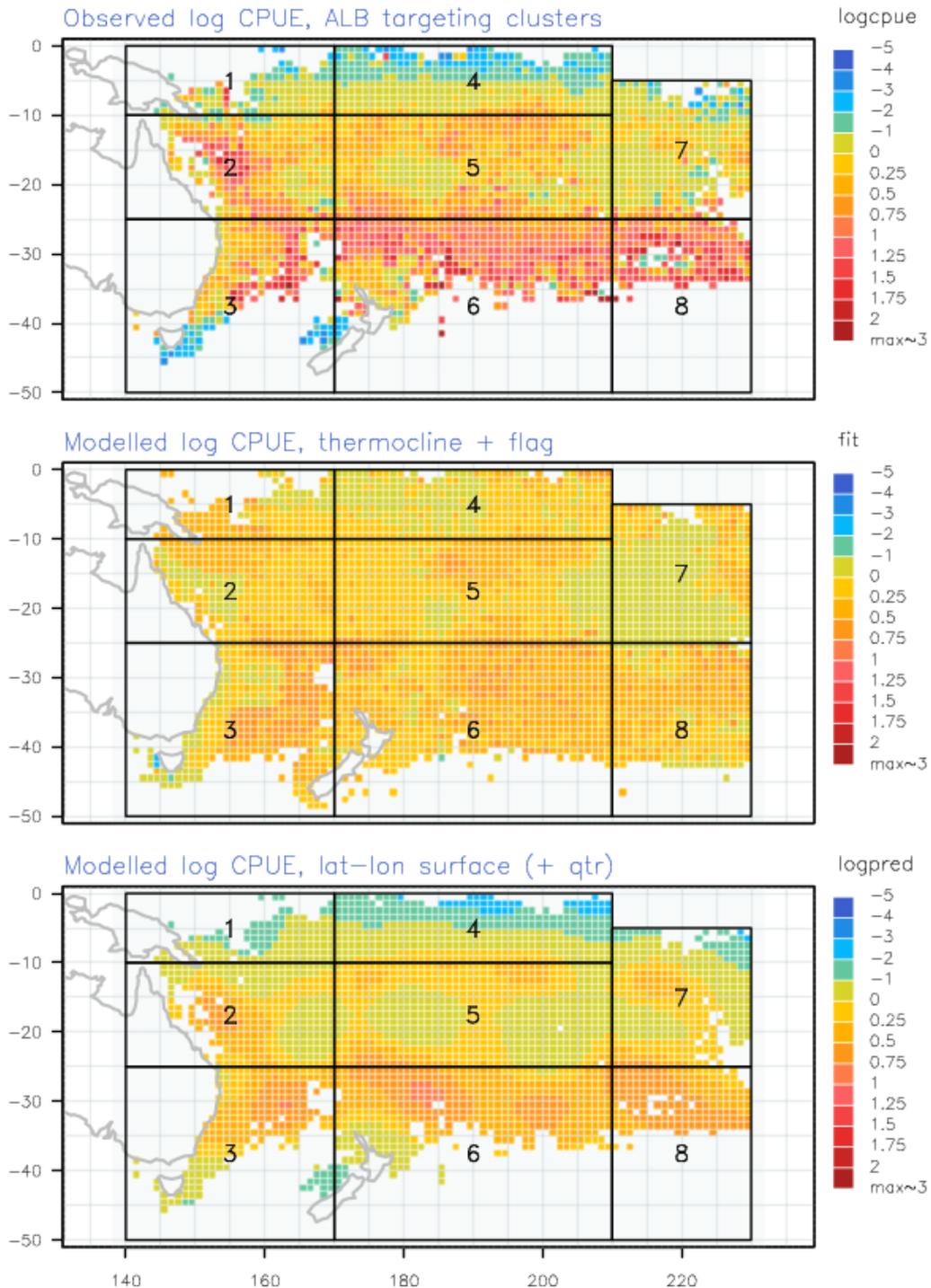
Figure 11: Observed log CPUE (Number of fish/hundred hooks) for quarter 3 (July-September) over 1975-2014 for albacore targeting sets (top); fitted model, for this quarter only, for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance once thermocline and fleet have been accounted for.
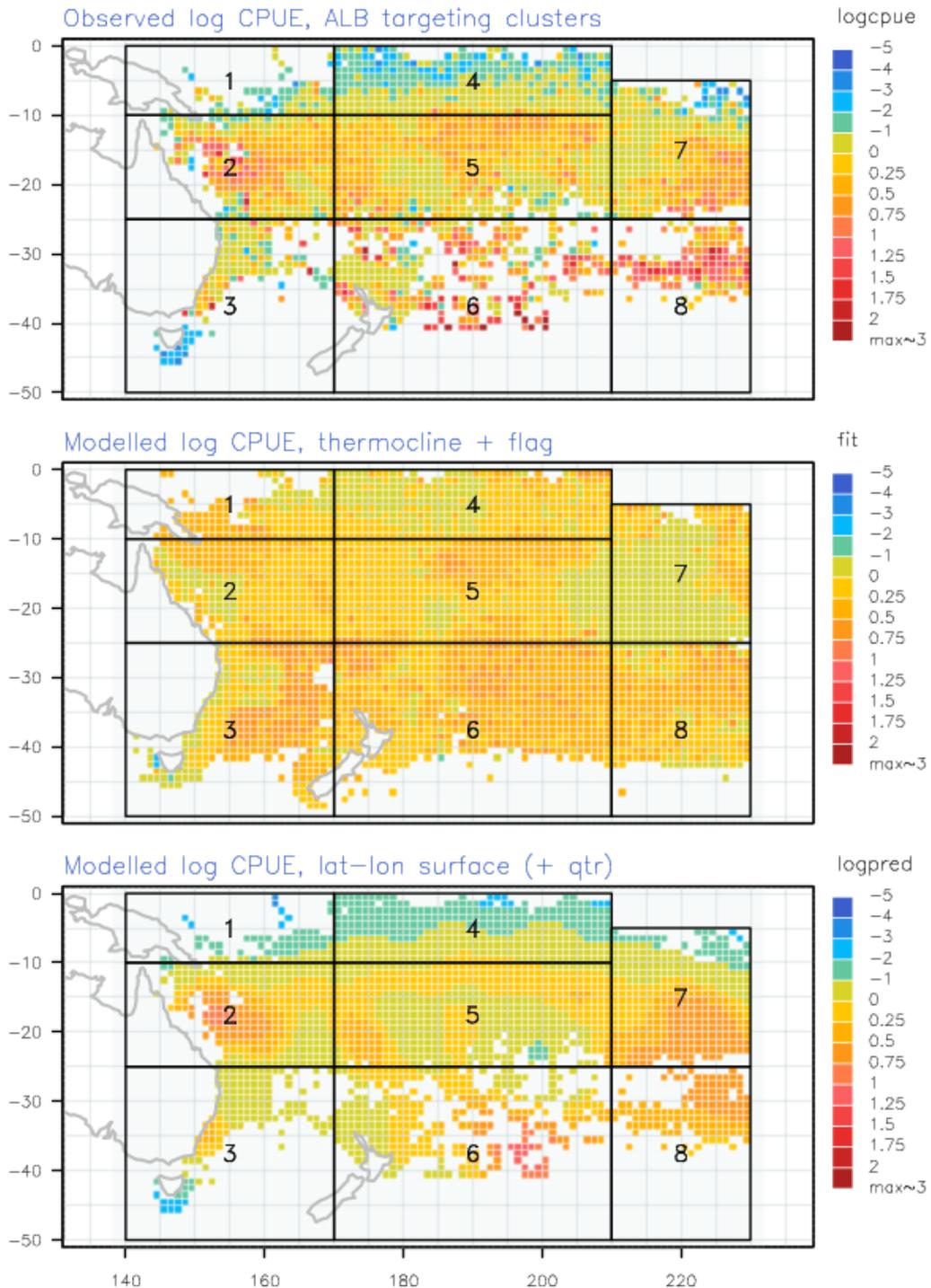
Figure 12: Observed log CPUE (Number of fish/hundred hooks) for quarter 4 (October-December) over 1975-2014 for albacore targeting sets (top); fitted model, for this quarter only, for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance once thermocline and fleet have been accounted for.
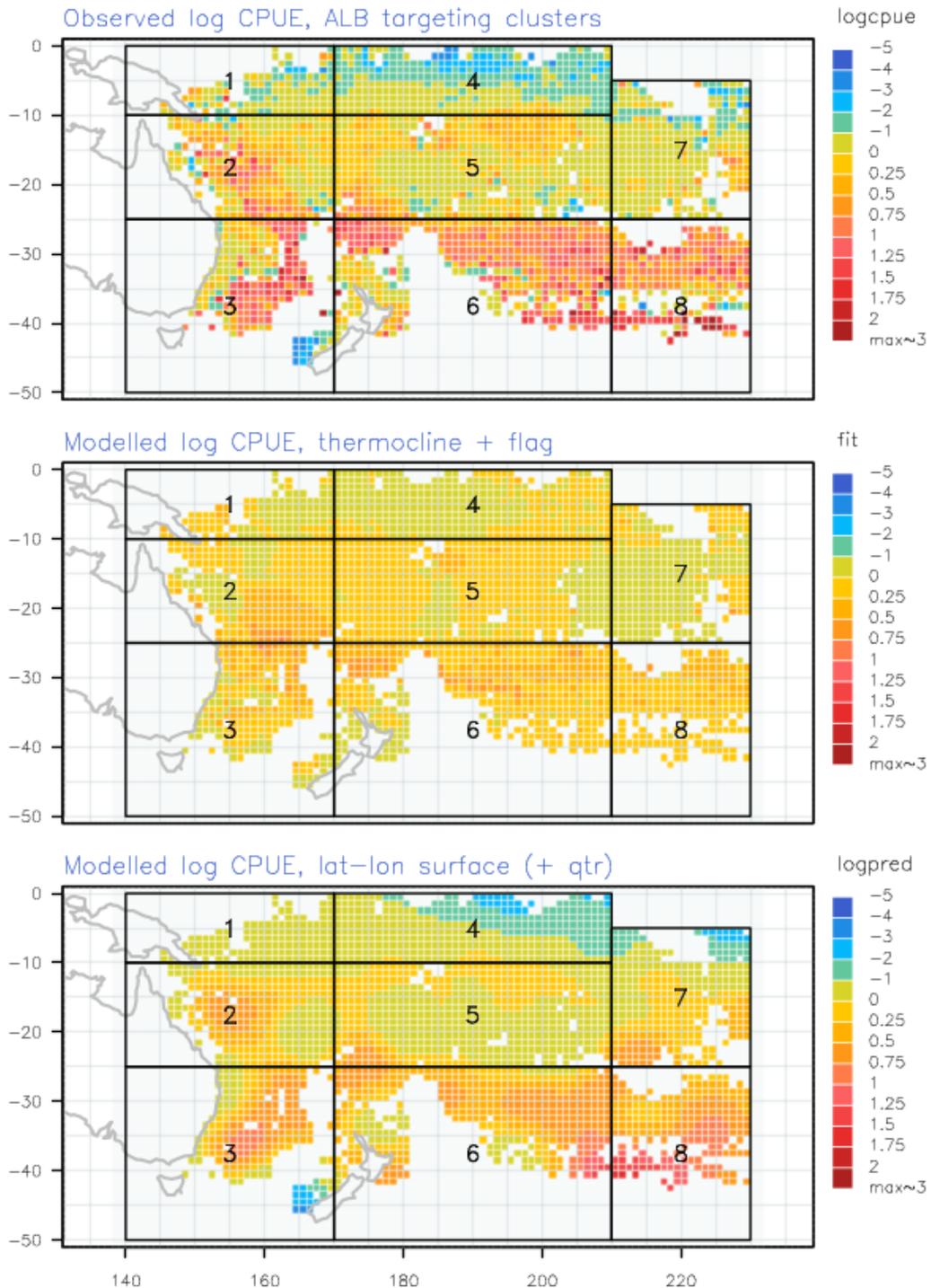
Figure 13: Observed log CPUE (Number of fish/hundred hooks) for 2008-2014 for albacore targeting sets (top); fitted model for the effect of thermocline and fleet (middle); and fitted model of relative abundance once thermocline and fleet have been accounted for, with all quarters included in the response variable and no quarter interaction in the shape of the lon-lat surface.
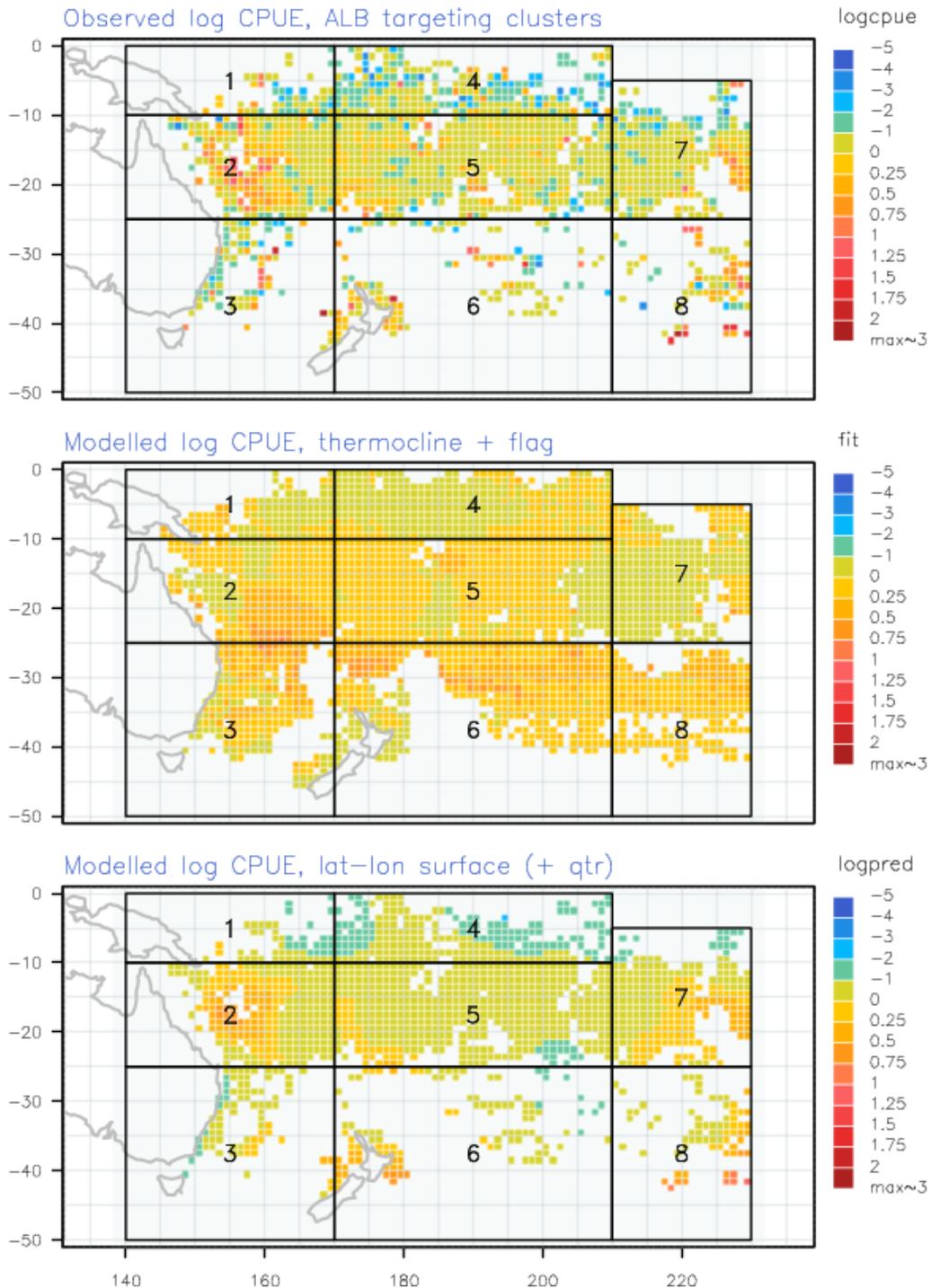
Figure 14: Observed log CPUE (Number of fish/hundred hooks) for quarter 1 (January-March) over 2008-2014 for albacore targeting sets (top); fitted model for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance, once thermocline and fleet have been accounted for.
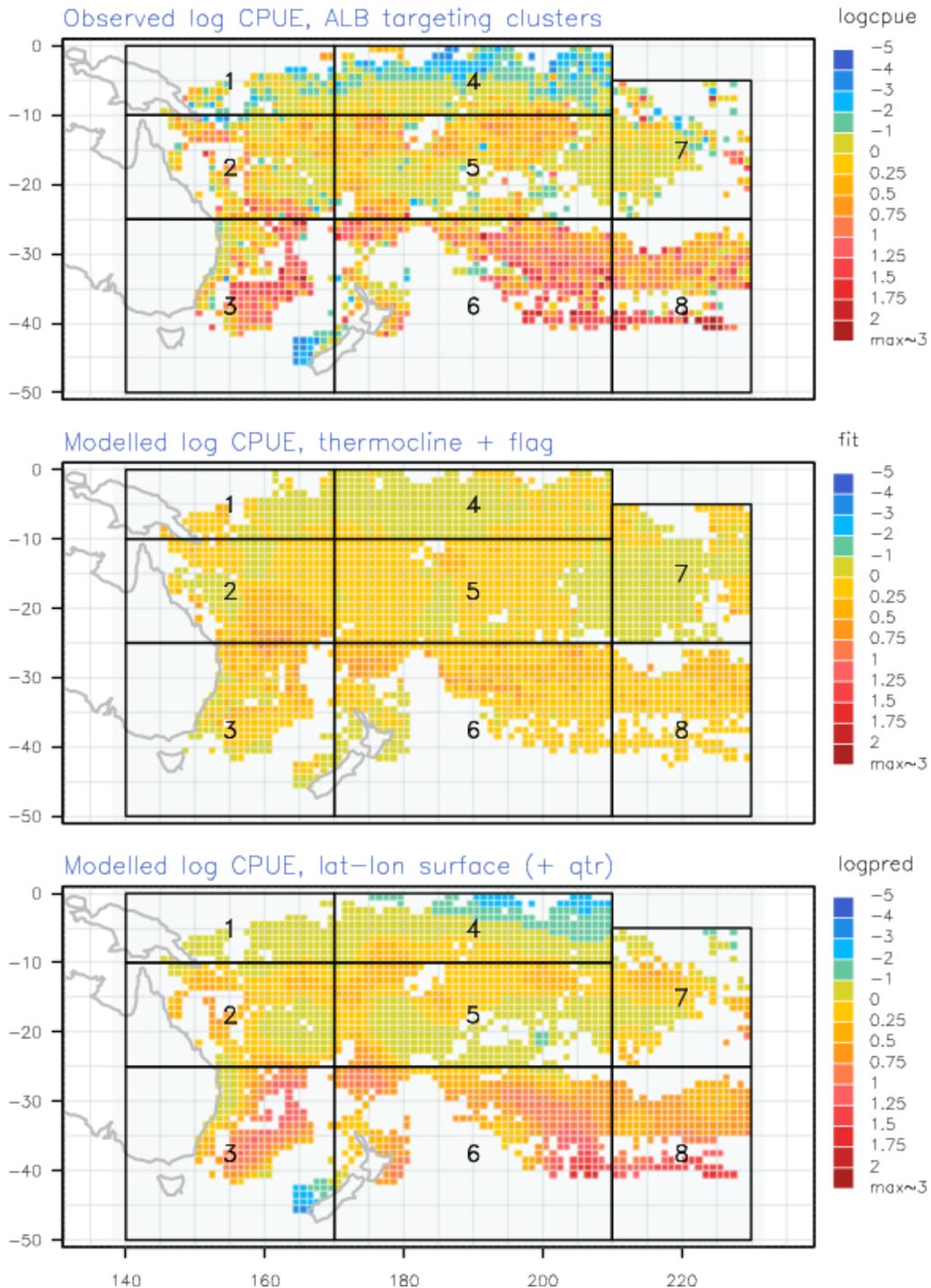
Figure 15: Observed log CPUE (Number of fish/hundred hooks) for quarter 2 (April-July) over 2008-2014 for albacore targeting sets (top); fitted model for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance, once thermocline and fleet have been accounted for.
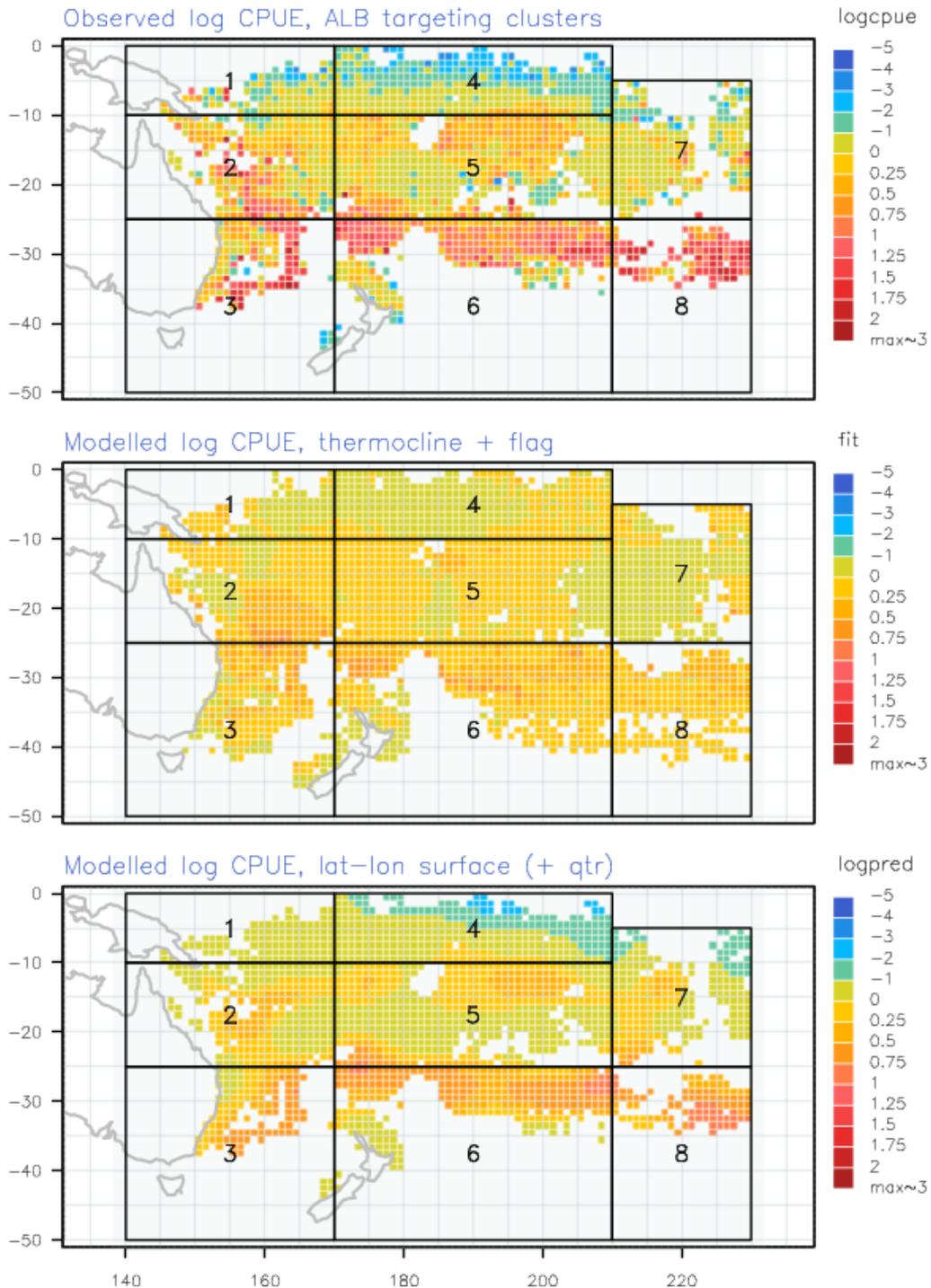
Figure 16: Observed log CPUE (Number of fish/hundred hooks) for quarter 3 (July-September) over 2008-2014 for albacore targeting sets (top); fitted model for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance, once thermocline and fleet have been accounted for.
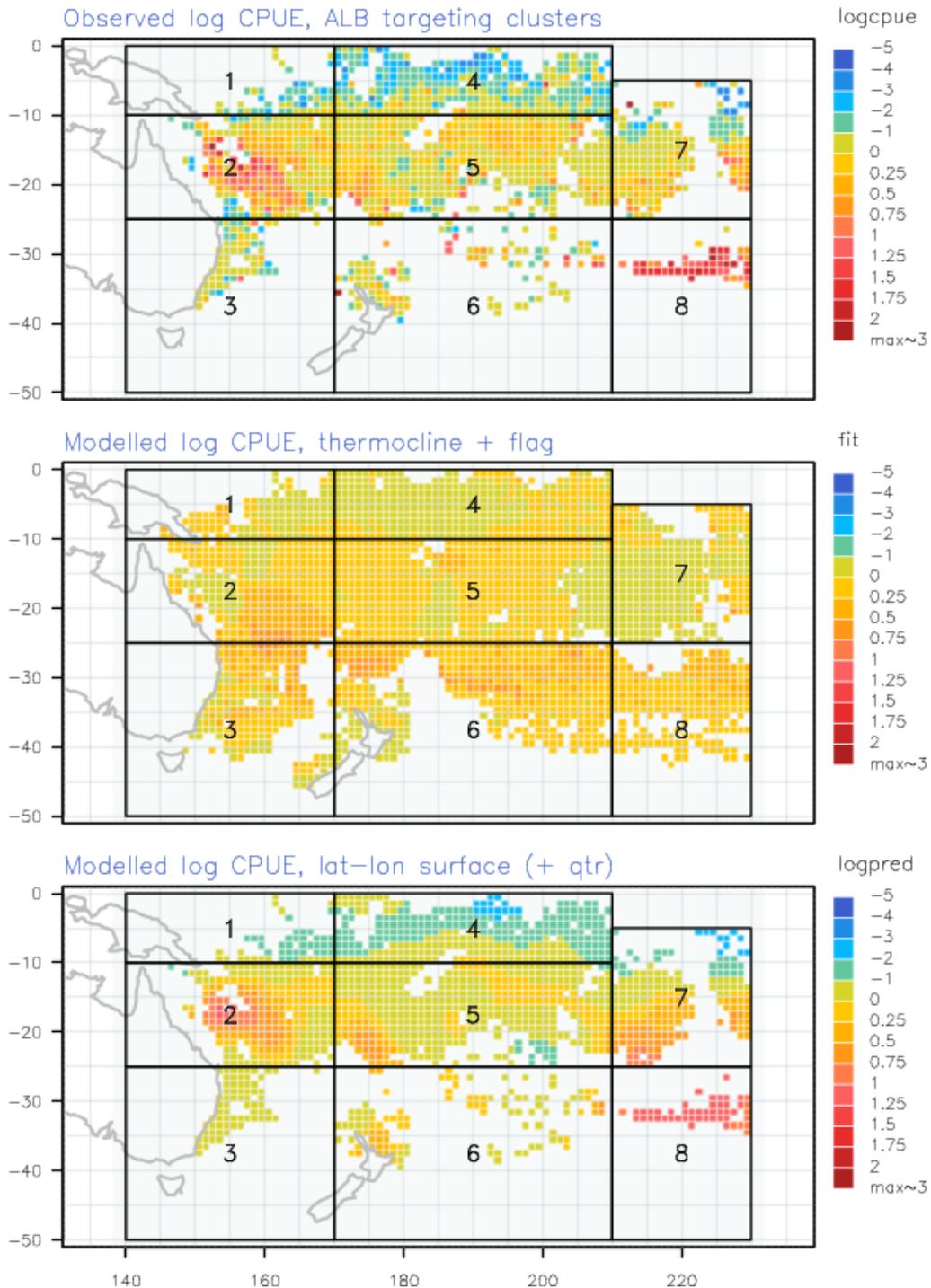
Figure 17: Observed log CPUE (Number of fish/hundred hooks) for quarter 4 (October-December) over 2008-2014 for albacore targeting sets (top); fitted model for the effect of thermocline and fleet (middle; fit included all quarters); and fitted model, for this quarter only, of relative abundance, once thermocline and fleet have been accounted for.

7 Appendix
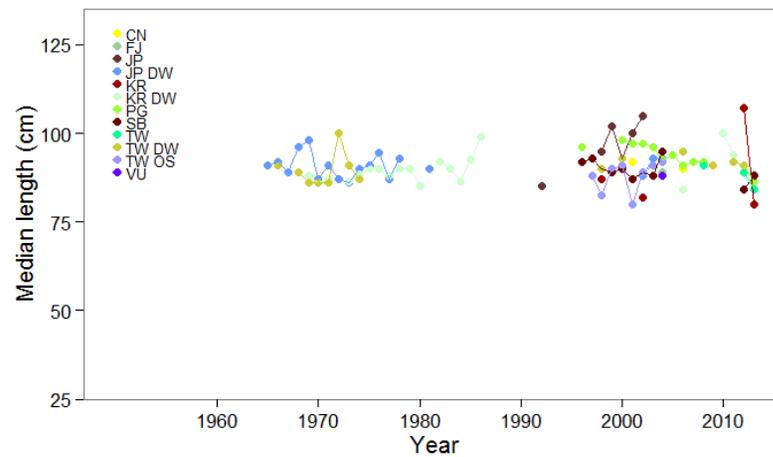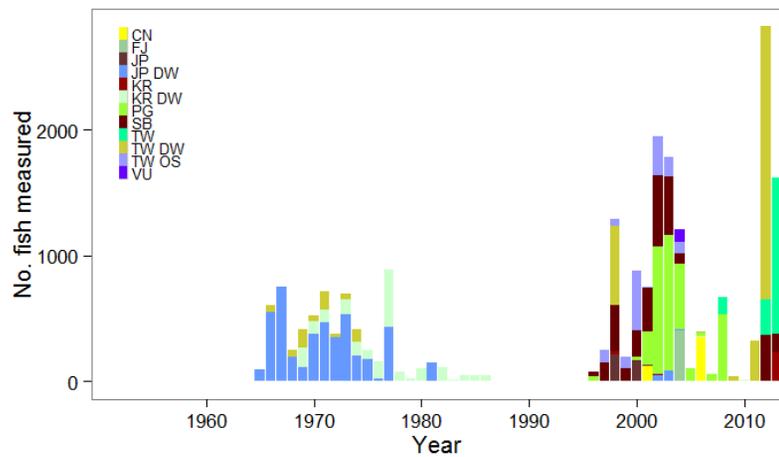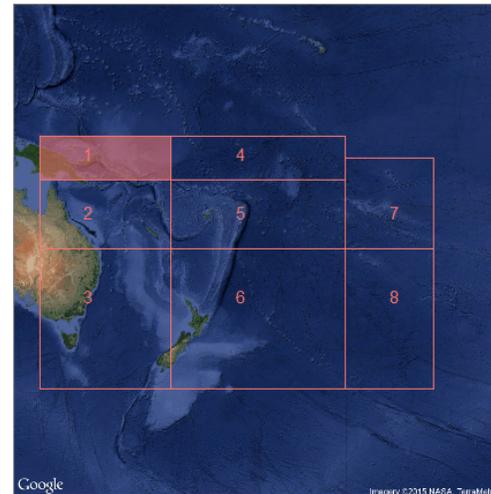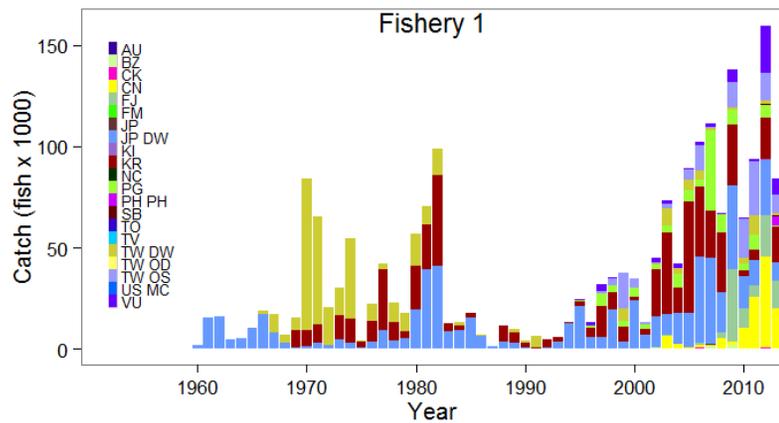
Figure 18: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 1.

Figure 19: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 2.
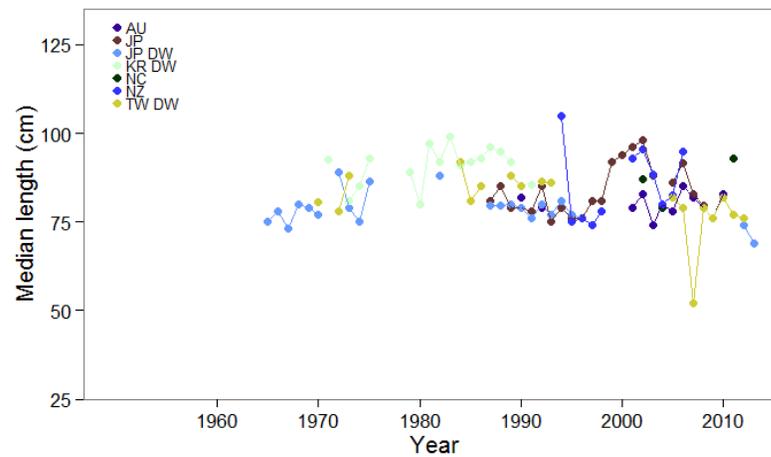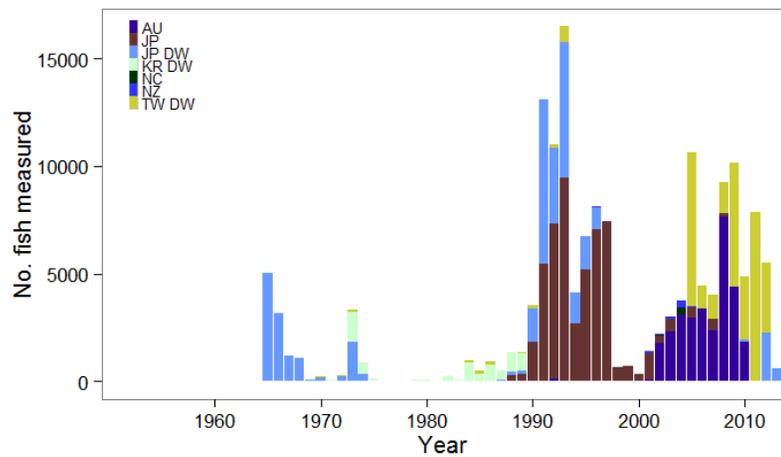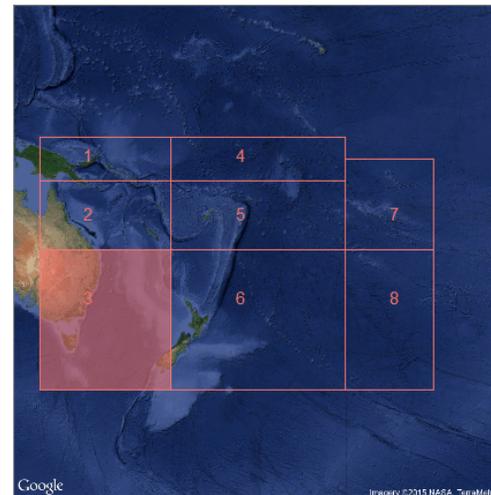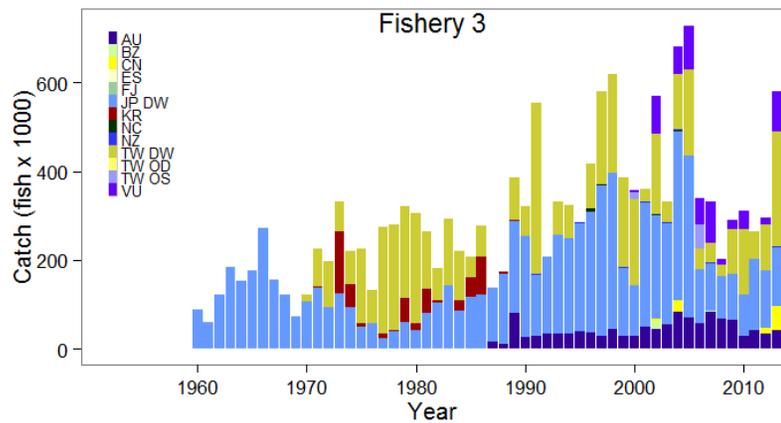
Figure 20: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 3.
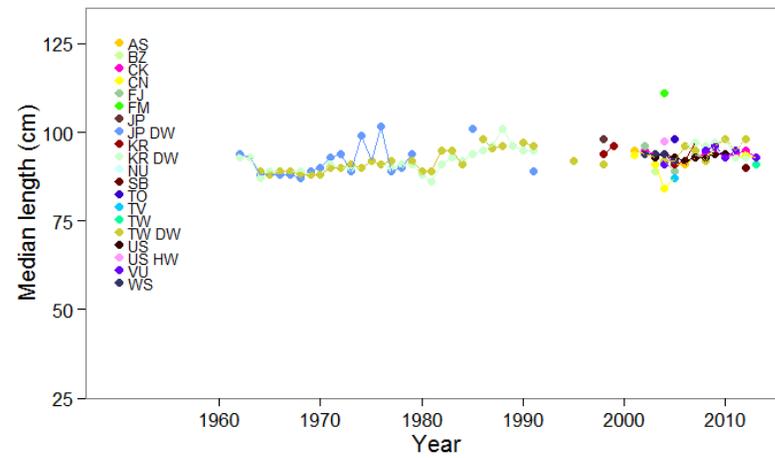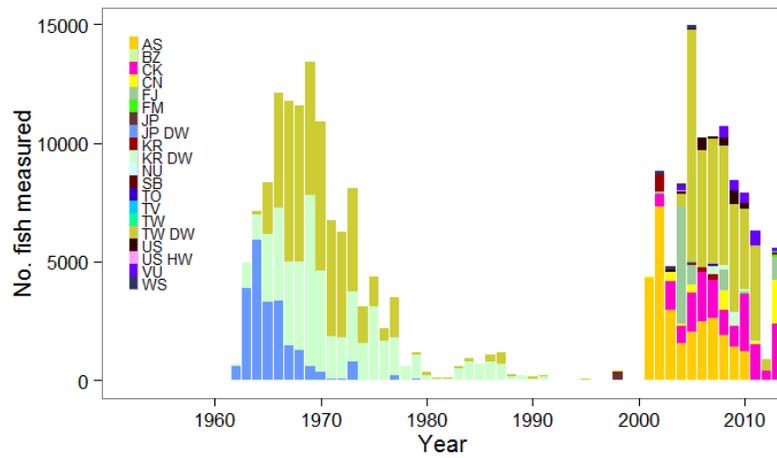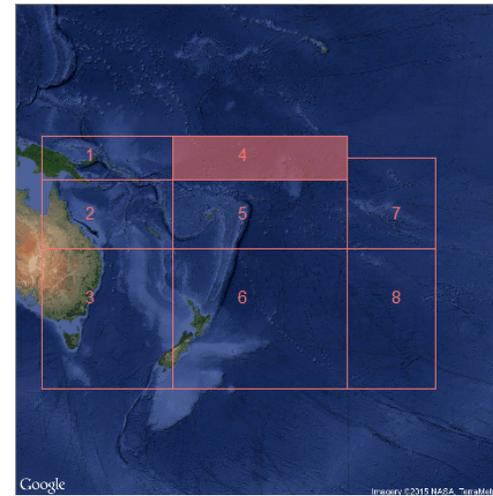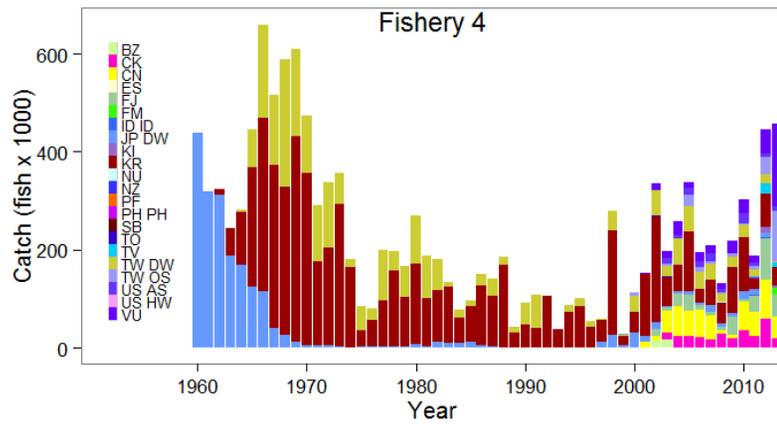
Figure 21: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 4.
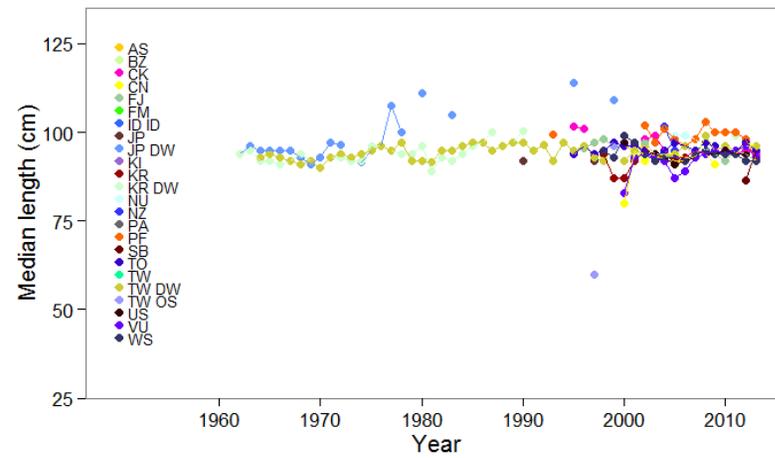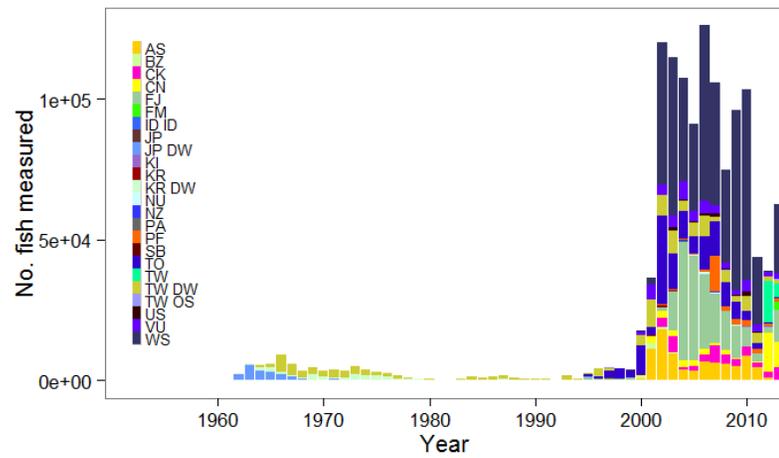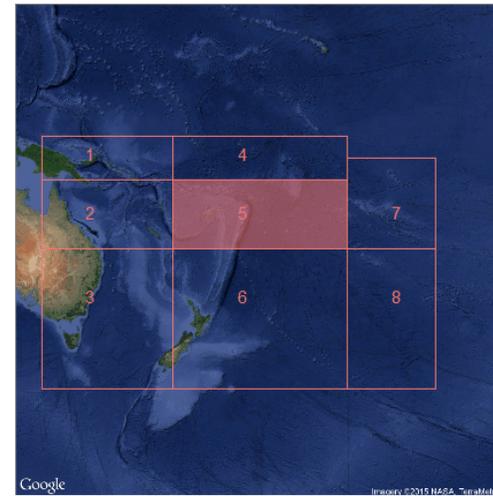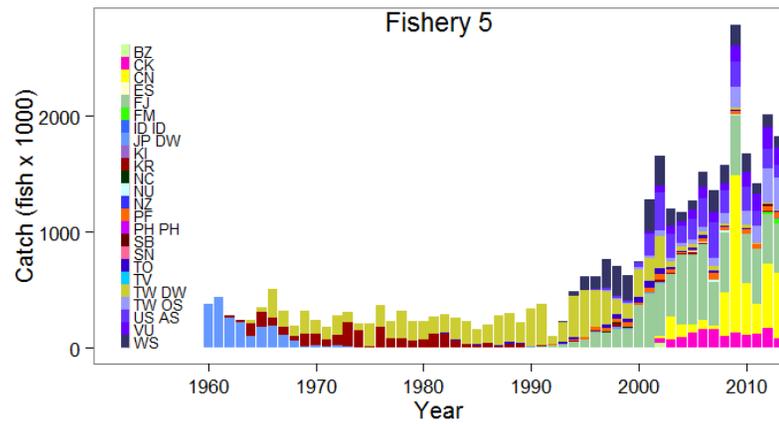
Figure 22: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 5.
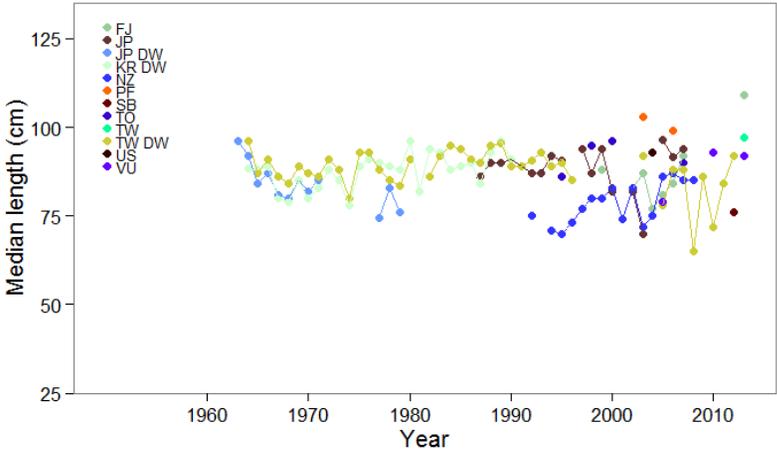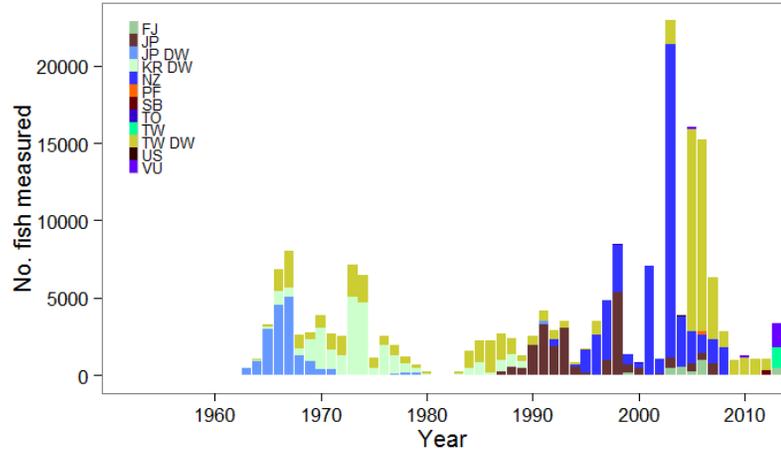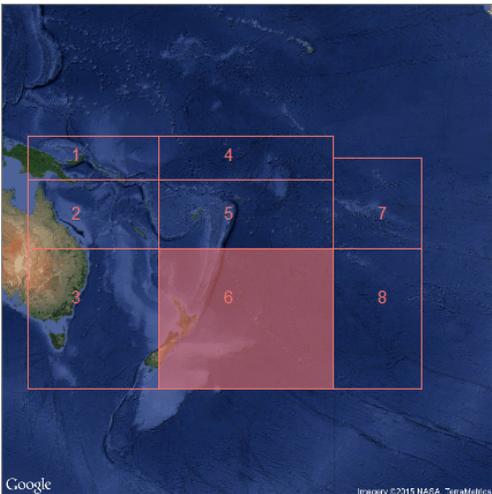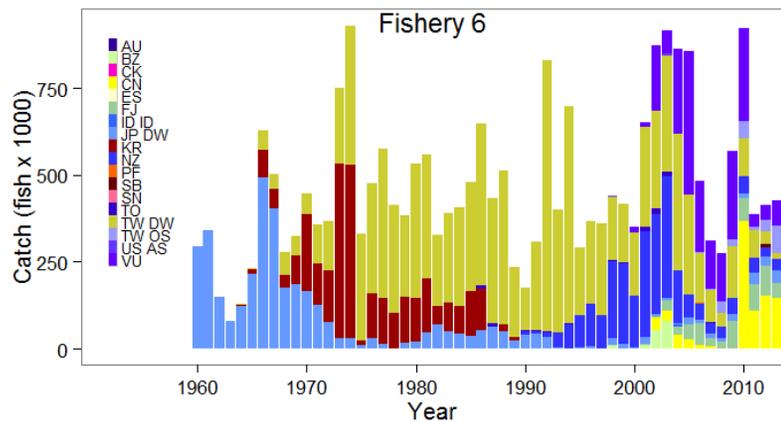
Figure 23: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 6.
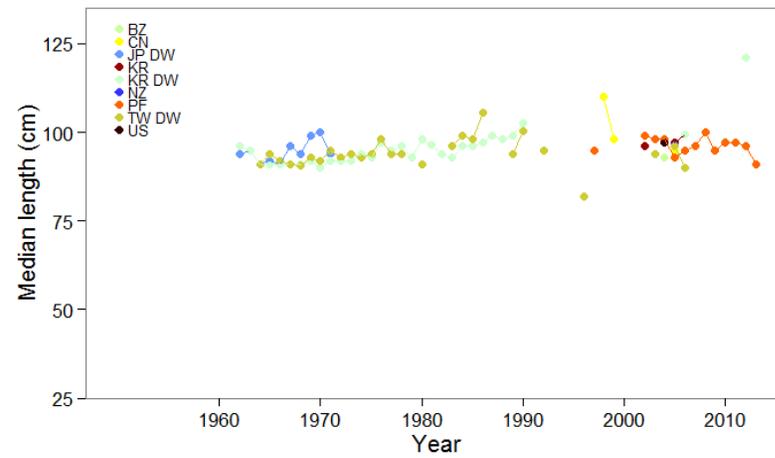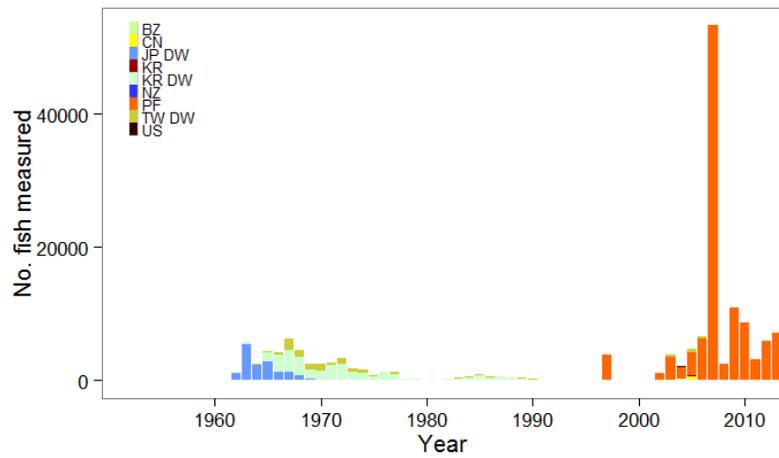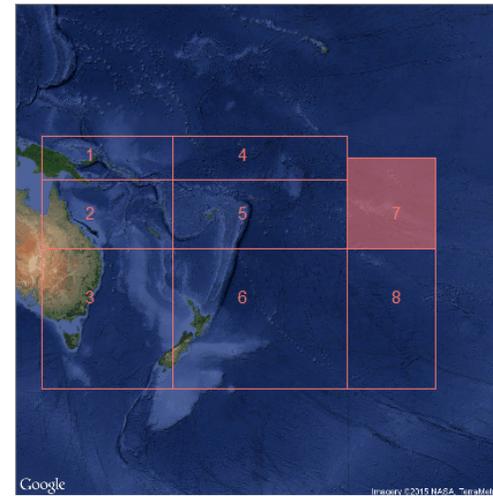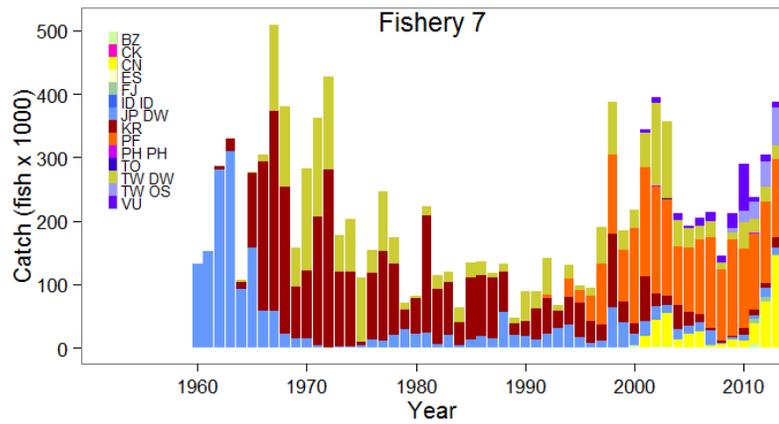
Figure 24: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 7.
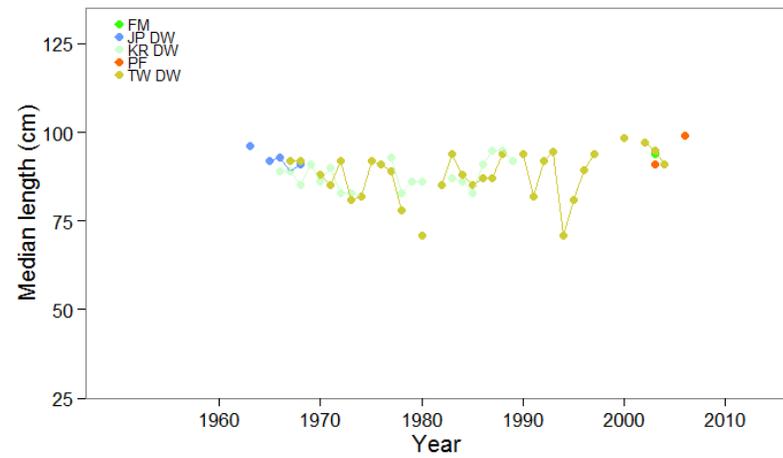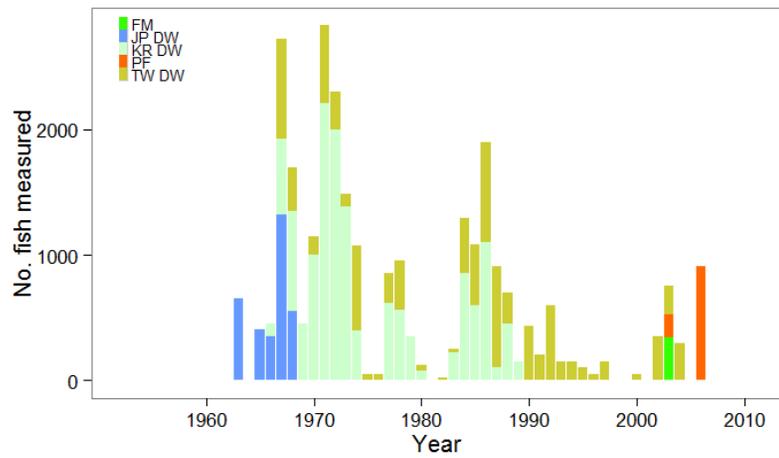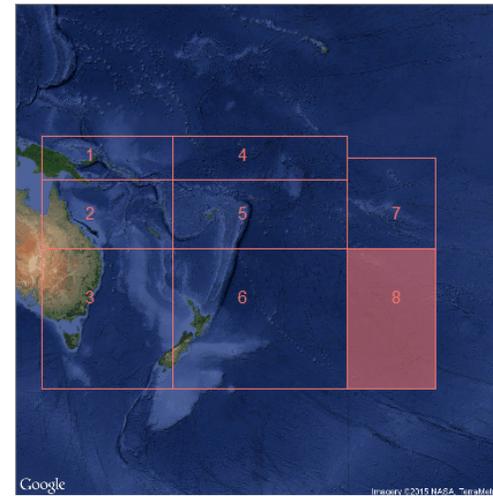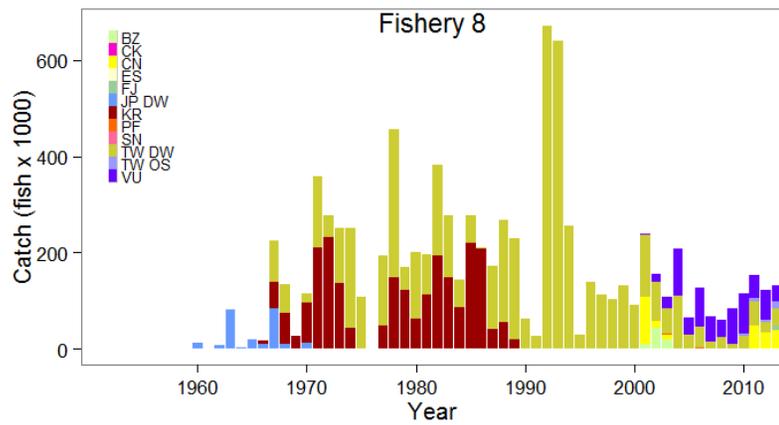
Figure 25: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for longline fishery 8.
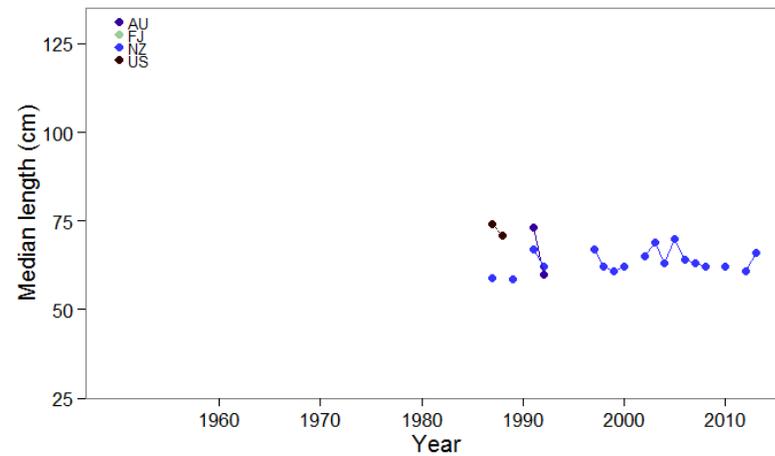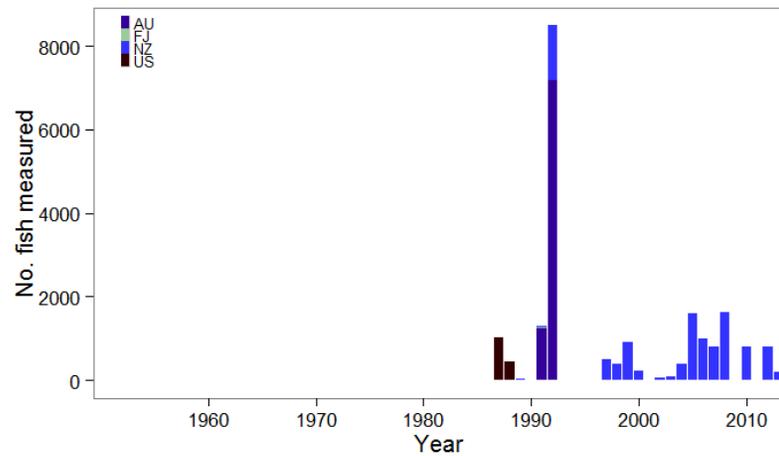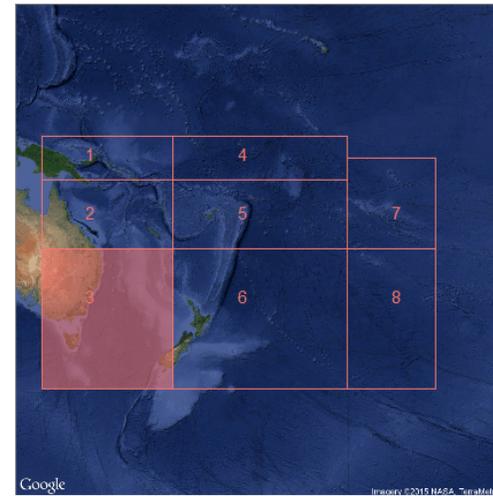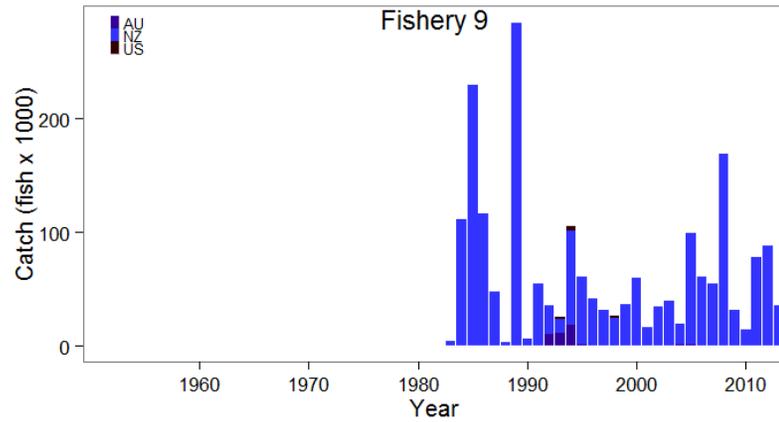
Figure 26: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for troll fishery 9.
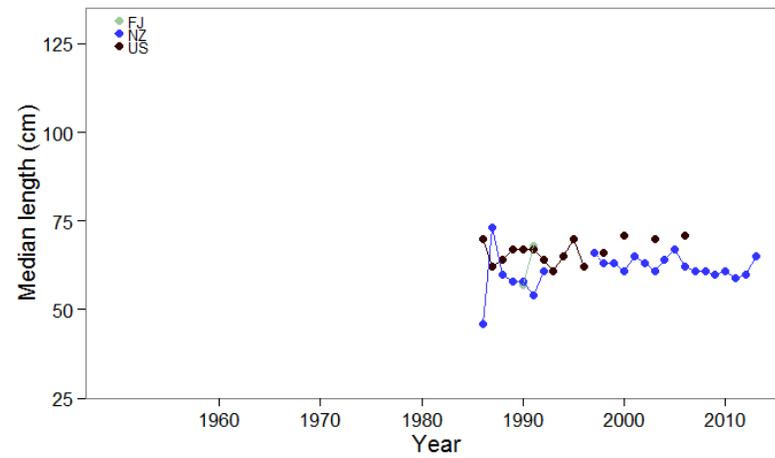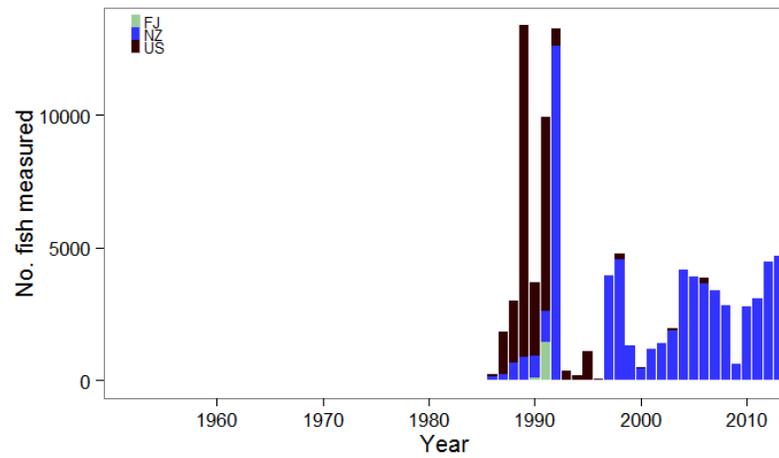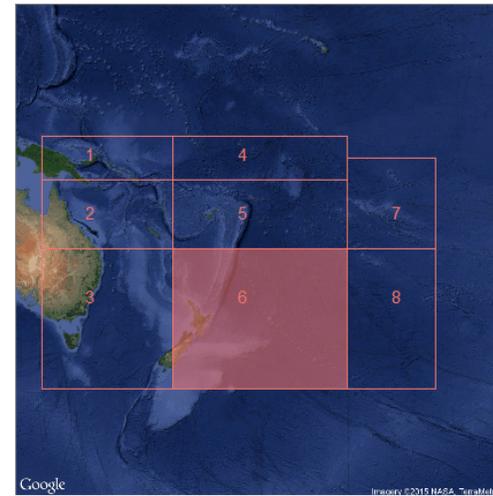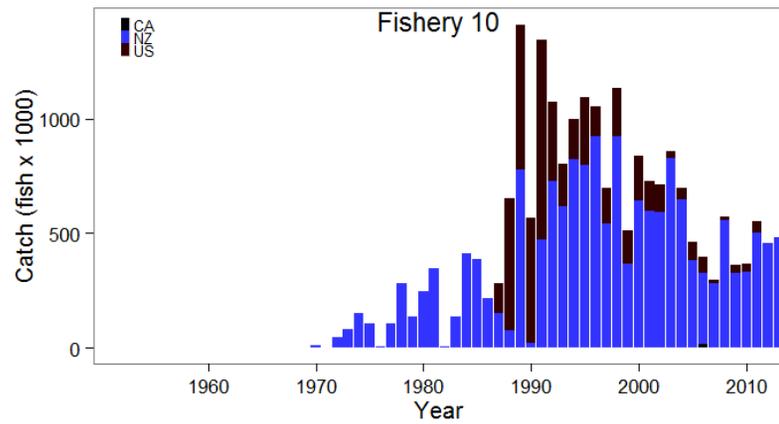
Figure 27: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for troll fishery 10.
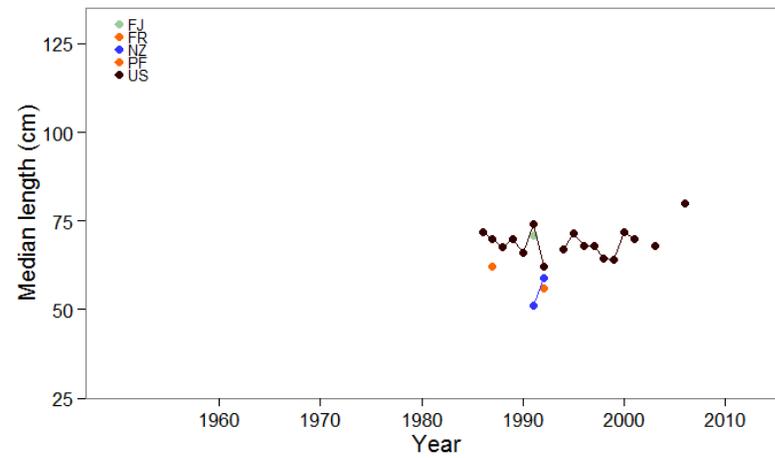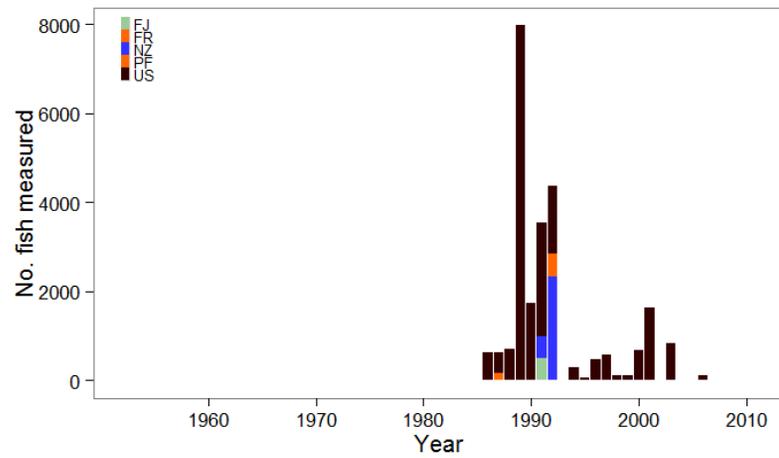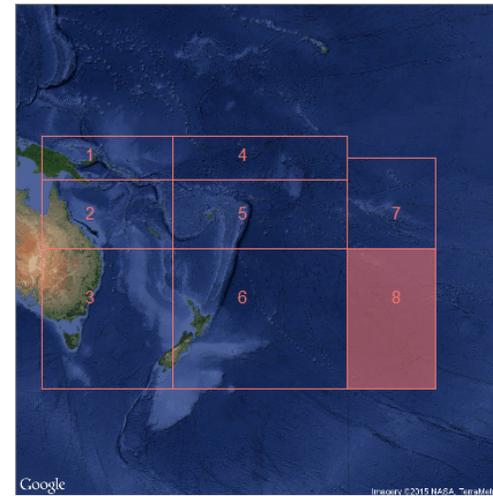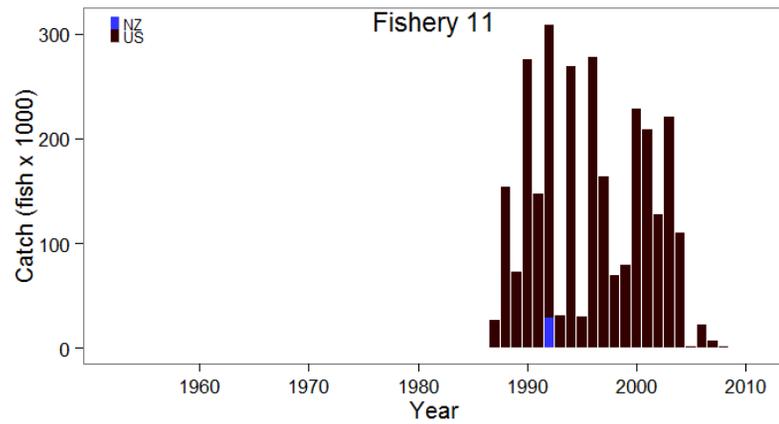
Figure 28: Catch (top left; 1,000s of fish), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for troll fishery 11.
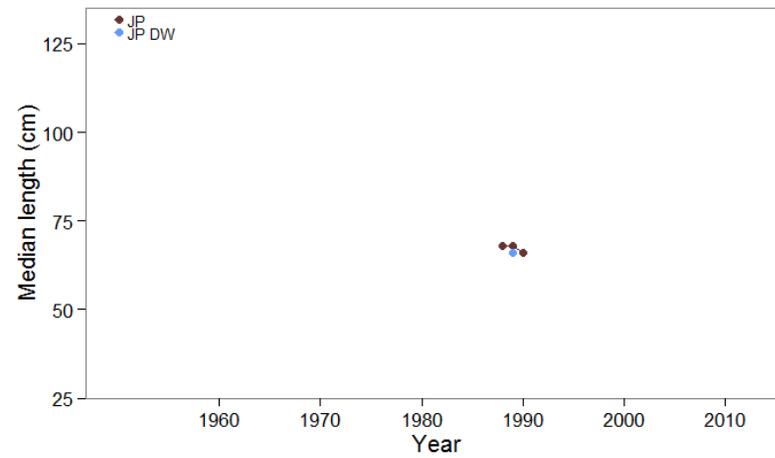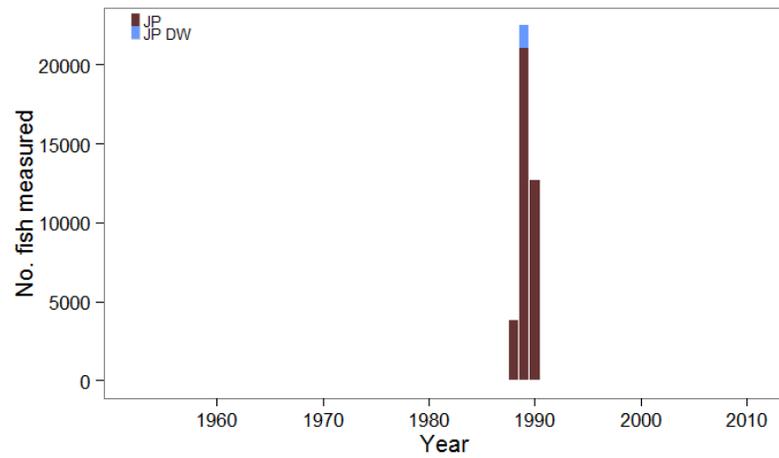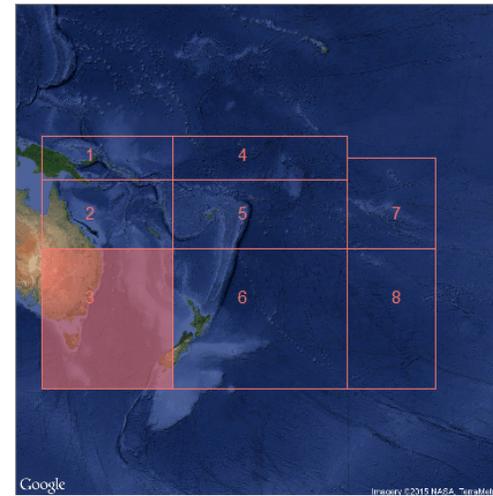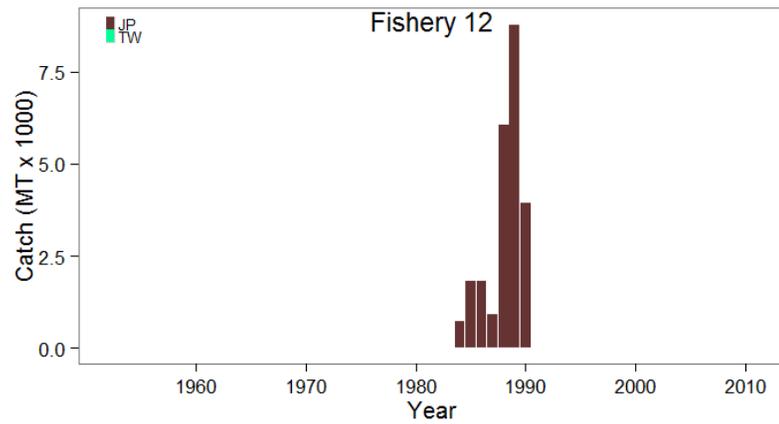
Figure 29: Catch (top left; 1,000s of metric tonnes), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for driftnet fishery 12.
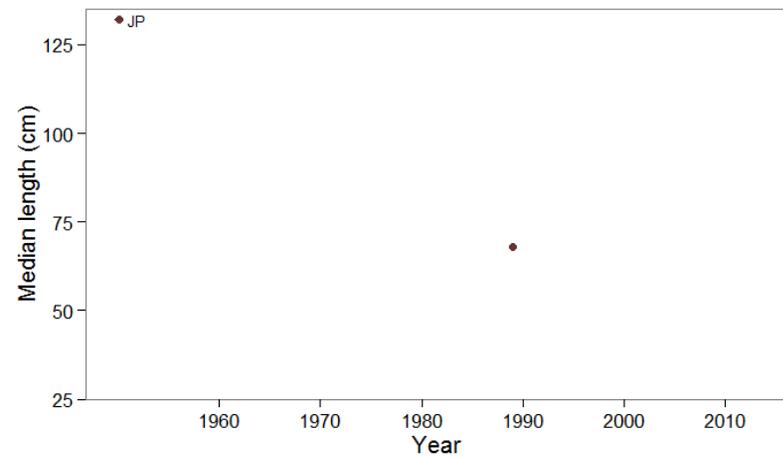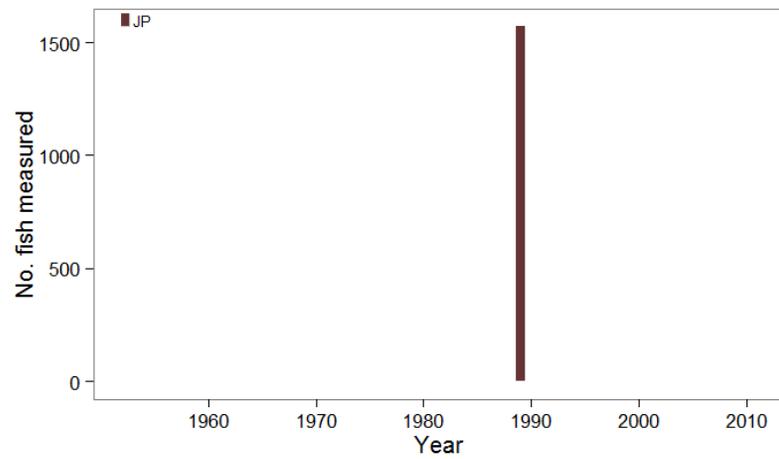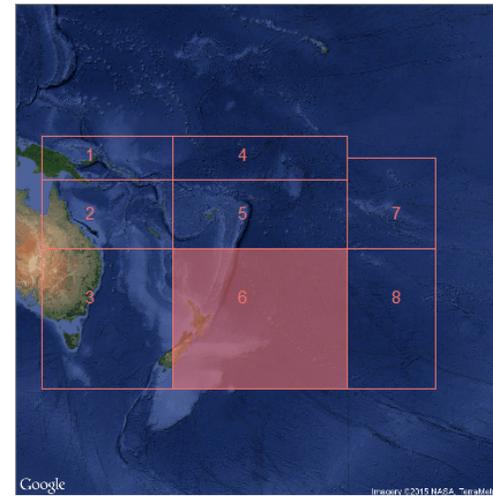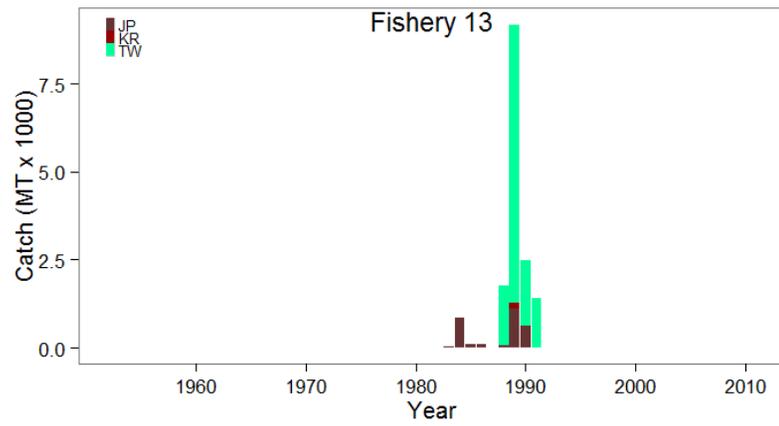
Figure 30: Catch (top left; 1,000s of metric tonnes), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for driftnet fishery 13.
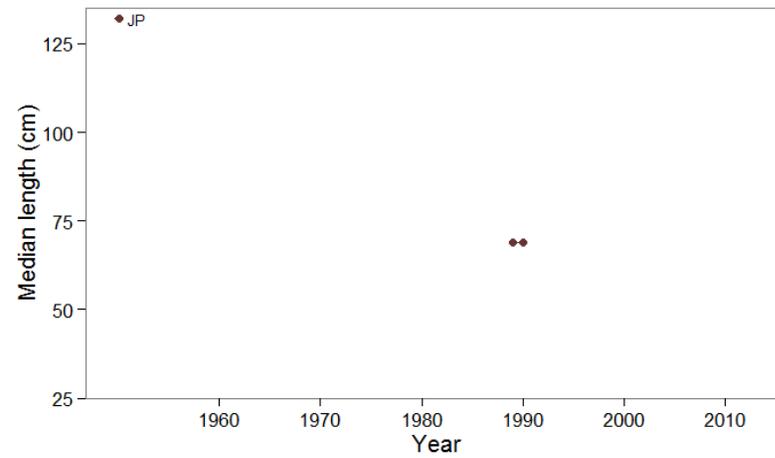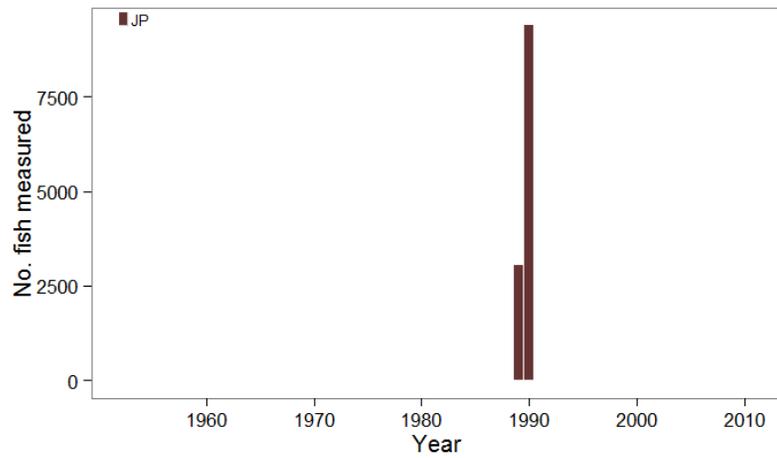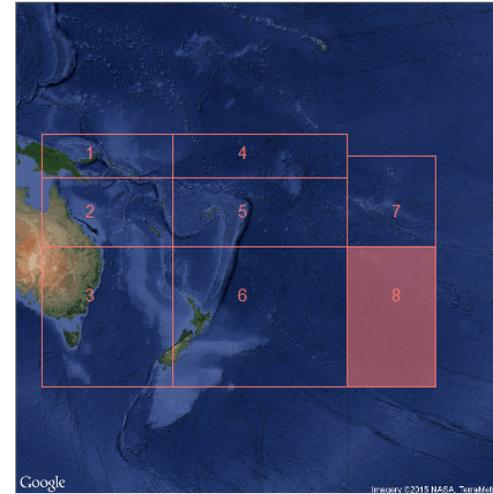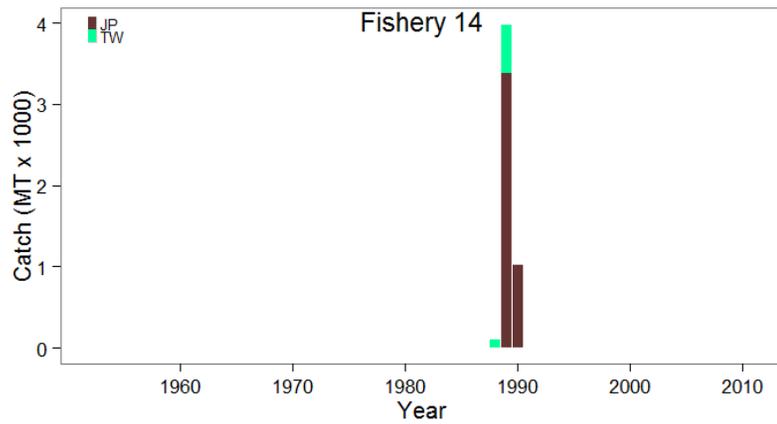
Figure 31: Catch (top left; 1,000s of metric tonnes), location (top right), the number of length samples available (bottom left) and median length of fish measured (bottom right), by fleet, for driftnet fishery 14.