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Indicator based analysis of the status of New Zealand blue, mako and porbeagle sharks

New Zealand Fisheries Assessment Report 2014/69

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TABLE OF CONTENTS

EXECUTIVE SUMMARY

Francis, M.P.; Clarke, S.C.; Griggs, L.H.; Hoyle, S.D. (2014). Indicator based analysis of the status of New Zealand blue, mako and porbeagle sharks.

***New Zealand Fisheries Assessment Report 2014/69.* 109 p.**

Cartilaginous fishes generally have low productivity because of their low to moderate growth rates, and their low fecundity. Despite their vulnerability to over-fishing, a lack of suitable data means that conventional stock assessments are rarely possible. To address that limitation, this report performs indicator analyses for blue, porbeagle and mako sharks − three shark species that are taken primarily as bycatch in the New Zealand tuna longline fishery. The main data sources were the Ministry for Primary Industries (MPI) commercial catch-effort database for the 2005 to 2013 fishing years, and the MPI observer database for the 1993 to 2013 fishing years. Our analyses were restricted to the surface longline fishery, and divided into two regional strata − North region comprising Fisheries Management Areas (FMAs) 1, 2, 8, and 9, and South region comprising FMAs 5 and 7. The following indicators were calculated: high-CPUE (the proportion of half-degree rectangles having unstandardised catch per unit effort (CPUE) greater than a specified threshold); proportion-zeroes (the proportion of half-degree rectangles having zero reported catches in a fishing year); geometric mean index (the geometric mean of the species abundances in catches, for both the catch of all species including teleosts, and the catch of just the three sharks); standardised CPUE (for both commercial and observer data); proportion of males in the catch; and median lengths of males and females.

None of the indicators for the period 2005−2013 suggested that any of the shark species were declining in either North or South regions. In fact, some of the indicators suggested positive trends for all three species. We caution that there are a number of important caveats associated with our indicator analyses, especially relating to data quality and availability, and goodness of model fit in the CPUE analyses. Nevertheless we conclude that there is no evidence that the stocks of blue, porbeagle and mako sharks in New Zealand waters have been adversely affected by fishing at the levels experienced since 2005, and that there are good signs that they are increasing. Observer data, which span a longer time period than commercial fishery data, suggest that blue and mako shark abundance may have declined during the late 1990s and early 2000s, and then increased since the mid 2000s, an interpretation that is consistent with the indicators based on the more recent commercial data. Porbeagle shark abundance may have declined rapidly in the early 2000s before stabilising at a relatively low level. The indicators presented here cover only the most recent portion of a longer fishing history that was characterised by greater effort levels in the 1980s and early 1990s by foreign fishing vessels. There is no information on the effect of this earlier fishing effort, as there are no shark catch data from that period, nor effort data from before 1980. Furthermore, the three shark species are capable of migrating outside the New Zealand Exclusive Economic Zone where foreign fishing may also have impacted on the wider South Pacific stocks of these species. In order to understand trends in the wider stocks, and to quantify their status in relation to management reference points, regional stock assessments are now required.

1. INTRODUCTION

Cartilaginous fishes (sharks, skates, rays and chimaeras) generally have low productivity because of their low to moderate growth rates, and their low fecundity which results from small litter sizes and long (frequently multi-year) reproductive cycles. About 113 cartilaginous species occur in New Zealand waters, of which 11 are managed under the Quota Management System. Of the eleven shark species in the quota management system, comprising 27 management units or “stocks”, a full quantitative stock assessment, integrating information on catch, catch rates, age, and length data into an assessment model, is available for one shark stock (rig in SPO 7) (Ministry for Primary Industries 2014). Less data-intensive assessments using standardised catch-per-unit-effort (CPUE) analyses are available for 15 stocks, and unstandardised CPUE analyses are available for three highly migratory shark species (Ministry for Primary Industries 2014).

Recognizing the data-poor nature of many of the world’s shark fisheries, scientists have recently turned to alternative methods for assessing threats to the sustainable utilisation of chondrichthyan resources. These methods have the advantage of being more forgiving of data gaps, less reliant on assumptions structuring population dynamics, and more readily updated than traditional stock assessments. One type of approach has involved various forms of ecological risk assessment. Another approach is to apply a series of stock status indicators to assess the response of the population to fishing pressure. Such indicators are usually straightforward to compute (except for standardised CPUE) and track over time, thus providing the opportunity to observe trends which can serve as early signals of overexploitation. Interpreted as a suite, indicators of stock status can be useful for initial assessments and/or for prioritising future data collection or analytical work (Clarke et al. 2013).

An indicator approach was adopted as an initial step in the Western and Central Pacific Fisheries Commission’s (WCPFC) Shark Research Plan (Clarke et al. 2011; 2013). The concept for the Shark Research Plan was to use the indicator analysis for an initial assessment of population status for all of the WCPFC key shark species and then, having highlighted those in greatest need of further analysis, to proceed with more complex stock assessments. For blue and mako sharks, the WCPFC region probably covers the same stock that is fished in New Zealand and is the subject of the present study; however, shark stock relationships in the southwest Pacific are poorly understood.

This report performs indicator analyses for three important Highly Migratory Species (HMS) of sharks – blue, porbeagle and mako sharks. These species are taken primarily as bycatch in the New Zealand tuna longline fishery, but porbeagles are also caught by midwater trawl fisheries (Francis 2013). Four types of indicators are developed for each species: distribution, percentage catch composition, standardised CPUE, and median size/sex ratio. The first two indicators, and median size, have not been developed previously for these species. Standardised CPUE has been the subject of a recent unpublished study (T. Kendrick, Trophia Ltd, unpubl. data) using tuna longline data for the three HMS sharks from the northern North Island fishery up to 2009−10. The present project extends that study by adding the southern tuna longline fishery, and updating the time series using more recent data. Sex ratios (expressed as proportion of males) have been developed recently for the three HMS sharks caught in the tuna longline fishery up to 2011–12 (Francis 2013); these time series are here extended with more recent data.

These indicators are developed as annual time series and assessed for their utility in describing trends in stock abundance or status. The indicators can be updated at regular intervals in the future to monitor changes in population status in response to fishing and other impacts, and existing and new management measures. The indicators can also be provided to regional fisheries management organisations (e.g., WCPFC, Commission for the Conservation of Southern Bluefin Tuna, CCSBT) for incorporation into the assessment and management of these HMS sharks over greater spatial scales.

The Overall Research Objective of this study was:
To monitor trends in stock status of selected HMS sharks in New Zealand using indicator analyses.

Specific Research Objectives were:
1. To conduct distribution indicator analyses on mako, porbeagle and blue shark.
2. To conduct percentage catch composition indicator analyses on mako, porbeagle and blue shark.
3. To update the standardised CPUE analyses for mako, porbeagle and blue shark.
4. To conduct median size and sex ratio indicator analyses on mako, porbeagle and blue shark.

2. GENERAL METHODS

The four Specific Objectives are addressed below, one in each of Sections 3−6. The scope of the study is New Zealand-wide, as the three shark species are each managed as a single stock occurring throughout the Exclusive Economic Zone (EEZ) (Ministry for Primary Industries 2013).

The main data sources used for this study were the Ministry for Primary Industries (MPI) catch-effort database *warehou*, and the MPI observer database *COD*. Data were extracted for relevant periods, i.e. 2004−05 to 2012−13 fishing years for *warehou* and 1992−93 to 2012−13 fishing years for *COD*. The start date for the *warehou* data series was determined by the introduction of the three HMS sharks into the Quota Management System (QMS) in October 2004, and the requirement that all processed and discarded or released HMS sharks be recorded on fishing returns. The start date for the *COD* data series was the date when all observers were accurately distinguishing porbeagle and mako sharks. Hereafter, all years are reported as fishing years (1 October to 30 September), and they are labelled after the second of the two years (e.g. 2004−05 is referred to as 2005).

Our analyses are restricted to the surface longline (SLL) fishery that targets mainly southern bluefin tuna, bigeye tuna, and broadbill swordfish (Griggs & Baird 2013). This fishery accounted for 98−99% of the New Zealand blue shark catch, 92−95% of the mako shark catch, and 74−84% of the porbeagle shark catch between 2008 and 2011 (Francis 2013). Commercial catch data were extracted from Tuna Longlining Catch Effort Returns (TLCERs) submitted by SLL fishers to MPI and entered into *warehou*. Some observer trips or sets in *COD* have previously been flagged as having inaccurate data ranging from poor species identification to incomplete data recording, and these were omitted from all analyses.

SLL fishing effort is concentrated in two distinct regions of the EEZ – off the north-east coast of North Island and off the west coast of South Island. As in previous studies (Francis 2013), we analysed data from these two regions separately: North region comprised Fisheries Management Areas (FMAs) 1, 2, 8, and 9, and South region comprised FMAs 5 and 7. Effort and catches were very low in the remaining FMAs.

Detailed methods relevant to each of the four Specific Objectives are provided in Sections 3−6.

3. DISTRIBUTION INDICATOR ANALYSES

3.1 INTRODUCTION

A distribution indicator seeks to monitor trends in the status of a stock by assessing changes in the spatial distribution of the fish (Clarke et al. 2011). An increase in stock abundance may become apparent as an expansion of the range inhabited by the fish, and a decrease may be signalled by a contraction of the range.

3.2 METHODS

In this study, we calculated two distribution indicators:

- The *high-CPUE indicator* was the proportion of half-degree rectangles having unstandardised CPUE greater than a specified threshold in the commercial TLCER data. It was calculated as the number of high-CPUE rectangles divided by the total number of rectangles with reported effort. This indicator acts as a measure of the spatial extent of high abundance areas. [Observer data were too sparse and limited in their spatial distribution to be useful for this purpose.] CPUE was calculated as the total number of sharks caught per rectangle divided by the total number of hooks set in the rectangle (in thousands) in each fishing year. Following preliminary tests using a range of potential thresholds, indicator thresholds were arbitrarily set at 25 sharks per 1000 hooks for blue shark, and one shark per 1000 hooks for porbeagle and mako sharks.
- A *proportion-zeroes indicator* was calculated as the number of half-degree rectangles having zero reported catches in a fishing year divided by the total number of rectangles with reported effort in that year.

For both of the above indicators, only rectangles having more than 5000 hooks of fishing effort in a given fishing year were included in the analyses so that extreme catch rates from a small number of sets did not bias the result. A limit of 5000 hooks ensures that each included rectangle has at least three domestic sets or two foreign charter vessel sets[1].

Both of these indicators could be affected by inter-annual variation in the amount and distribution of fishing effort, and targeting. Ideally, the analyses should be restricted to a standard area that was fished every year. However, 520 rectangles were fished in the period 2005−2013, but only 77 (15%) were fished every year. To assess the potential impact of inter-annual variation, we calculated the high-CPUE indicator for both the full dataset (i.e. all rectangles fished in a given year) and a reduced dataset of 77 rectangles that were fished every year[2]. The indicators varied minimally for mako and blue sharks in both North and South regions, and porbeagle shark in North region. For porbeagles in South region, indicator values differed between datasets for individual years but the overall trends were similar. We therefore believe that the indicators are relatively unaffected by the level of inter-annual spatial variation occurring in this dataset.

The TLCER data for 2005–2013 contained 24 593 longline sets. Twenty-two sets were removed because they had implausibly high estimated catches of sharks (18 sets with more than 10 t of blue sharks, 1 set with more than 5 t of mako sharks, and 3 sets with more than 5 t of porbeagle sharks). A further 11 sets with missing start or finish positions were also removed, leaving 24 560 sets.

Set location was taken as the midpoint of the reported start and finish of set positions, and all sets were assigned to half-degree rectangles on that basis. A rectangle has a height of 55.6 km (30 n.m.) which is comparable to the length of domestic longlines (median length 22 n.m., maximum length about 40 n.m.) but less than that of chartered Japanese longlines (median length 73 n.m., maximum length 89 n.m.).

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[1] For domestic vessels, the mean number of hooks per set was 986 with a maximum of 2500. For chartered vessels, the mean number of hooks per set was 3240 and the maximum was 3780.
[2] The 5000 hook criterion was not imposed on the reduced dataset for this comparison, as it would have further reduced the dataset from 77 to 29 rectangles.

TLCERs have separate panels for recording catch that is processed (with some part of the shark being retained), and catch that is discarded or released under Schedule 6 of the Fisheries Act (which allows release of blue, porbeagle and mako sharks that are alive and likely to survive, or discard if authorised by an MPI observer). Total catches (as both weights and numbers) were calculated by summing the reported processed and discarded/released values.

Previous CPUE studies of New Zealand HMS sharks have been based on catch numbers rather than weight (Francis et al. 2001; Griggs & Baird 2013), as the former are believed to be more accurate than the latter (which are often estimated). Furthermore, there were slightly more records of catch numbers than weights in the TLCER data, indicating that some weights were not reported by fishers: the numbers of catch weight records were 98.8%, 97.7% and 99.2% of the numbers of catch number records for blue, porbeagle and mako sharks respectively. We therefore used catch numbers in preference to catch weight for calculating a CPUE index. The numbers of sets with reported catch number records in the whole TLCER dataset were 18 859 (76.7% of all records) for blue shark, 5444 (22.2%) for porbeagle shark, and 8515 (34.7%) for mako shark.

3.3 RESULTS

Fishing effort

The number of hooks set by SLLs in the TLCER dataset declined from about 3.7 million per year in 2005–2007 to 3.1 million in 2009–2012, and 2.7 million in 2013 (Figure 1). The distribution of effort by half-degree rectangles shows a clear separation of North and South region fisheries in all years (Appendix 1). The spatial distribution of effort in North region was similar in all years, but in South region, the effort was deployed over a single contiguous area in some years, and split across two disjunct areas in other years.

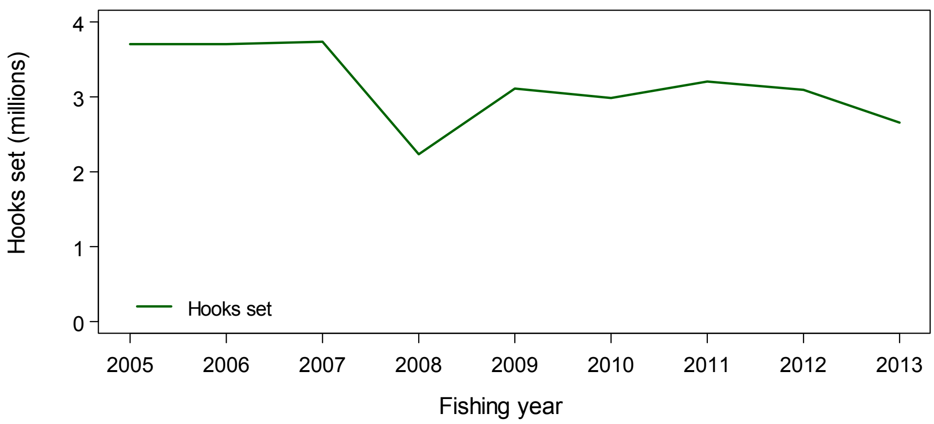

Figure 1: Number of hooks set by surface longline vessels and reported on TLCERs.

Blue shark

The total weight of blue sharks reported on TLCERs, after removal of implausible outliers, increased steadily from 708 t in 2005 to a peak of 1659 t in 2012, followed by a decline to 1315 t in 2013 (Figure 2). The component of total catch made up of discarded and released sharks increased steadily through time, and it increased faster than the processed shark component. By 2013, the weight of discarded or released sharks equalled the weight of processed sharks. Processed weight values were very close to the Monthly Harvest Return (MHR) values obtained independently from actual landed weights reported to MPI by quota holders, indicating that the TLCER processed weights were accurately reported overall.

The distributions of aggregated catches and CPUE by half-degree rectangles are shown in Appendices 2 and 3. High catch rates were present throughout North and South regions.

The high-CPUE indicator increased steadily throughout the time series in both North and South regions (Figure 3). The proportion-zeroes indicator was zero or near zero in all years in both regions, because blue sharks were common enough to be caught in nearly every half-degree rectangle where the number of hooks deployed exceeded 5000 per year.

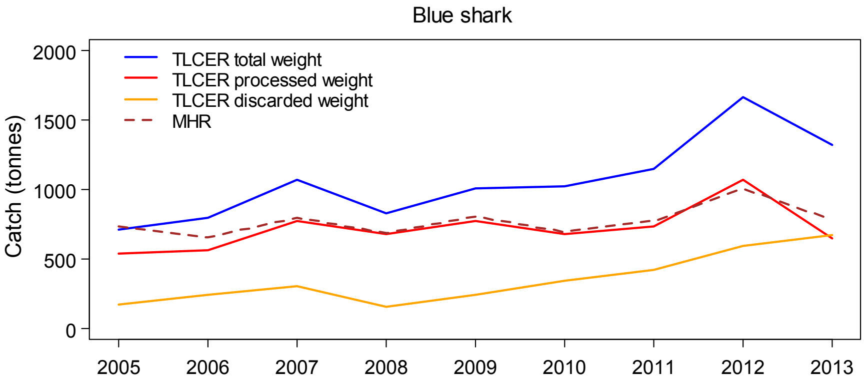

Figure 2: Estimated blue shark catches (whole weight) in the surface longline fishery for the 2005 to 2013 fishing years as reported on TLCERs. A breakdown of the total weight by processed and discarded categories is also provided. Monthly Harvest Return (MHR) landings for all fishing methods are also shown (source: Ministry for Primary Industries (2013)).

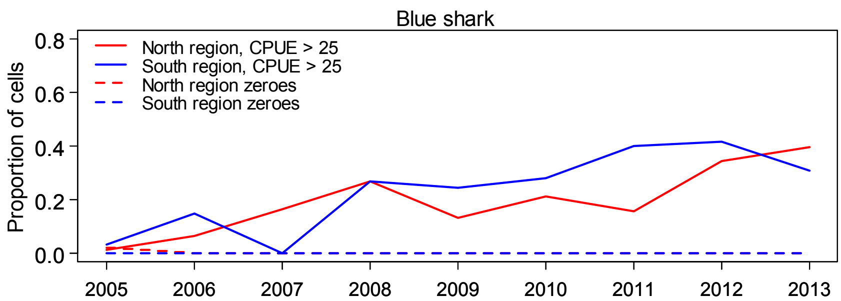

Figure 3: Blue shark distribution indicators. Proportions of 0.5 degree rectangles having CPUE greater than 25 per 1000 hooks, and proportions of rectangles having zero catches, for North and South regions by fishing year, based on estimated catches (processed and discarded combined) reported on TLCERs.

Porbeagle shark

The total weight of porbeagle sharks reported on TLCERs averaged 35 t from 2005 to 2008, and then rose sharply to 84 t in 2012 before dropping back to 63 t in 2013 (Figure 4). The component of total catch made up of discarded and released sharks increased steadily through time, and it increased faster than the processed shark component. By 2013, the weight of discarded or released sharks nearly equalled the weight of processed sharks. Processed weight values were well below the MHR values, except in 2012, because significant amounts of porbeagle shark are also taken by midwater trawlers, which report their catch on different fishing return forms.

The distributions of aggregated catches and CPUE by half-degree rectangles are shown in Appendices 4 and 5. Porbeagle catch rates were highest between Great Barrier Island and Hawke Bay and, in some years, off the north-western coast of South Island.

The high-CPUE indicator increased steadily through the time series in both North and South regions, reaching a plateau in 2011 in North region and in 2012 in South region (Figure 5). However, the South region indicator may have been affected by the rather sparse and uneven distribution of fishing effort among years, combined with the often higher CPUE of porbeagles in northern South Island waters closer to the coast than seen in southern offshore waters (Appendix 5). The proportion-zeroes indicator declined steadily in North region, but was relatively stable in South region.

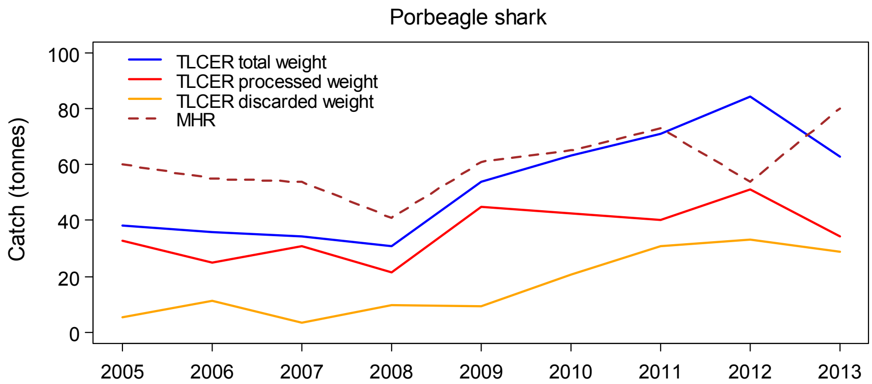

Figure 4: Estimated porbeagle shark catches (whole weight) in the surface longline fishery for the 2005 to 2013 fishing years as reported on TLCERs. A breakdown of the total weight by processed and discarded categories is also provided. Monthly Harvest Return (MHR) landings for all fishing methods are also shown (source: Ministry for Primary Industries (2013)).

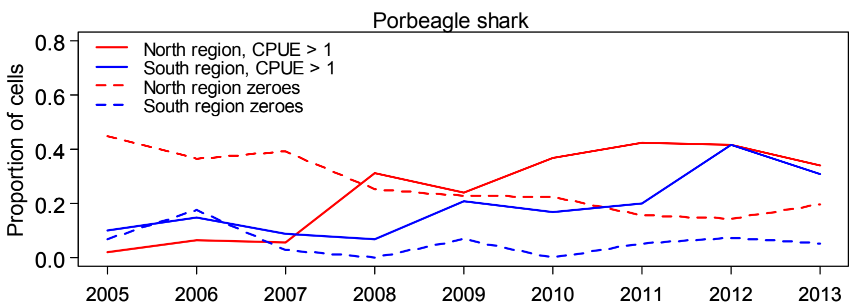

Figure 5: Porbeagle shark distribution indicators. Proportions of 0.5 degree rectangles having CPUE greater than 1 per 1000 hooks, and proportions of rectangles having zero catches, for North and South regions by fishing year, based on estimated catches (processed and discarded combined) reported on TLCERs.

Mako shark

The total weight of mako sharks reported on TLCERs was stable and averaged 107 t from 2005 to 2010. It then rose sharply to 186 t in 2012 before dropping back to 141 t in 2013 (Figure 6). The component of total catch made up of discarded and released sharks increased rapidly after 2009 and exceeded the weight of processed sharks in three of the last four years. Processed weight values were below the MHR values, except in 2012, reflecting the capture of mako sharks in other fisheries that report their catch on different fishing return forms.

The distributions of aggregated catches and CPUE by half-degree rectangles are shown in Appendices 6 and 7. Mako shark catch rates were much higher in North region than South region, and were greatest between Great Barrier Island and Hawke Bay.

The high-CPUE indicator increased steadily in North region, reaching a plateau in 2010 (Figure 7). The preference of mako shark for warmer waters, and the resultant low catch rates in South region, mean that the high-CPUE indicator is relatively uninformative and inappropriate for South region. However, the proportion-zeroes indicator declined steadily in South region until 2009, and remained stable thereafter. There were few zeroes in North region, but the proportion-zeroes still declined from 4–6% of rectangles in the first half of the time series to 0–3% in the second half.

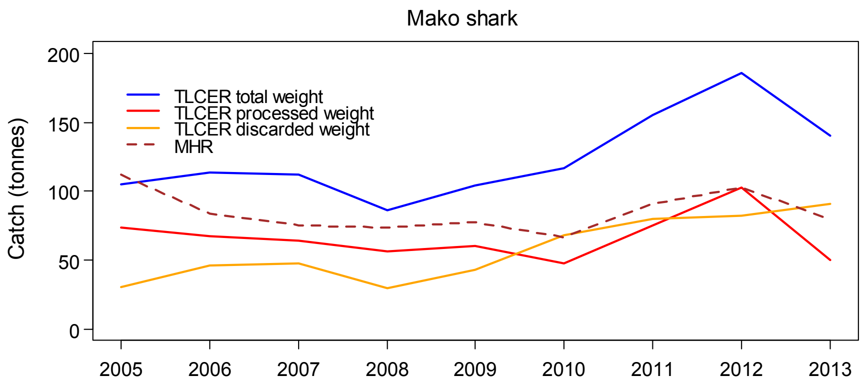

Figure 6: Estimated mako shark catches (whole weight) in the surface longline fishery for the 2005 to 2013 fishing years as reported on TLCERs. A breakdown of the total weight by processed and discarded categories is also provided. Monthly Harvest Return (MHR) landings for all fishing methods are also shown (source: Ministry for Primary Industries (2013)).

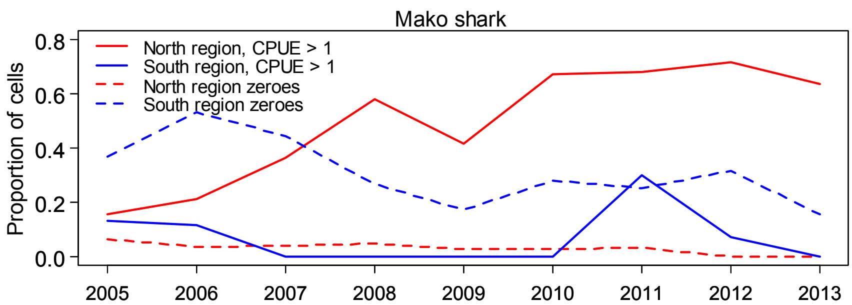

Figure 7: Mako shark distribution indicators. Proportions of 0.5 degree rectangles having CPUE greater than 1 per 1000 hooks, and proportions of rectangles having zero catches, for North and South regions by fishing year, based on estimated catches (processed and discarded combined) reported on TLCERs.

3.4 CONCLUSIONS

The high-CPUE indicator showed increasing trends over the last nine years for all three species in both North and South regions, except for mako shark in South region. Mako sharks are uncommon in the cool waters around South Island, so it is not surprising that this indicator failed to show any trend. Use of a threshold lower than one shark per 1000 hooks might have revealed a pattern but we did not attempt this because a high-CPUE distribution indicator is most appropriately applied to the main habitat of a species, not marginal habitat. Nevertheless, the proportion-zeroes indicator showed a declining trend over the first half of the time series for South region mako sharks, before becoming stable. The proportion-zeroes indicator also declined for North region makos and North region porbeagles, but showed no clear trend for South region porbeagles. Thus all indicators for which trends were discernible suggested the populations of all three species in New Zealand waters were increasing; the remaining indicators showed no evidence of decreasing population sizes.

4. SPECIES COMPOSITION INDICATOR ANALYSES

4.1 INTRODUCTION

Three indicators assessed in this study (distribution, CPUE, and size and sex ratio) measure changes occurring in particular shark species. In contrast, a species composition indicator operates at a multi-species, rather than a single-species, level. By assessing whether certain shark species are becoming more or less dominant in the catch, and assuming that catches reflect abundance (as in the CPUE analysis), the species composition indicator can reflect whether the community as a whole is changing over time. Minimizing the risk that fishing activities are driving irreversible changes in natural assemblages is one of the key tenets of ecosystem based fisheries management (Pikitch et al. 2004).

The concept of species composition is often intertwined with that of biodiversity (e.g., see Tuomisto 2010). Considerable progress has been made, particularly in terrestrial ecosystems, in developing quantitative measures of community structure, such as species richness and evenness, as a means of monitoring and reducing the loss of biodiversity (Magurran & McGill 2011). When applying such methods to fisheries data, differences relating to the non-random nature of the sampling (i.e. data potentially influenced by shifts in targeting and derived only from areas where fishing operations have occurred) and in some cases the lack of taxonomic discrimination (e.g. when using commercial fishing returns) must be acknowledged. Furthermore, while the protection of biodiversity has been enshrined in many national and international policy instruments, foremost among these the 1993 Convention on Biological Diversity, fished ecosystems may need to be managed for economic productivity and sustainability as well as for the number and relative abundance of species *per se*. For these reasons, terrestrial biodiversity assessment approaches may differ from those which are most appropriate for an active fishery.

Another difference between the application of indicators to New Zealand’s shark fisheries and the body of literature on terrestrial biodiversity assessment relates to the prioritisation of species. In New Zealand 100 species/species groupings have been included in the Quota Management System (QMS) and three of these, i.e. blue, mako and porbeagle sharks, are included in this analysis. Nine fish species, seven of them elasmobranchs, are subject to national protected species legislation. This situation implies that certain taxa have been granted priority for management and stands in contrast to traditional biodiversity indices which usually measure the number and evenness of species present, and sometimes the overall abundance, without reflecting any preference for the status of particular species (Buckland et al. 2005). In this analysis three QMS species were prioritised for analysis, with other chondrichthyan species and other non-chondrichthyan species treated as agglomerated categories.

In considering both the literature on species composition indicators and the objectives of this study, this section assesses species composition in two ways:

- the proportion of the catch composed of blue, mako and porbeagle sharks relative to other chondrichthyan fishes and other non-chondrichthyan catch (i.e. five groups assessed); and
- the relative proportions of blue, mako and porbeagle sharks in the total catch of these three species (i.e. three groups assessed).

This analysis thus addresses how the proportion of chondrichthyan fishes changes relative to non-chondrichthyan fishes as well as how the proportions of the three species of interest change relative to each other. For these analyses it would be ideal if changes in catch composition represent changes in the natural assemblage rather than changes in the efficiency of fishing operations, e.g. catchability or targeting, but the latter possibility must be given careful consideration. Also, the objective of the analyses is to determine whether there have been changes in species composition. Judging whether or not these changes are desirable is beyond the scope of this assessment.

4.2 METHODS

Data Description

The data used in this analysis derive from the TLCER records from 2005–2013 and observer records from 1993–2013. A detailed description of each dataset's fields and grooming is provided in Section 5. As the data requirements for the species composition analyses were less demanding than those for the CPUE standardisation modelling, only those records which were outside the key fishing grounds (i.e. outside the boundaries of FMAs 1, 2, 5, 7, 8 and 9); from vessels flagged to countries other than New Zealand or Japan; or for which the data quality was poor (observer data only) were excluded from the analysis (Section 5, Table 1). The number of sets remaining in each dataset after this grooming was 24 059 (1922−2968 per year) for the TLCER dataset and 5796 (119−511 per year) for the observer data. The TLCER data analysis begins in 2005 because the requirement to report both landed and discarded/released sharks was implemented in October 2004; before that reported catches of blue, mako and porbeagle sharks may not accurately reflect actual catches. The observer data analysis begins in 1993 because before that time species identifications were not always reliable for porbeagle and mako sharks.

Analysis for both datasets was conducted on the basis of number of individuals, rather than weight for several reasons. First, for these two datasets records of numbers are more accurate and complete than records of weight. Second, most ecological community analyses are based on abundance rather than biomass (Cerfolli et al. 2013) and as a result most species composition indices described in the scientific literature are formulated for abundance data. Third, for sharks using abundance rather than biomass data helps to avoid biases arising from sampling species with sex- and life-stage-specific aggregation behaviours (Nakano 1994; Mucientes et al. 2009; Francis 2013), e.g. female sharks are often larger than males, and pregnant females in pupping grounds would be larger still.

Data were subset for consistency with, and based on information drawn from, the CPUE standardisation analysis. In that analysis, the TLCER data were first subset into North (FMAs 1, 2, 8 and 9) and South (FMAs 5 and 7) regions based on previous analyses (Francis 2013), and then the South region was further subset to separate the Japan and domestic fleets. This split was made because of clear differences in fishing grounds, operational characteristics and reporting practices between the two fleets (see Section 5).

The indicators proposed in this study are designed to show annual stock status. If data are collected in a standardised manner throughout the year, seasonal variations in the presence or abundance of certain species would be accounted for in the calculation of an annual species composition indicator. One caution with this approach is that TLCER data, and even more so observer data, may be biased toward certain months (seasons) in certain areas reflecting both seasonal operational patterns and observer coverage. Despite the potential drawback of the data being seasonally unrepresentative of the full year, if both the patterns and the distribution of effort are consistent from year to year, bias in an annual indicator would not be expected. In order to explore this issue, the proportion of sets in each month for each year was plotted for the three TLCER datasets and for the observer dataset partitioned to reflect the area-fleet partitioning of the TLCER dataset (Figures 8 and 9).

Figure 8: The proportion of sets in the TLCER Japan South, TLCER Domestic South, TLCER North datasets by month for each sampled year. The total number of sets in each year is annotated at the top of each column.

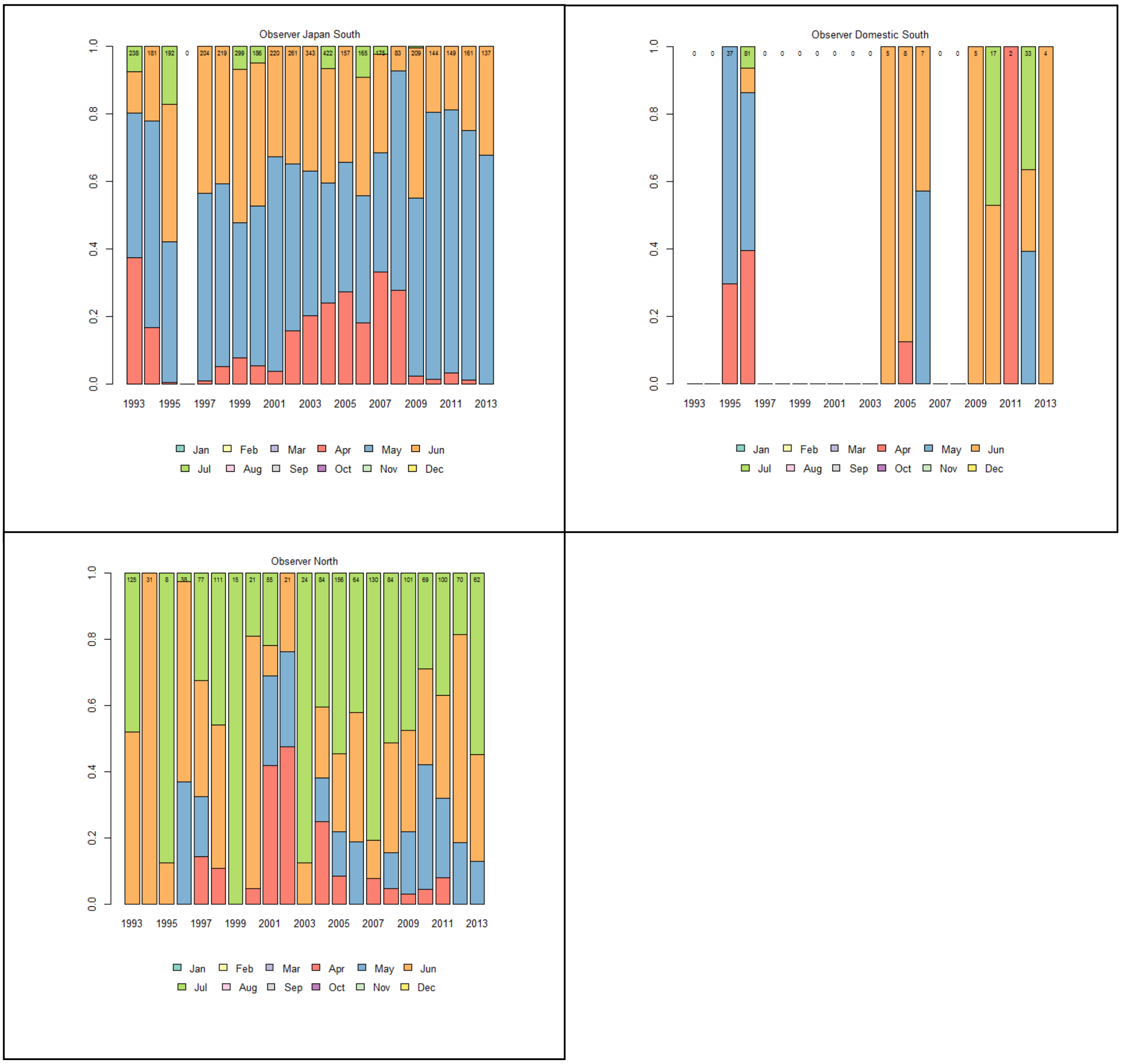

Figure 9: The proportion of sets in the observer dataset (partitioned to represent the area-fleet subsets in the TLCER dataset shown in Figure 8) by month for each sampled year, 1993−2013. The total number of observed sets in each year is annotated at the top of each column.

As expected due to high observer coverage, there is close agreement between the TLCER Japan South and Observer Japan South dataset's seasonal sampling patterns. Both datasets show that the bulk of the sampling occurs in May and June with non-negligible sampling in April prior to 2009. While a shift in species composition around 2009 may thus be expected, it is not likely to be large given that the time shift is less than one month. The short series represented in the TLCER Japan South (2005–2013) dataset appears representative of the longer series in the Observer Japan South dataset (1993–2013). Therefore both datasets should show consistent results and either dataset can be used as the basis for an annual indicator, but the relatively longer time series and high observer coverage (average 78%, Griggs & Baird 2013) favour use of the Observer Japan South dataset.

The TLCER North dataset shows a remarkably consistent pattern of monthly sampling in 2005–2013, with many different months represented. This consistency is not obvious in the Observer North dataset with its emphasis on June–July sampling in most years but with more frequent April–May sampling since 2000. These plots suggest that while either the TLCER or observer datasets could be used as a species composition indicator for the North region, they would not necessarily be expected to show similar results. As the observer coverage is relatively low (under 10%, Griggs & Baird 2013), despite its longer timespan, the TLCER North dataset would probably provide a more consistent indicator of species composition due to its higher and more widely dispersed samples.

The TLCER Domestic South dataset is, like the TLCER Japan South dataset, weighted toward sampling in May–June, but it shows slightly more sampling in March–April especially since 2010. The Observer Domestic South dataset is also weighted toward May–June sampling but the proportions vary widely from year to year and do not correspond well with the TLCER Domestic South dataset. This can probably be attributed to very low observer coverage of this fishery (in fact, many years completely lack coverage). For these reasons, a species composition indicator should be based on the TLCER Domestic South dataset rather than observer data.

Analytical Methods

For the following analyses, shark and non-shark catches by species were tallied by year and divided by the number of hooks fished/observed (in thousand hooks) in that year. While a simple tally (i.e. without adjusting for effort (hooks)) would suffice for an analysis based on proportions alone, converting the data to a normalised measure of abundance allows for the application of indices which measure both the evenness of the distribution of the species (the similarity of the abundances among species) and their abundances over time (Buckland et al. 2005). In other words, if using proportions alone 60 blue sharks, 16 mako sharks and 10 porbeagle sharks in Year A and 30 blue sharks, 8 mako sharks and 5 porbeagle sharks in Year B would produce the same index value. In contrast, using both proportions among species and abundances over time would give a reduced index value in Year B reflecting the overall decrease in abundance. Clearly both approaches are vulnerable to under- or mis-reporting biases if these biases shift from year to year, but are relatively robust if the biases remain constant over time.

The advantages and disadvantages of a wide range of species composition indices have been reviewed in recent years (Buckland et al. 2005; Lamb et al. 2009; Van Strien et al. 2012). Among those frequently evaluated are the traditional Simpson and Shannon diversity indices which give low values when a few species dominate and high values when no species dominate. In the reviews both indices were found to perform poorly in two respects: i) the direction of change in the index is not always consistent with the direction of change in the abundances of the species (monotonicity); and ii) the proportion of change in the index is not always consistent with the degree of change in the abundances of the species (proportionality (Van Strien et al. 2012)). A modified Shannon index was proposed by Buckland et al. (2005) to remedy these issues. The modified index is, like the original Shannon index, based on the proportions of species present, but annual Shannon values are scaled to a base year to allow the modified index to decrease if the overall abundance decreases but the proportions of species remain the same. However, as discovered by Van Strien et al. (2012) and in calculations for this study, when abundances in years subsequent to the base year increase by as little as a factor of three the index becomes unstable.

In examining an index that would reflect both relative proportions and absolute abundances, all three investigators noted the robust performance of an index based on the geometric mean of the species' abundances, although Lamb et al. (2009) highlighted its inability to handle zero counts. In the Van Strien et al. (2012) analysis the geometric mean was found to have the most favourable properties of the ten indicators evaluated. Since annual counts of blue, mako and porbeagle sharks were infrequently zero, and if occurring could be easily adjusted by means of adding a small constant (in this case 1), the geometric mean in year j (G_j) relative to the base year was adopted as the annual species composition index for this study. It was calculated as (Buckland et al. 2005; Van Strien et al. 2012)):

$$G_j = \exp\left(\frac{1}{m}\sum_{i} log\frac{d_{ij}}{d_{i1}}\right)$$

where m is the number of taxonomic groups in the analysis, and d represents the standardised counts for taxonomic group i in year j.

4.3 RESULTS

Shark catch versus total catch

The abundances of blue, mako, porbeagle and other sharks (including all other sharks, skates and chimaeras), as well as other catch (including both target and non-target species), are shown for the TLCER and observer datasets in Figures 10 and 11 respectively. The proportion of the catch in each taxonomic group by year is given in Appendix 8, tables A1 and A2.

Blue shark comprises the majority of the total catch in both the TLCER Japan South and the TLCER Domestic South datasets, i.e. the number of blue sharks exceeds the number of all other species combined in most years. There are, however, differences between the two southern TLCER datasets. The Japanese fleet reports considerably lower numbers of sharks per hook. Also, while the TLCER Japan South dataset reports a substantial proportion of its catch as “other sharks”[3], the TLCER Domestic South returns contain very few records of other shark catches and relatively more catches of mako and porbeagle sharks. These patterns are repeated in the observer datasets for these two fleets. The likely explanation for these differences is the spatial separation of the areas fished by the two fleets: the Japanese fleet fishes well offshore, beyond the 1000 m depth contour in southern waters (mainly 41–47 ^{o}S) whereas the domestic fleet fishes over the continental shelf (particularly on the inner Challenger Plateau) or around the 1000 m contour in more northern waters (mainly 39–44 ^{o}S). The TLCER North dataset also records few other shark catches and also more mako and porbeagle shark catches than the TLCER Japan South dataset. Higher catches of makos would be expected in the TLCER North dataset given the northerly distribution of mako sharks (Francis 2013). In the TLCER Japan South and TLCER North datasets abundances were highest in 2012–2013 due to high catches of blue sharks.

The geometric mean index values for the TLCER datasets show annual values scaled to the value in the first year of the time series (2005=1) (Figures 10, 12). In the TLCER Japan South and North datasets the values are highest in 2012–2013 whereas the highest index value for the TLCER Domestic South dataset was recorded in 2011. It should be noted that the index values reflect both the evenness of the proportions and the total abundance such that for the TLCER Japan South dataset 2013 has a considerably higher index value than 2012 because its evenness is higher whereas its abundance is nearly the same. Similarly, in the TLCER North dataset the index value for 2011 is higher than the preceding years not because its abundance is greater but because its evenness is higher.

[3] Japan-flagged vessels reported 8720 “other” sharks on their returns between 2005 and 2013 of which 70% were deepwater dogfish (mainly Owston’s dogfish, *Centroscymnus owstoni*) and 20% were threshers (*Alopias* spp.). Of the reported catch of deepwater dogfish, 99% were reported as discarded; 79% of the threshers were reported as discarded.

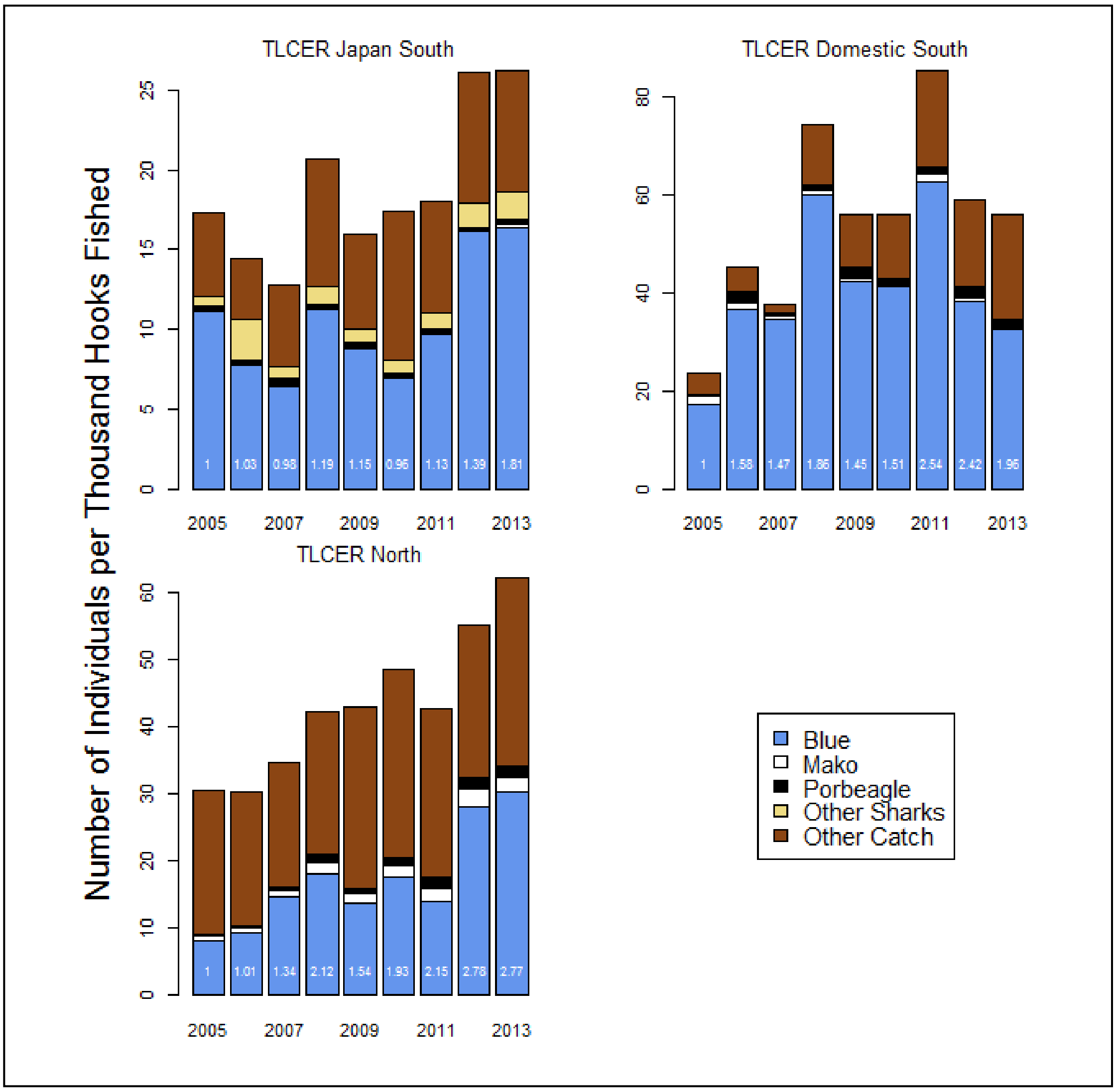

Figure 10: The abundance of blue, mako, porbeagle and other sharks, and other catch, in the TLCER Japan South, TLCER Domestic South and TLCER North datasets. The data represent catch in numbers normalized for fishing effort by dividing by thousands of hooks. Index values shown in white at the base of each column are the geometric mean of the abundances in the five groups in that year expressed relative to the base year (2005). Higher index values indicate higher abundances and/or evenness.

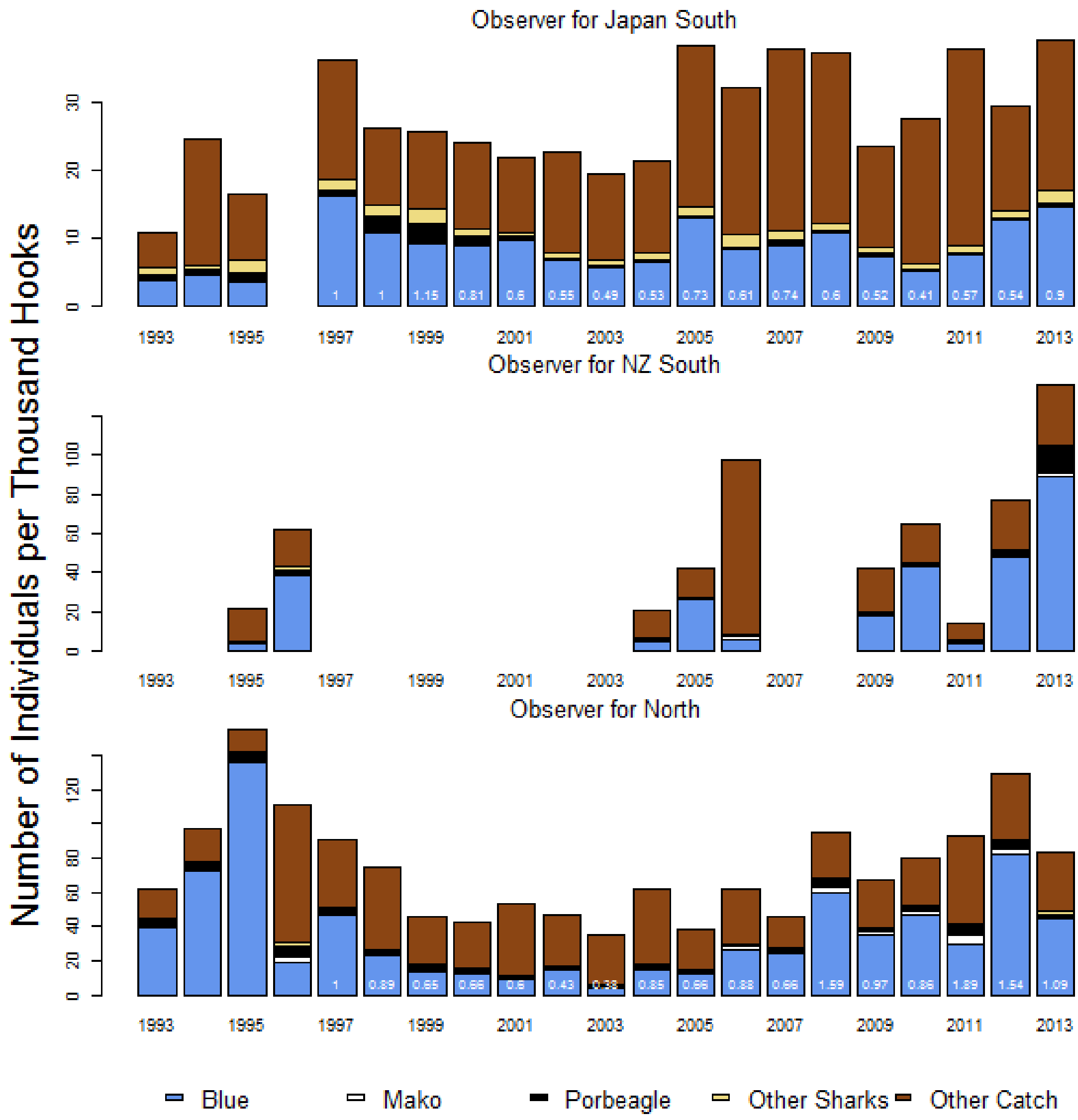

Figure 11: The abundance of blue, mako, porbeagle and other sharks, and other catch, in the observer dataset (partitioned to represent the area-fleet subsets in the TLCER dataset shown in Figure 10). The data represent catch in numbers normalized for fishing effort by dividing by thousands of hooks. Index values shown in white at the base of each column are the geometric mean of the abundances in the five groups in that year expressed relative to the base year (1997). Higher index values indicate higher abundances and/or evenness. The base year was selected so as to avoid gaps due to lack of observer coverage; an index was not calculated for the Domestic South fleet due to low coverage.

To a large extent, the patterns seen in the TLCER datasets are repeated in the observer datasets (Figures 11, 13). As noted above the low coverage for the domestic fleets (north and south) may be the source of some of the discrepancies observed. In contrast to the TLCER Japan South dataset, the observer Japan South dataset suggests that the share of blue sharks in the catch (by number) is less than that of "other" non-chondrichthyan catch. Both datasets agree however that the proportion of other sharks is high relative to the proportions of mako and porbeagle sharks in the Japan South fishery. Observers noted particularly high catches of porbeagle sharks in 2013 in the southern domestic fishery and mako sharks in 2011 in the northern domestic fishery but these patterns do not mirror those shown in the TLCER datasets and may arise from unrepresentative observer sampling. Relative abundances in the observer Japan South dataset have been higher since 2005 mainly due to increased abundances of non-chondrichthyan species. In contrast, in the observer north dataset increased blue shark catches have been responsible for slightly higher overall abundances since 2008.

Index values were calculated for the observer Japan South and observer North datasets using 1997 as the base year. Gaps in observer coverage for the observer domestic South dataset prevented calculation of an index over a meaningful time series. Index values for the observer Japan South series appeared low in 2000–2012 (less than 0.74) due to a particularly high score for the assemblage in the arbitrarily chosen base year of 1997. In fact, the index has fluctuated and rose in 2013 due to increased abundances of blue, porbeagle and other sharks. For the observer north dataset, the index has been greater than 1 in recent years (2011–2013, and also 2008) primarily due to greater abundances of mako and porbeagle sharks.

Overall, there is no indication in the most relevant datasets, i.e. the TLCER Domestic South, TLCER North and Observer Japan South, of any decrease in the abundances or evenness over time of shark taxa assessed (i.e. blue, mako, porbeagle and "other" as a group). Instead, the proportion of sharks in the catch appears to have increased in 2012–2013 in two of the three datasets (not in the TLCER Domestic South dataset) due to increases not only in blue sharks, but in mako, porbeagle and other sharks as well.

Relative proportions of blue, mako and porbeagle sharks and changes over time

Given that the focus of this study is on blue, mako and porbeagle sharks, it was considered that analysis of these species in conjunction with other chondrichthyan and non-chondrichthyan fishes might overlook small, but important, changes in proportions between them. Therefore, proportions were calculated for these three species only (Appendix 8, tables A3 and A4) and index values were recalculated (Figures 12 and 13). This section will focus on interpreting the index values in terms of the proportions.

In all of the TLCER datasets, the index values in the final two years of the series (2012–2013) are higher than the base year (2005) indicating that there is higher species evenness and/or overall abundance. Although blue shark remains an overwhelmingly dominant component of the catch, the proportions of mako and porbeagle sharks do not appear to be declining and in some cases (e.g. the TLCER North dataset) appear to be increasing.

Examining the observer datasets' longer time series reveals that the choice of 1997, when overall abundance and evenness were quite high, as a base year results in low index values for subsequent years in the Observer Japan South dataset. During this period the overall abundances have fluctuated but are currently near their former (1997) level. The proportion of porbeagles has however decreased which is reflected in the lower index values. In contrast, in the Observer North dataset recent index values (2010–2012) are higher than the base year and the proportions of mako and porbeagle sharks in 2011 are some of the highest since the base year (Appendix 8, Table A4). Data for 2013 show a lower index value reflecting a greater dominance of blue shark and lower proportions of porbeagle and mako sharks compared to 2010–2012.

The results of this re-analysis focused on blue, mako and porbeagle sharks only, has confirmed the results of the five-group analysis presented above. Despite the dominance of blue sharks, mako and porbeagle proportions appear generally stable or possibly increasing in the northern region.

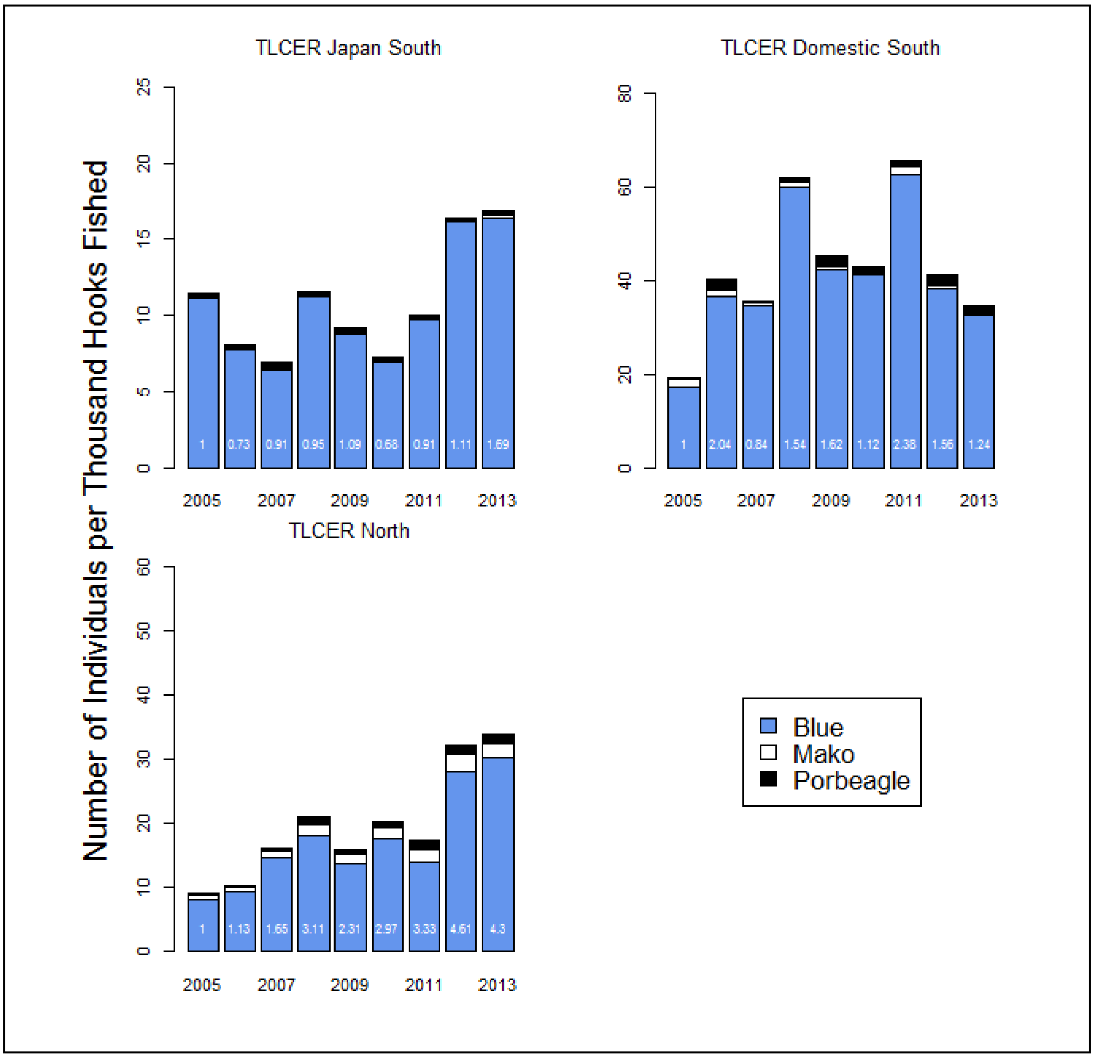

Figure 12: The abundance of blue, mako and porbeagle, sharks in the TLCER Japan South, TLCER Domestic South, TLCER North datasets. The data represent catch in numbers normalized for fishing effort by dividing by thousands of hooks. Index values shown in white at the base of each column are the geometric mean of the abundances in the three groups in that year expressed relative to the base year (2005). Higher index values indicate higher abundances and/or evenness.

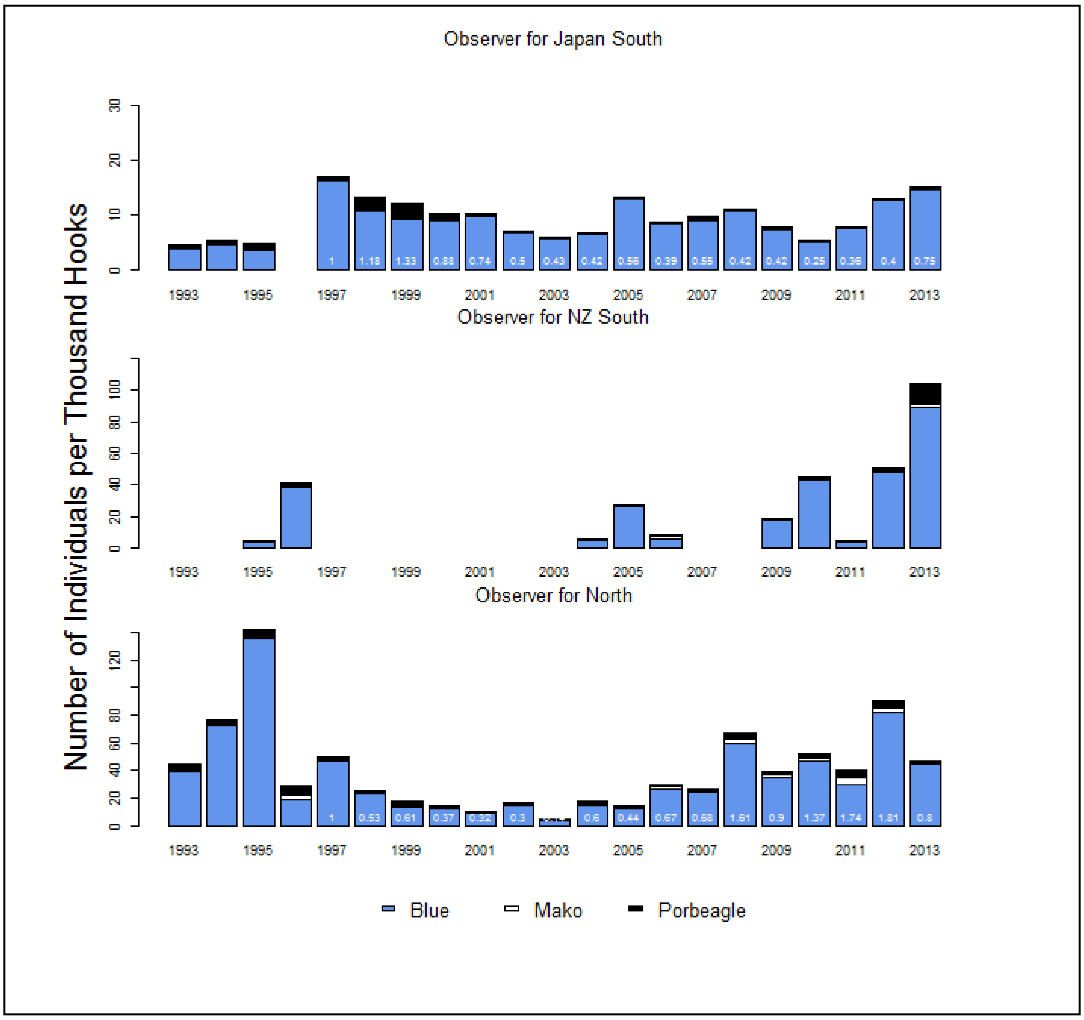

Figure 13: The abundance of blue, mako and porbeagle sharks in the observer dataset (partitioned to represent the area-fleet subsets in the TLCER dataset shown in Figure 12). The data represent catch in numbers normalized for fishing effort by dividing by thousands of hooks. Index values shown in white at the base of each column are the geometric mean of the abundances in the three groups in that year expressed relative to the base year (2005). Higher index values indicate higher abundances and/or evenness. Due to gaps in observer coverage the base year is set as 1997 for the Japan South fleet and the North fleet; an index was not calculated for the Domestic South fleet due to low coverage.

4.4 CONCLUSIONS

Use of a species composition indicator in this study drew upon concepts developed for terrestrial biodiversity assessment, but the use of fishery-dependent data for sharks introduces some important caveats. In particular, while an increase in abundance across all species would usually be taken as a positive result, such an increase in this study represents an increase in catch and this could arise from higher abundances, a shift toward fishing grounds or practices with higher catch rates (including potentially greater targeting), or a combination of both. While none of the fisheries assessed in this study claim to be targeting sharks, it is noted that there has been, during the time series analysed, market demand for shark fins and meat which could have incentivised catches (Clarke et al. 2013). Therefore, it is important to cross-check any sharply increasing catches against other indicators to look for signals of depletion due to targeting or other overexploitation.

It is also important to consider the role of under- or non- reporting. The observer data are expected to be free of this potential bias, but the TLCER data analysis was limited to years in which reporting was believed to be most accurate (i.e. 2005 onwards). Despite this approach, accurate reporting in this time period is expected mainly for species in the Quota Management System (QMS), including blue, mako and porbeagle sharks. The extent of under- or non-reporting of non-QMS chondrichthyan fishes is unknown, and if significant could have affected the analyses incorporating "other" taxonomic categories. For this reason, analyses were conducted with and without these other species included.

In neither case was there evidence of a strong trend in overall abundance of the species analysed, nor was there a strong trend of decreasing evenness in the proportions of these species in the catches. Recent (2012–2013) overall abundances were at their highest levels in the past decade in the TLCER Japan South and TLCER North datasets mainly due to increased catches of blue shark, a species which has long dominated catches. However, these years and datasets also showed large proportions of mako, porbeagle and other sharks compared to previous years, thereby suggesting no material change in the assemblage of sharks analysed.

This absence of evidence of adverse impacts stands in contrast to findings on the species composition of pelagic sharks in other areas. For example, a species composition analysis applied to the Western Central Pacific Fisheries Commission's observer dataset showed a marked disappearance of oceanic whitetip shark (*Carcharhinus longimanus*) after 2004 and was one of the first signals of the severe decline of this species in the Pacific (Clarke et al. 2011). This finding was subsequently reinforced by catch per unit effort analyses in other datasets (Brodziak & Walsh 2013; Clarke et al. 2013), and a finding that zero catch sets of oceanic whitetip sharks had increased from 75% in 1995 to 95% in 2010 (Walsh & Clarke 2011).

Another example of a simple species composition indicator for pelagic shark populations is a comparison of the proportion of blue and mako sharks in the FAO global capture production data for 1998–2011 (FishstatJ Databases, http://www.fao.org/fishery/statistics/software/fishstatj/en). During this time period, the proportion of the catch that was comprised of blue sharks grew by 9.0% per year, but the proportion comprised of mako sharks rose only 7.5% per year (exponential models with R^2 values of 0.887 and 0.892, respectively). Given the higher productivity of blue sharks (Cortés et al. 2010), one possible explanation is that the higher rate for blue sharks reflects this species' greater ability to keep pace with exploitation levels. Mako sharks, while equally distinctive and more valuable, and thus equally likely to be reported at the species level, are less productive. As a result, although mako catches appear to be rising as a result of an overall trend in increased species-specific reporting, this rate analysis suggests their relative abundance may actually be falling in comparison to more productive species (H. Eriksson & S. C. Clarke, unpubl. data).

These examples illustrate how species composition can serve, along with other simple indicators, to identify trends of concern in shark populations for further investigation. In this analysis of the species composition of blue, mako and porbeagle sharks in New Zealand's SLL fisheries, no such trends were identified. Nevertheless, as the time series of reliable TLCER data extends and if observer coverage, particularly for the domestic fisheries improves, this analysis should be revisited. When doing so, care should be exercised with regard to accounting for targeting and reporting practices. A better understanding of these issues may provide for new interpretations of existing and prospective data.

5. CATCH PER UNIT EFFORT INDICATOR ANALYSES

5.1 INTRODUCTION

One of the most common approaches to assessing trends in stock status is to calculate CPUE as an index of abundance. Nominal CPUE indices are simple to compute for the SLL fishery where the number of hooks fished represents a consistent unit of effort[4]. Annual values can be computed as the number of sharks of each species caught per thousand hooks, and if average catchability is constant the resulting time trend is expected to indicate the trajectory of stock abundance.

One drawback of using nominal CPUE as an indicator of stock status is that it can be skewed by factors which change the catch rates over time by changing the average catchability and obscuring the abundance signal. These factors may include changes in fishing techniques (e.g. gear, bait or time of day), changes in effort expended in various parts of the fishing grounds (e.g. area, season or depth), or changes in the vessels or skill of fishers working in the fishery (e.g. number or identity of vessels, fleet composition) (Maunder & Punt 2004). In addition, changes in the accuracy of catch reporting (e.g. implementation of catch reporting requirements, the presence of an observer, or high catch quantities which reduce the time available for record-keeping) may also bias CPUE-based abundance indices. In order to remove the annual variation in the data not attributable to changes in abundance, standardisation of CPUE series is often attempted using statistical models. These models are used to estimate coefficients representing the variation due to year alone and the trend of these year coefficients is either used as a stand-alone indicator of stock status, or in a stock assessment as an index of abundance.

Standardising CPUE for fisheries described by multiple datasets (e.g. fishing returns, observer and/or fishery-independent surveys) and numerous potential explanatory variables (e.g. gear, operational and oceanographic data) represents both an opportunity and a challenge. On one hand datasets with more variables are more likely to contain the information necessary to explain why catch rates differ in various circumstances. However, a large number of variables and datasets can present a daunting array of potential models to compare and contrast. In this indicator study, unlike in single-species CPUE standardisation for stock assessment purposes, the methods are intended both to remove biases and be straightforward to compute and track over time (Clarke et al. 2013). Furthermore, although blue, mako and porbeagle sharks differ in habitat preferences and productivity characteristics, when developing a set of stock status indicators for each species it is desirable to maintain as consistent an approach as possible.

5.2 METHODS

Data Description

Most of the blue, mako and porbeagle sharks caught in New Zealand waters are taken as bycatch by the SLL fishery[5]. This fishery consists of domestic and foreign charter vessels (flagged to Japan) fishing in northern waters from FMA 2 (Central (East)) through FMAs 1 and 9 (Auckland, West and East) to FMA 8 (Central Egmont), and in southern waters from FMA 7 (Challenger Plateau) through FMA 5 (Southland) to FMA 6 (Sub-Antarctic). Most of the operations in southern waters reported targeting southern bluefin tuna (*Thunnus maccoyii*) whereas northern operations reported focusing primarily on bigeye tuna (*Thunnus obesus*) and to a lesser extent on southern bluefin tuna.

All SLL operations are required to report catches on TLCER, and since October 2004 (fishing year 2005) reporting of both landed and discarded/released sharks has been required. In addition to the TLCER data, catches can also be characterised by observer records. Observer coverage in recent years

[4] For other fisheries, such as purse seine fisheries, the appropriate unit of effort for computing CPUE can be very difficult to obtain from available fishery statistics.
[5] Porbeagles are also caught by midwater trawl fisheries (Francis 2013).

has averaged 78% (by hooks fished) for foreign charter vessels but remains below 10% for domestic vessels (Griggs & Baird 2013). As a result of the limited observer coverage of the domestic fleet, it was originally considered that the TLCER data since October 2004 would provide the best results for a CPUE standardisation exercise. However, due to the poor results achieved for initial models applied to some of the TLCER data, it was decided that observer data CPUE should also be standardised for comparison.

Both datasets were streamlined and cleaned to remove fields and contents not suitable for analysis. New data fields were created as follows:

- Soak time was calculated as ((haul start-set end) + (haul end-set start))/2 to represent the midpoint between the time all hooks were fished and any hooks were fished (Carruthers et al. 2009);
- Time of day of the set was calculated as the midpoint between set start and set end, with all sets after 6 pm and before 7 am classified as night sets and all others as day sets; and
- Change in sea surface temperature (SST) was calculated (where possible) as the absolute difference between SST at the start of the set and SST at the end of the set.

The following data grooming criteria were then applied to remove missing data, outliers or otherwise unrepresentative data:

- Sets for which the number of hooks fished was less than the 1st percentile in the dataset;
- Sets which were outside the boundaries of FMAs 1, 2, 5, 7, 8 and 9;
- Sets made by vessels flagged to a country besides New Zealand or Japan;
- Sets missing set start, set end, haul start or haul end times, or for which these times were not in chronological order;
- Sets which recorded a bottom depth of less than the 99.9th percentile in the dataset (bottom depth was not recorded in the observer data set);
- Sets for which the soaktime (as calculated above) exceeded the 99.9th percentile in the database;
- Sets missing the number of floats or baskets (used to create an explanatory variable for hook fishing depth); and
- Sets annotated as having low quality observer data (observer dataset only).

The number of sets which met each of the criteria for exclusion are shown in Table 1. The data grooming resulted in removal of 3.2% of the TLCER data (remaining n=23 789) and 14.6% of the observer data (remaining n=7188). The higher number of excluded sets for the observer dataset is primarily due to a larger proportion of records for sets fished outside of the core fishing areas and by vessels flagged to countries such as Australia and the Philippines in the early years of the observer programme.

Table 1: Number of sets meeting the criteria for exclusion from analysis in the TLCER (2005 to 2013) and observer databases (1987 to 2013). (Note: as some sets met more than one criterion, rows will not tally to the total number of sets shown).

Criterion	TLCER	Observer
Too few hooks	251	311
Outside key fishing grounds	503	656
Flag not New Zealand or Japan	94	285
Bad time data	40	240
Bottom depth too shallow	32	–
Extremely long soak time	62	23
Missing hook fishing depth	186	20
Low quality observer data	–	209
TOTAL SETS REMOVED	798	1 233
NUMBER OF SETS REMAINING	23 789	7 188
PERCENT REMOVED	3.2%	14.6%

In addition to the exclusion criteria above, error checking criteria were applied to correct data rather than exclude the set as a whole from the analysis. This more moderate form of error control requires assumptions that may bias the resulting data. Therefore, it was only applied when the number of sets which would have been otherwise excluded from the analysis was large and when excluding this quantity of records may have jeopardized the representativeness or statistical power of the analysis. These error checking criteria included:

- TLCER sets for which recorded bait type percentages did not sum to 100% were retained in the dataset but assigned a percent squid bait value of “NA” (percent squid bait values in the observer data set were assigned by hand and were assumed to be error-free);
- TLCER and observer sets for which the set start sea surface temperature (SST) was missing but the haul end SST was available were assigned a set start SST equivalent to the haul end SST.

***A priori* identification of potential explanatory variables and interactions**

Potential explanatory variables for the standardisation models were identified based on ecological theory, knowledge of SLL fishing operations and reference to previous CPUE standardisation studies (Table 2). The type, format and data quality of potential explanatory variables in the TLCER and observer datasets varies but where possible consistency was maintained in identifying variables to be modelled. The formatting of variables for soak time, time of day of set and change in SST are described above.

Table 2: Potential explanatory variables for standardising blue, mako and porbeagle shark CPUE in the TLCER and observer datasets.

Potential Explanatory Variable	Present in TLCER Dataset	Present in Observer Dataset	Rationale
Habitat variables			
Fishing Year	X	X	To produce an annual CPUE index
Month	X	X	To capture temporal changes within each year
Area	X	X	To capture spatial effects in latitude and longitude
Hook depth	X	X	To capture spatial effects in the vertical dimension
Time of Day of Set	X	X	To represent diel temporal variation
SST	X	X	To capture climate based changes in habitat
Change in SST	X	X	To indicate where sets were conducted at the edge of oceanographic fronts where sharks are known to congregate
Operational variables			
Fleet Identifier	X	X	To account for operational differences between domestic and Japan-flagged vessels
Vessel Identifier	X	X	To account for changes in fishing power or skill due to vessel or crew factors
Target (as identified by fishers)	X	X	One potential means of classifying fishing strategies
Bait Type	X	X	Another potential means of classifying fishing strategies
Soak Time	X	X	May reflect targeting strategy and/or possibly fishing effort
Number of Hooks Fished	X	X	A potential measure of fishing effort
Number of Lightsticks Used	X		To account for changes in catch rates due to attraction/repulsion
Other variables			
Presence of Observer	X		To capture any change in reporting behaviour when an observer is present
Number of bigeye tuna caught	X	X	Could capture other habitat preference factors or propensity to report accurately as total catch varies
Number of southern bluefin tuna caught	X	X	Could capture other habitat preference factors or propensity to report accurately as total catch varies
Number of swordfish caught	X	X	Could capture other habitat preference factors or propensity to report accurately as total catch varies

For the TLCER dataset, area was taken as the three-digit New Zealand general statistical area as these represent smaller areas, often 2 × 2 degrees, within each FMA. These provided better estimation, due to data aggregation, than arbitrary grids using latitude and longitude. For the observer data, New Zealand general statistical areas were not readily available and the number of samples per latitude-longitude 1 × 1 degree cell was low. Therefore, FMA was used as the x-y spatial variable.

The number of hooks fished was the number of hooks recorded in the TLCER dataset and the number of hooks observed in the observer dataset[6]. A proxy for hook depth was computed as either the number of hooks divided by the number of floats (for TLCER), or baskets (for observers) minus one.

SST was assumed to be the SST at the start of the set. Bait type was simplified (i.e. from squid, fish, artificial or other) by assuming that the bait profile was represented by the percentage of bait that was squid (i.e. the predominant bait type in both datasets). The percentage of squid bait used was then divided into ten categories (i.e. 0–9%, 10–19%, etc). All other variables are self-explanatory.

These potential explanatory variables were tabulated and plotted against recorded catches of blue, mako and porbeagle sharks to determine which had sufficient contrast and predictive power to include in the models. Collinearity, i.e. explanatory variables that are themselves correlated, was also considered (Maunder & Punt 2004). Time of day of set was excluded on the basis that very few sets were made during the day (fewer than 1% in the TLCER dataset and fewer than 1% in the observer dataset) and thus predictive power would be low. Furthermore, time of day of set is believed to be closely related to targeting strategy therefore having both variables in the model should be unnecessary. Change in SST was excluded on the basis that very few of the sets (3% in the TLCER, and 6% in the observer dataset) showed a change of more than 1 ^{o}C between set start and haul end.

Fleet was not needed as an explanatory variable in the TLCER models because CPUE standardisation was conducted separately for the domestic and Japan-flagged vessels in South region, and Japan-flagged vessels were few (less than 1% of TLCER records) in North region. Fleets in South region were modelled separately because there was a clear separation in their fishing grounds, i.e. mostly south-central coastal areas fished by the domestic fleets, and offshore and Fiordland coastal areas fished by Japan-flagged vessels. In addition, there was a very strong consistency in operational parameters in the Japan-flagged vessels compared to domestic fleets (i.e. much less variability in hook depth, bait type and soak time). Finally, there were considerably fewer zero-catch sets recorded by the Japan-flagged vessels than the domestic vessels (fewer than 1% of Japan-flagged vessel sets versus 12% of domestic vessel sets). Fleet was considered as an explanatory variable in the observer data-based models, but vessel identifiers were preferred as they would capture both vessel and fleet characteristics. In some cases the number of vessels was high and the number of data points per vessel was low and this affected the performance of the model (see below for details).

High catches of sharks were recorded mainly for sets which used few lightsticks. However, low numbers of sharks were recorded for sets with both few and many lightsticks and there appeared to be no clear relationship between the number of lightsticks and shark catch in preliminary analysis. Studies in other areas have found that shark catch rates are highest for sets targeting swordfish, fishing shallow at night (Walsh et al. 2009). While such sets would also be most likely to use lightsticks, the characteristics of these sets would presumably be accounted for by the target species and hook depth explanatory variables, and thus number of lightsticks was excluded from the model.

It has been suggested that catch rates of most shark species increase with soak time (Ward et al. 2004). In this sense soak time may be collinear with other measures of fishing effort such as number of hooks fished. It is also expected that the soak time would reflect the targeting strategy of the vessel and thus this information could be captured through inclusion of a targeting strategy variable. For these reasons soak time was excluded.

Finally, the utility of including the catch of bigeye tuna, swordfish or southern bluefin tuna as an explanatory variable varies by region and fishery. For example, bigeye tuna are predominantly caught in the north and can be excluded from models in the south. Swordfish are also mainly caught in northern waters and may not provide much explanatory value in southern fleets. Southern bluefin tuna is considered a target of both fleets and thus should be considered for inclusion in all models.

[6] Observers do not always monitor all the hooks in a set.

In addition to including each variable as a main effect, interactions between these variables should also be considered. However, interactions involving the year factor complicate estimation of an annual index of abundance and as a result they are either usually explicitly ignored or handled through special numeric methods (Maunder & Punt 2004). Although the latter approach would probably deliver greater scientific rigour, the time involved to generate and test interaction estimation methodologies for multiple species and datasets was not considered compatible with an indicator approach. In future, if software packages become available which automate such estimation processes inclusion of year-month and year-area interactions in the CPUE standardisation model can be reconsidered. Beyond these methodological issues, it should also be noted that in the TLCER dataset, only 42% of the year-area combinations recorded more than 20 sets and thus estimation power for year-area interactions is likely to be low even if automated algorithms become available. Interactions which do not involve the year factor are simpler to accommodate within CPUE standardisation models producing an annual index of abundance. Of the many possible interactions which could be considered, the most common, besides those involving year, are month-area interactions. While these interactions may be useful in explaining some of the variance in shark catch rates, only 30% of the month-area combinations in the TLCER dataset and only 52% in the observer dataset recorded more than 20 sets. This level of information was *a priori* considered insufficient to include a month-area interaction in the TLCER models. Inclusion of this interaction term was attempted for the observer dataset but even the simplest models failed to converge when this term was included.

To summarize, as a result of the considerations listed in Table 2 and preliminary tabulation and plotting of available data the most useful explanatory variables were identified as:

- Habitat variables: year, month, area (fisheries statistical area for TLCER, and FMA for observer data), hook depth and SST;
- Operational variables: fleet (only if both fleets are modelled together with each having a sufficient number of observations, and if vessel cannot be included in the model due to deficient sample sizes), vessel (if possible given sample sizes), target species, bait type and number of hooks fished;
- Other variables: presence of an observer (TLCER only), catch of bigeye tuna (north only), catch of swordfish (mainly for northern fishing grounds), and catch of southern bluefin tuna.

Analytical methods used to standardise CPUE, including the various forms of models tested, the variables selected, and the diagnostics examined are described in the following section.

5.3 RESULTS

Blue shark

Data sets and histograms

As introduced above and for reasons which will be described further below, the TLCER data were subset into three separate datasets for further analysis: a North region dataset (FMAs 1, 2, 8 and 9), a South region domestic dataset (FMAs 5 and 7, domestic vessels only), and a South region Japan-flagged dataset (FMAs 5 and 7, Japan-flagged vessels only). This subsetting was required because of the different seasonal, vessel and targeting characteristics associated with each subset and the potentially related characteristic of the number of zero catch sets recorded. The observer dataset was not subset by region or fleet; its CPUE was standardised within a single model.

The Japan-flagged South dataset was the smallest of the three TLCER datasets with only 1609 records. The dataset was further reduced to 1446 by removing records from March and July (16 and 24, respectively) and sets outside of fisheries Statistical Areas 031, 032, 501, 705 and 706 (a total of 123 sets). These five areas were consistently fished throughout the period 2005–2013 whereas the other areas had only intermittent fishing. Although this dataset is small it is the most consistent and informative of the three TLCER datasets in terms of statistical power (i.e. number of observations relative to the number of factors to be estimated). It also had the lowest number of zero blue shark catches (4) of any of the modelled data sets (Figure 14) and a mode of 13 blue sharks caught per set (n=48).

The TLCER domestic South dataset contained 1872 records but was further trimmed to remove sets from the shoulder fishing months of January and November (14 sets), areas outside of core fishing areas 033, 034, 035, 036, 703, 704 and 705 (56 sets), and percentages of squid bait of less than 50% (11 sets). Of the remaining 1788 sets 194 recorded zero catch of blue shark (Figure 14) and the mode for the non-zero catches was ten blue sharks (n=85).

The TLCER North dataset was large (n= 20 227) compared to the TLCER South datasets. After removal of records from areas with low sample sizes (areas 015, 019, 041, 101–103, 206 and 801; total of 95 sets removed), sets targeting albacore or yellowfin tuna (285 sets) and sets missing area data (390 sets), 19 457 sets remained. Percentages of squid bait lower than 50% were aggregated into a “low” category to avoid problems with estimating effects for low percentages with small sample sizes. Since the sample size was ample, an additional 1150 set records which were missing values of SST or bait type were removed to allow unbiased testing of models with and without these variables (n=18 307). The number of zero blue shark sets was very high (4546) and the mode of positive catches was two blue sharks (n=1214; Figure 14).

For the observer data set, from the 7188 set records remaining after data grooming a further 964 set records for 1987–1993 were removed due to low coverage in those years. As a result, observer data analysis was limited to the years 1994–2013. As there were very few sets not recorded as targeting either southern bluefin or bigeye tuna, all of these other sets were combined as an “other” target strategy. Similarly, records for FMA 8 were few (n=10) and were combined with FMA 9 (n=283). An additional 441 set records which were missing values of SST or bait type were removed to allow unbiased testing of models with and without these variables. The histogram of blue shark catches per set for the observer dataset as a whole showed 147 zero catches and 5636 non-zero catches (Figure 15). The mode for the positive catches in this dataset was two blue sharks (n=243). For reference Figure 15 also shows histograms for observer records from the southern Japan-flagged fishery, the southern domestic fishery and the northern fishery which were modelled separately in the TLCER analysis.

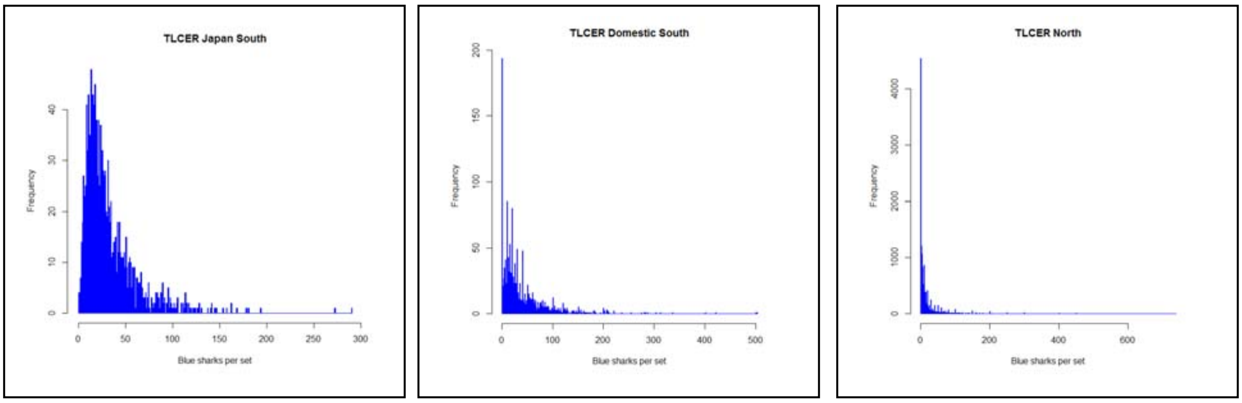

Figure 14: Histograms of blue sharks per set in the TLCER Japan South dataset (n=1446 of which four sets recorded zero blue sharks), the TLCER Domestic South dataset (n=1788 of which 194 sets recorded zero blue sharks), and the TLCER North dataset (n=18 307 of which 4546 sets recorded zero blue sharks).

Blue shark model selection

Blue shark is one of the most abundant of the pelagic sharks and is commonly caught by SLL fisheries throughout the world (Clarke et al. 2014). Other analyses of blue shark catch rates over broad areas and multiple years have suggested that it is reasonable to expect that most SLL sets of several thousand hooks would catch at least one blue shark (Nakano & Clarke 2006), Clarke et al. 2011). TLCER data for Japan-flagged vessels fishing in New Zealand's southern waters show that less than 1% of all sets caught zero blue sharks. The distribution of positive catches shows a classic Poisson or negative binomial distribution (i.e. numerous observations centred around a low, but positive, mean value with a long tail of higher values). For the other data sets, a greater incidence of sets with a zero catch of blue shark (i.e. 2% in the observer data, 11% in the southern domestic fishery and 25% in the northern, mainly domestic, fishery) was observed. In the observer dataset these zero catches are likely to represent a true absence of blue sharks whereas the higher zero catch rates in the TLCER data probably represent both true absence and under-reporting.

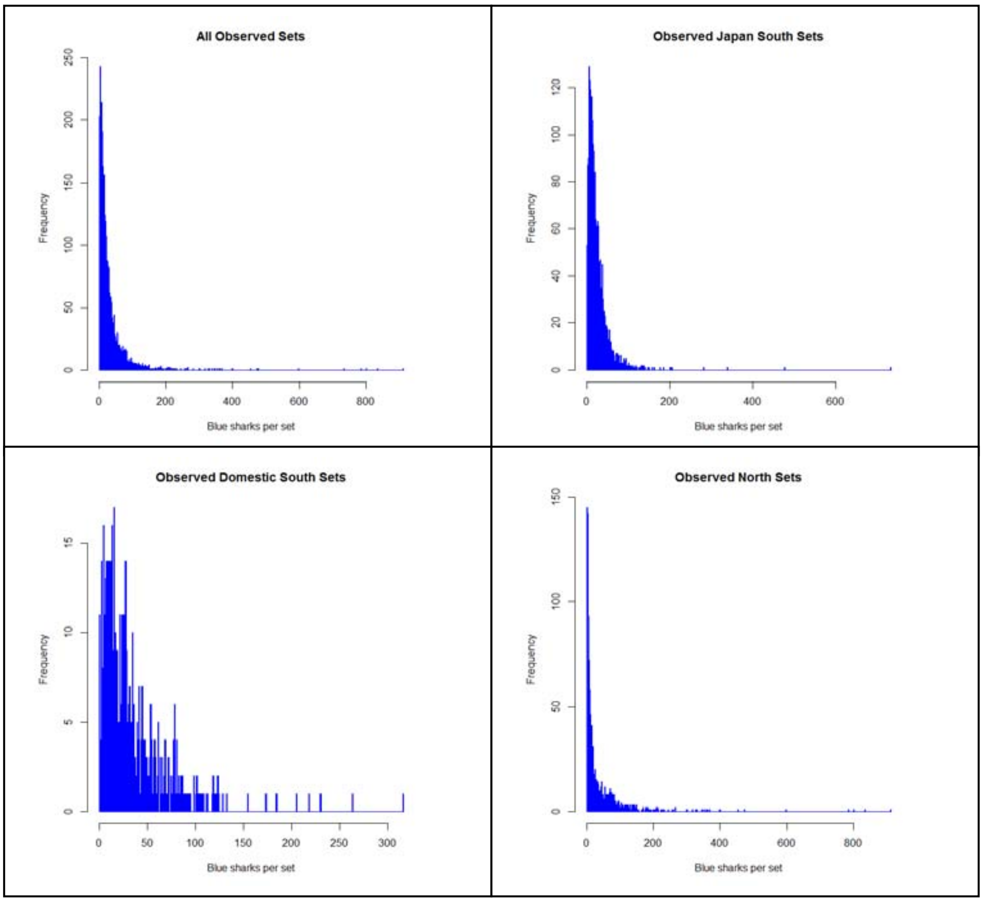

Figure 15: Histograms of blue sharks per set in the observer dataset overall (n=5783 of which 147 sets recorded zero blue sharks), and subset by Japan South, Domestic South and North fisheries.

Regardless of the reason, higher proportions of zero catches warrant consideration of other model forms. CPUE standardisation of datasets containing high occurrences of zero catches is often modelled using a zero-inflated negative binomial (Minami et al. 2007; Brodziak & Walsh 2013). This approach models the presence/absence of the species of interest, and the number caught if the catch is not zero, as separate processes. While zero-inflated negative binomial models may provide better results, their data requirements are higher (i.e. because separate coefficients for zeroes and counts must be estimated) and presentation of confidence intervals and diagnostics can be complicated.

Blue shark abundance indices – TLCER Japan South

Regression trees (using the R package "tree") were applied to identify which of the fourteen explanatory variables (see last paragraph Section 5.2) should be included in the initial model. Year, month and area were identified as the most important factors in explaining blue shark catches, with vessel, SST and southern bluefin tuna catches important in some years. For the TLCER Japan South dataset, Poisson and negative binomial models were fitted using a generalised linear model containing all of the variables identified by the regression tree as significant: year, month, area, vessel, southern bluefin tuna catch and SST. Year, month, area and vessel were fitted as factors. A polynomial spline was applied to SST with three degrees of freedom based on an examination of the distribution of SST data. The number of hooks fished was specified as an offset. Model selection was attempted to simplify the initial model but all of the explanatory variables were significant ($p<0.05$). Furthermore, hook depth, bait type, target strategy and time of day of set could not be included in the model due to lack of contrast in the data, and presence of an observer and soak time did not meet the criterion of an improvement of 1% in the AIC value. Other than the default year effect (necessary when deriving an annual index), the factors month, area and vessel have the largest effect on the index with catch of southern bluefin tuna and SST adjusting the trend only slightly (Appendix 21).

In the Poisson model overdispersion was detected and corrected using a quasi-GLM which estimates an overdispersion parameter to correct the variance. However, in this case the overdispersion remained high (φ=17.7) suggesting that the data would be better fit by the negative binomial distribution. None of the included variables demonstrated collinearity (i.e. variance inflation factors all less than 2). Model diagnostics for the negative binomial were produced as discussed in (Zuur et al. 2009). The diagnostics for the TLCER Japan South blue shark model indicated very little skew in the residuals and very few outliers (Appendix 9), and the model explained 31% of the residual deviance (Table 3). Coefficient-distribution-influence (CDI) plots for the explanatory variables are shown in Appendices 33–37.

Table 3: Results for the CPUE standardisation of blue shark in the TLCER Japan South dataset.

Distribution:	**Negative Binomial**
Model:	Catch of blue shark ~ year + month + area + vessel + catch of southern bluefin tuna + ns(SST, df = 3) + offset(log(number of hooks))
Significance:	All variables significant at p<0.001 except for month (p<0.01).
Collinearity:	All variables <1.51
Diagnostics:	No major deviations from model assumptions observed (Appendix 9)
Percent Null Deviance Explained:	31%

The number of sets with zero catches of blue shark did not increase with time, and as discussed above was very low (Figure 16, left). The standardised index of abundance indicates an increase in blue shark catch rates over time which is similar to but more pronounced than the nominal index of abundance (Figure 16, centre and right). Confidence intervals for the annual estimates were predicted using the R glm object and the *predict* and *confint.default* functions. These suggest that the values in 2012 and 2013 are significantly higher than those in 2006–2011 (Figure 16, right).

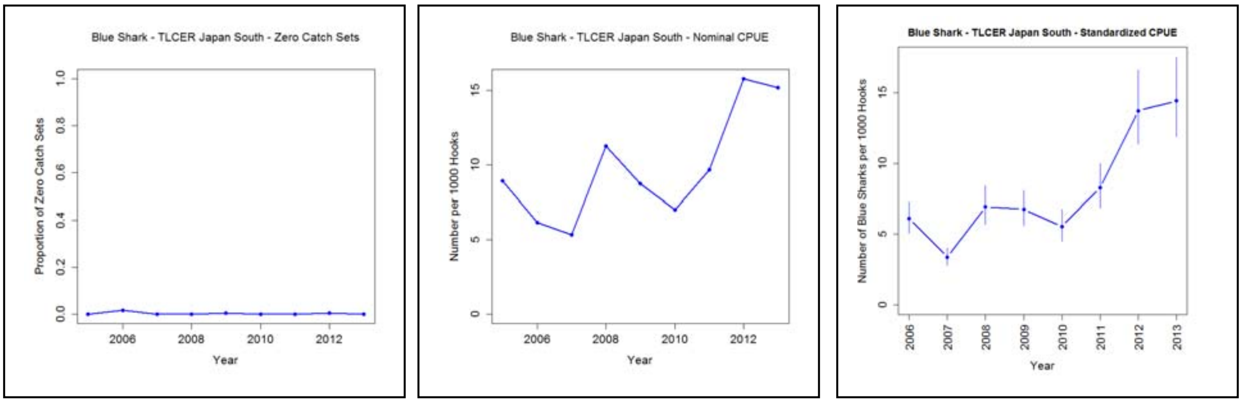

Figure 16: Proportion of sets in the TLCER Japan South dataset with zero blue sharks recorded by year (left panel), nominal blue shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the negative binomial model shown in Table 3 (right panel). Note that a year coefficient is not produced for the first year in the dataset (i.e. 2005) as the value for this year is modelled as a component of the estimated intercept. The ordinates of the annual standardised CPUEs are determined by the median values for all other variables which were used to predict values for each year and thus may differ from the ordinates in the nominal plot.

Blue shark abundance indices – TLCER Domestic South

Regression tree models for the TLCER domestic south dataset suggested that the variables of vessel, area and month have the best predictive power, with year and SST also important in some cases. As introduced above, given the disproportionate number of zero catch sets in the dataset it was expected that the zero-inflated negative binominal (ZINB) would be the most appropriate distribution for the standardisation model. A negative binominal model was also fitted for comparison. Both models began with all of the variables identified as important in the regression tree model, i.e. year, month, area, vessel and SST with hooks as an offset as described above for the TLCER Japan south dataset. Given that there were 31 vessels in the dataset, to improve estimation for the vessel factor these were aggregated into two groups as suggested by the regression tree model. Three sets with missing values of SST were removed from the analysis. AIC and likelihood ratio tests were performed to test sequential dropping of each variable from the negative binomial and both the zero and count portions of the ZINB suggested that the fits were not improved through model simplification or elaboration.

The ZINB model performed better than the negative binomial model according to AIC values (11 401 versus 11 800) and a Vuong likelihood ratio test ($p<0.001$, Vuong 1989). None of the explanatory variables in the final negative binomial model showed collinearity as measured by variance inflation factors and all were statistically significant (these statistics are not available for the ZINB). SST had a relatively small influence on the index as compared to year, month, area and vessel factors (Appendix 22). The diagnostics showed a lack of fit of both the NB and ZINB models to the data with a poor correlation between observed and predicted values (Appendix 10). It is not possible to assess the percent deviance explained for a ZINB model but for reference the negative binominal form explained 24% (Table 4). CDI plots were not produced for the ZINB model.

Table 4: Results for the CPUE standardisation of blue shark in the TLCER Domestic South dataset.

Distribution: Zero-inflated Negative Binomial

Model:
Catch of blue shark ~ year + month + area + vessel + ns(SST, df = 3) + offset(log(number of hooks)) (counts)
Catch of blue shark ~ year + month + area + vessel + ns(SST, df = 3) (zeroes)

Significance: Not available for ZINB
(In negative binomial all variables were significant at $p<0.001$ except for SST ($p<0.01$))

Collinearity: Not available for ZINB
(In negative binomial all variables <1.59)

Diagnostics: Poor correlation between observed and predicted values indicates a lack of model fit (Appendix 10)

Percent Null Deviance Explained: Not available for ZINB
(In negative binomial 24%)

The number of sets in the TLCER domestic south dataset with zero catches of blue shark was relatively low and showed no clear trend over time (Figure 17, left). The standardised index of abundance produces a different time trend to that shown in the nominal CPUE series but both peak in 2011 and decline in 2012 and 2013 (Figure 17, centre and right). Confidence intervals suggest that the catch rate in 2013 was significantly less than the peak catch rate in 2011 (Figure 17, right). The extremely wide confidence intervals in 2007 derive from a sample size of only three sets for this year.

Blue shark abundance indices – TLCER North

The number of zero catch sets in the TLCER North dataset was the largest of any of the datasets used in this study (25%). Given this distribution of catches, the ZINB was considered the most appropriate model but the negative binomial model was also applied for comparative purposes, in particular because it was fit to these data in a previous study (T. Kendrick, Trophia Ltd, unpubl. data). Regression tree models for the TLCER North dataset suggested that targeting strategy and year are the greatest influences on blue shark catches. (Vessel factors and General Statistical Area factors could not be used in the regression tree models due to estimation limits for factors with many levels. FMA areas were tested instead). Those sets which were described as targeting southern bluefin tuna were significantly more likely to catch high numbers of blue sharks than were sets described as targeting bigeye tuna or swordfish. Other parameters were tested sequentially using AIC values and likelihood ratio tests to determine whether the addition of each variable to the model was statistically significant and improved the information value by at least 1%. Only month and SST variables passed these tests and were included in the model (Appendix 23).

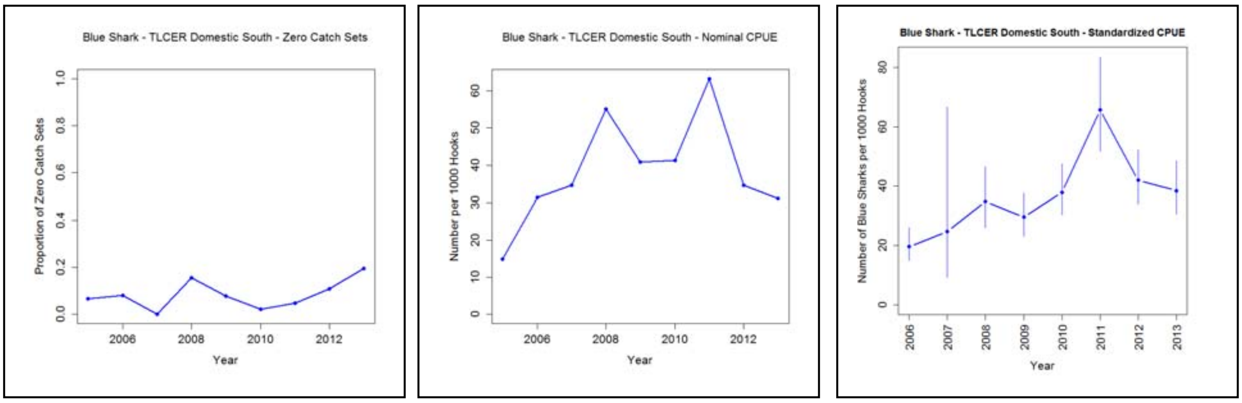

Figure 17: Proportion of sets in the TLCER Domestic South dataset with zero blue sharks recorded by year (left panel), nominal blue shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the ZINB model shown in Table 4 (right panel).

The ZINB model performed slightly better than the negative binomial model according to AIC values (119 407 versus 120 491) but the difference between the two models was not significant according to the Vuong likelihood ratio test. The two abundance indices were also very similar. Model diagnostics showed a lack of fit of both negative binomial and ZINB models to the data with a poor correlation between observed and predicted values. It is not possible to assess the percent deviance explained for a ZINB model but for reference the negative binominal form explained 32% (Table 5).

Table 5: Results for the CPUE standardisation of blue shark in the TLCER North dataset.

Distribution:	Zero-inflated Negative Binomial

Model:
Catch of blue shark ~ year + target + month + ns(SST, df = 3) + offset(log(number of hooks)) (counts)
Catch of blue shark ~ year + target + month + ns(SST, df = 3) (zeroes)

Significance:	Not available for ZINB (In negative binomial all variables were significant at p<0.001 except for SST (p<0.001))
Collinearity:	Not available for ZINB (In negative binomial all variables <1.38)
Diagnostics:	Poor correlation between observed and predicted values indicates a lack of model fit (Appendix 11)
Percent Null Deviance Explained:	Not available for ZINB (In negative binomial 32%)

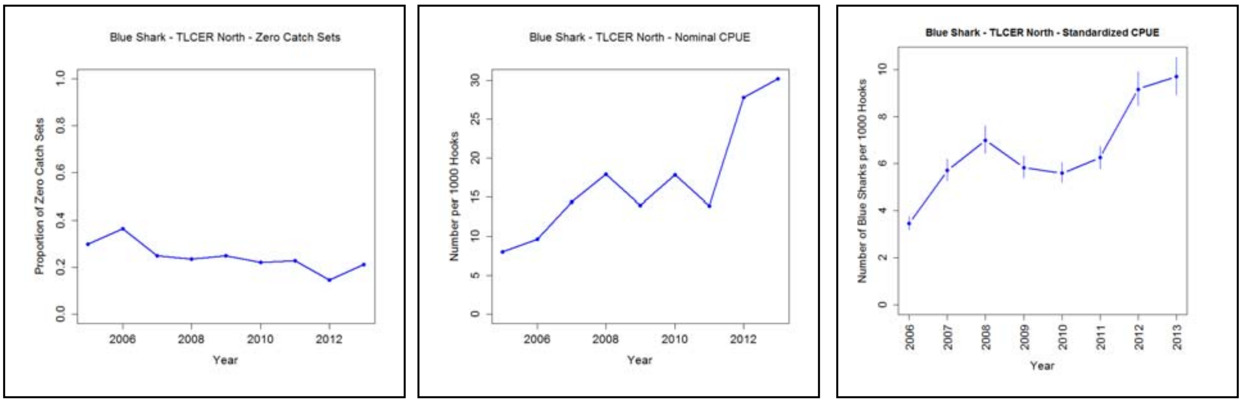

Figure 18: Proportion of sets in the TLCER North dataset with zero blue sharks recorded by year (left panel), nominal blue shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the ZINB model shown in Table 5 (right panel).

The number of sets in the TLCER domestic north dataset with zero catches of blue shark ranged from about 18–40% and declined slightly with time (Figure 18, left). The standardised index of abundance is similar to that shown in the nominal CPUE series with the highest value for both series occurring in 2012–2013 (Figure 18, centre and right). Confidence intervals suggest that the catch rates in 2012–2013 were significantly higher than those since 2005 (Figure 18, right). The relatively narrow confidence intervals for the TLCER North dataset are a result of the larger sample size for this dataset.

Blue shark abundance indices – Observer

Regression tree modelling of the observer data indicated that year, SST and area factors (in particular FMA 2 which recorded very high catches), were important in explaining blue shark catches. Bait type and catches of southern bluefin tuna were also important for some years. The number of zero catch sets in the observer dataset (2%) was low suggesting that a negative binomial or Poisson distribution adjusted for overdispersion might be appropriate. Other parameters were tested sequentially using AIC values to determine whether the addition of each variable to the model was statistically significant and improved the information value by at least 1%. Under these procedures a vessel identifier was added to the model. The vessel effect served to smooth and lower the catch rates predicted by the year factor alone (Appendix 24).

Models using year, area, vessel, catch of southern bluefin tuna, bait type and SST as explanatory variables indicated that the Poisson distribution could not be appropriately adjusted for over-dispersion (φ=23.5). Therefore the negative binomial distribution was selected. All explanatory variables in the model were statistically significant and none showed collinearity. Model diagnostics showed a reasonable fit to the data (Appendix 12). The negative binomial model explained 32% of the deviance (Table 6). Coefficient-distribution-influence (CDI) plots for the explanatory variables are shown in Appendices 38–42.

Table 6: Results for the CPUE standardisation of blue shark in the observer dataset.

Distribution:	Negative Binomial
Model:	

Catch of blue shark ~ year + area + vessel + catch of southern bluefin tuna + bait type + ns(SST, df = 3)

Significance:	All variables were significant at $p<0.001$
Collinearity:	All variables <1.89
Diagnostics:	No major deviations from model assumptions observed (Appendix 12)
Percent Null	54%
Deviance Explained:	

The number of sets in the observer dataset with zero catches of blue shark never exceeded 10% and declined to near zero in recent years (Figure 19, left). The standardised index of abundance is smoother than the nominal index but both show a decline until the early 2000s followed by an increase until 2008, a decline in 2009–2011, and very high catches in 2012 and 2013 (Figure 19 centre and right).

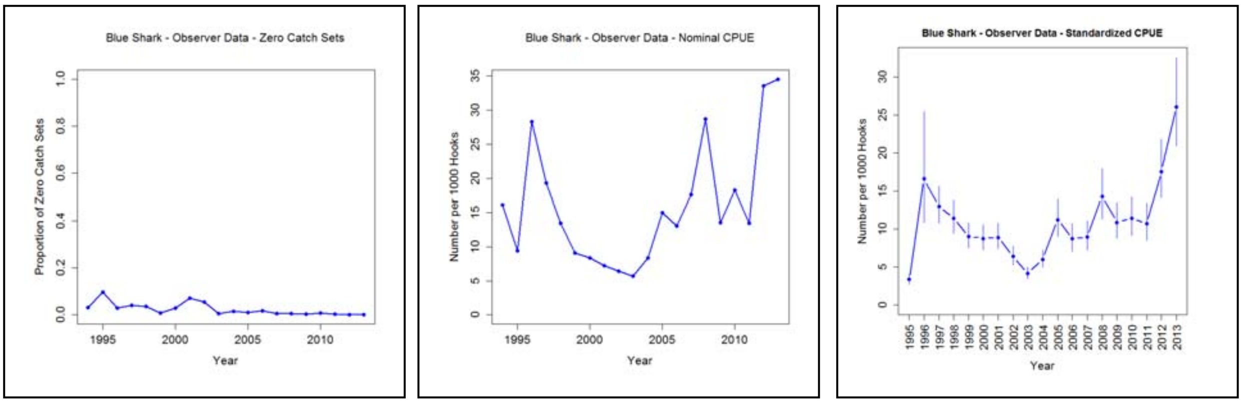

Figure 19: Proportion of sets in the observer dataset with zero blue sharks recorded by year (left panel), nominal blue shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the negative binomial model shown in Table 6 (right panel).

Summary of blue shark results

Blue shark catches from datasets with relatively low numbers of zeroes (TLCER Japan South and observer datasets) were fitted with negative binominal models whereas those with higher frequencies of zero catches were fitted with zero-inflated negative binomial models. Model fits were adequate for the negative binomial models but poorer for the zero inflated negative binomials with a poor correlation between observed and predicted values. All of the datasets except the TLCER Domestic South dataset indicated an increasing trend of abundance of blue shark in recent years with the highest values in the index occurring in 2012–2013. In the TLCER Domestic South dataset catch rates declined in 2012–2013 but these values were similar to or higher than those in 2006–2010.

Mako shark

Data sets and histograms

As for the blue shark analysis described above, the TLCER data were subset into three separate datasets (Japan South, Domestic South and North) for the mako shark analysis. The observer dataset was again standardised separately under a single model. Each dataset contained the same number of records as described above for the blue shark analyses. The extreme number of zero mako catch sets in the TLCER datasets (Figure 20; 83%, 74% and 62%, respectively) suggested that there would be even greater difficulty in fitting models to the mako catch data than to the blue shark catch data. The mode of the positive catches was one in each of the three datasets (n=201 for Japan South, n=200 for Domestic South and n=2181 for North datasets, respectively).

Although some of the zero catch records in the TLCER dataset may be due to under-reporting, the observer dataset also recorded zero catches of mako sharks in 62% of its sets (Figure 21). However, it is also noted that mako shark habitat overlaps with the New Zealand SLL fishery primarily in northern waters. This could explain why the proportion of zero catches in the observer data is the same as that recorded in the TLCER North dataset (62%).

Mako shark model selection

The models considered for the mako shark analyses were similar to those considered for blue shark except for a greater emphasis on the zero-inflated negative binomial to account for the high proportions of zeroes. In addition, due to the maximum number of makos recorded per set in the TLCER Japan South dataset being only four, the data are not overdispersed and a standard Poisson distribution-based model can be attempted.

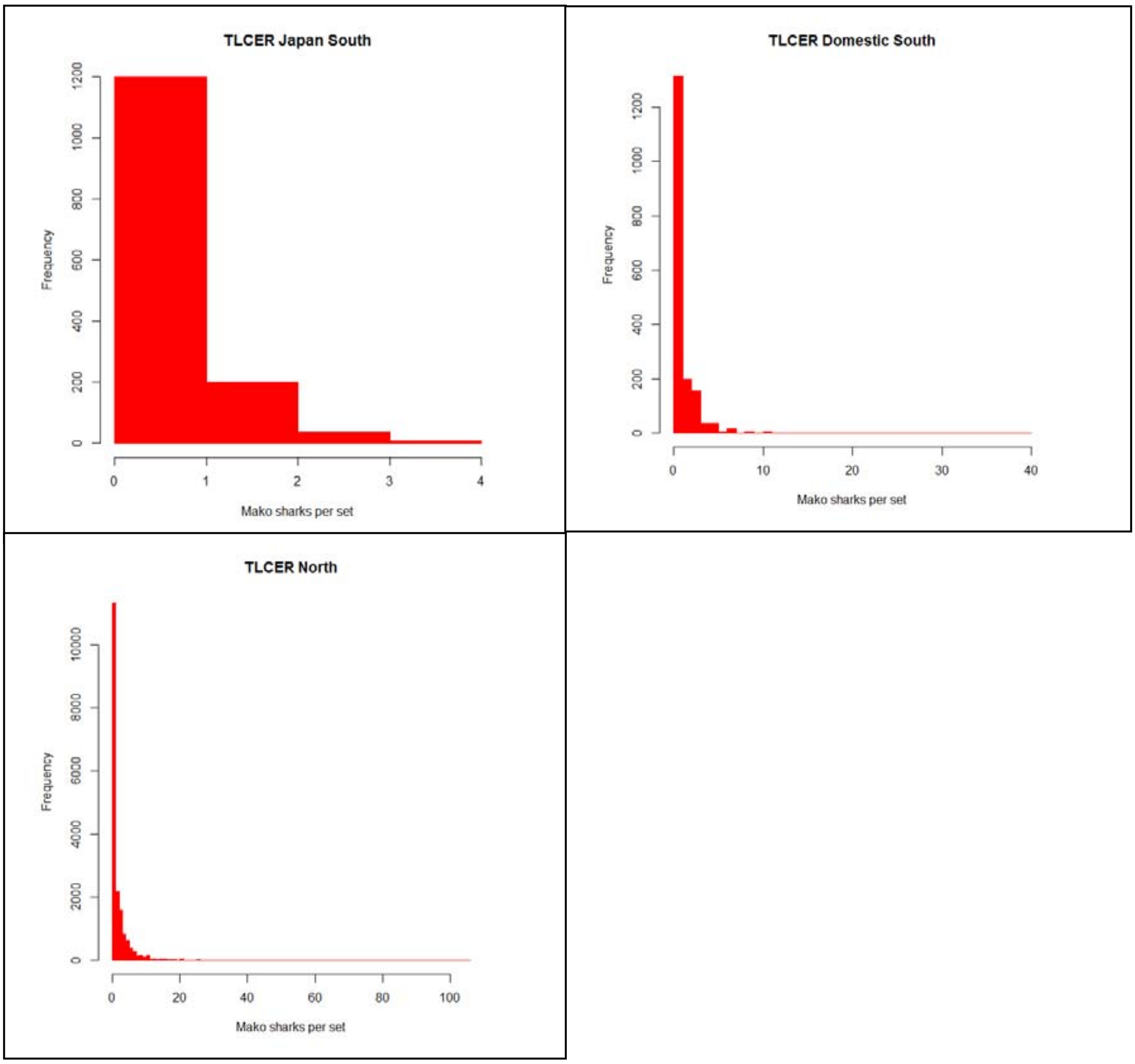

Figure 20: Histograms of mako sharks per set in the TLCER Japan South dataset (left panel, n=1446 of which 1200 sets recorded zero mako sharks), the TLCER Domestic South dataset (centre panel, n=1788 of which 1315 sets recorded zero mako sharks), and the TLCER North dataset (right panel, n=18 307 of which 11 325 sets recorded zero mako sharks).

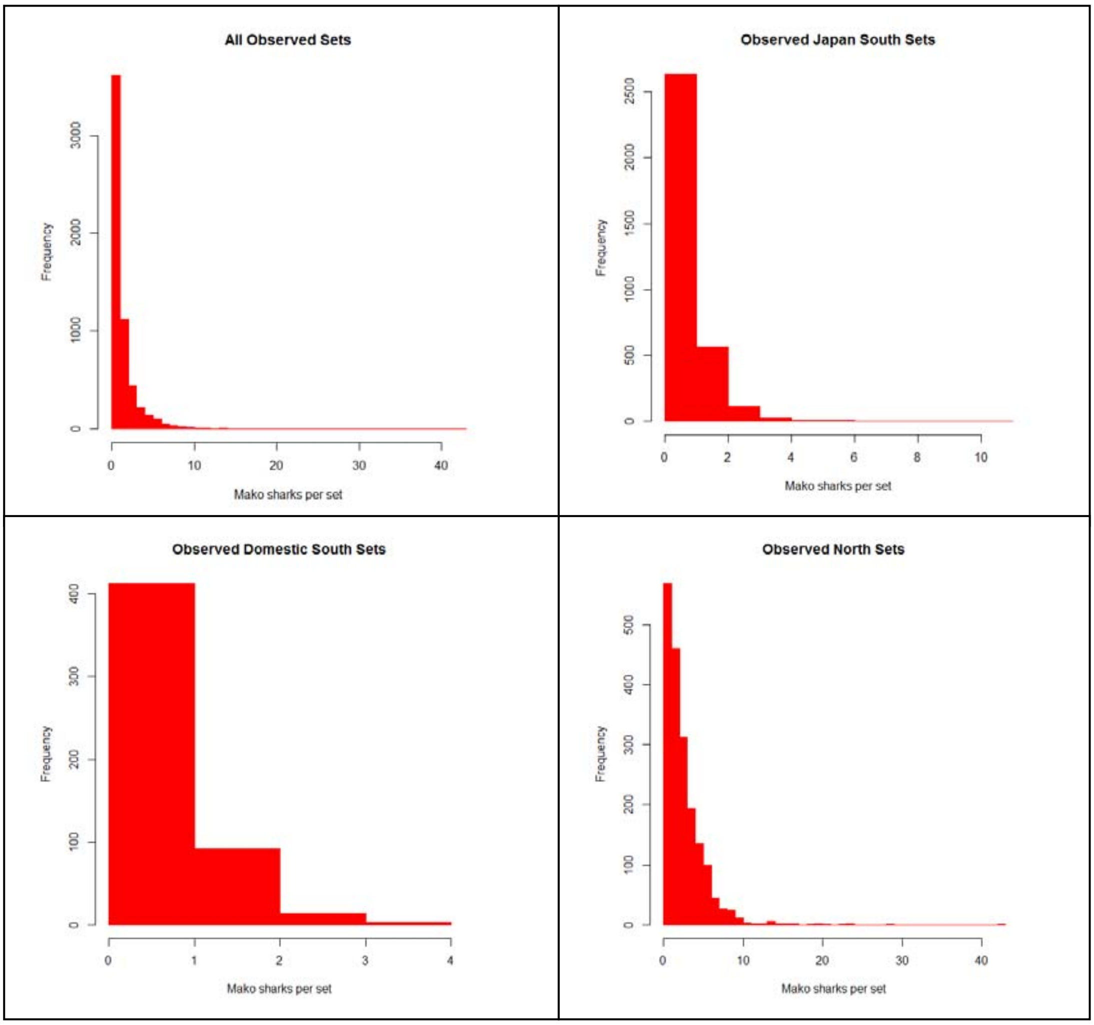

Figure 21: Histogram of mako sharks per set in the observer dataset (n=5783 of which 3619 sets recorded zero mako sharks), and subset by Japan South, Domestic South and North fisheries.

Mako shark abundance indices – TLCER Japan South

Regression tree models for the TLCER Japan South dataset indicated that year, area and catches of swordfish are the important variables explaining catches of mako sharks. Poisson and negative binomial models were fitted using a generalised linear model containing all of these variables. Model selection simplified the initial terms by removing swordfish catches. No additional variables were added using likelihood ratio testing and a criterion of a 1% improvement in AIC values. The area factor had little influence on the resulting index except for smoothing the high observed catches in 2013 (Appendix 25).

The negative binomial model performed slightly better than the Poisson model on the basis of AIC values (1562 versus 1575) and a Vuong likelihood ratio test ($p < 0.001$). Both year and area were statistically significant and neither demonstrated collinearity (i.e. variance inflation factors all less than 1.06). However, the amount of deviance explained by the model was very low (9%). Diagnostics showed patterns in the residuals, probably in part due to small sample sizes of positive catches, and suggested a poor fit at both low and high ends of the range of observations (Table 7, Appendix 13). Coefficient-distribution-influence (CDI) plots for the explanatory variable “area” is shown in Appendix 43.

Table 7: Results for the CPUE standardisation of mako shark in the TLCER Japan South dataset.

Distribution	Negative Binomial
Model	Catch of mako shark ~ year + area + offset(log(number of hooks))
Significance	All variables significant at $p<0.001$
Collinearity	All variables <1.06
Diagnostics:	Apparent patterns in the residuals and deviations from model assumptions (Appendix 13)
Percent Null Deviance Explained:	9%

The number of sets with zero catches of mako shark remained between 80–90% until 2013 when it dropped to about 60% (Figure 22, left). This corresponds to the higher recorded catch rates in the nominal and standardised indices for 2013 (Figure 22, centre and right). However, given the relatively wide confidence intervals estimated which overlap for all but the first and last years in the time series (Figure 22, right), there is no conclusive evidence of a significant trend in mako shark abundance visible in this dataset.

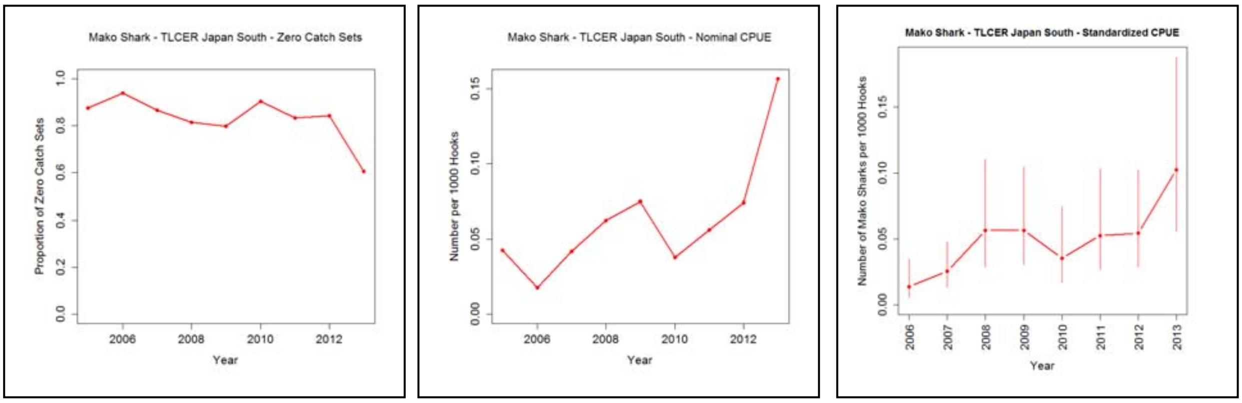

Figure 22: Proportion of sets in the TLCER Japan South dataset with zero mako sharks recorded by year (left panel), nominal mako shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the negative binomial model shown in Table 7 (right panel).

Mako shark abundance indices – TLCER Domestic South

The TLCER Domestic South dataset represents mako catches in fishing grounds adjacent to the TLCER Japan South dataset and also showed a high proportion of zero catches. In this case, however, the positive catches showed a high variance in counts (Figure 20). As introduced above, given the disproportionate number of zero catch sets in the TLCER Domestic South dataset it was expected that the zero-inflated negative binominal (ZINB) would be the most appropriate distribution for the standardisation model. A negative binominal model was also fitted for comparison.

Both models began with all of the variables identified as important in the regression tree model, i.e. year, month, area, vessel, target and SST. Vessels were aggregated into two groups as suggested by the regression tree model in order to improve estimation for the vessel factor. Three sets with missing values of SST were removed from the analysis. AIC and likelihood ratio tests performed to test sequential dropping of initial variables from, or adding others to, both negative binomial and ZINB (both zero and count) models suggested that the fit was improved by simplifying the model to include year, vessel and target only. Based on sequential plotting of model selection results, both vessel and target factors had a notable influence on the resulting index (Appendix 26).

AIC values (3487 versus 3513) and a Vuong test (Vuong 1989) with a p-value<0.001 indicated that the ZINB model better fit the data. None of the explanatory variables in the negative binomial model showed collinearity as measured by variance inflation factors (note: this cannot be calculated for ZINB). It is not possible to assess the percent deviance explained for a ZINB model but for reference the negative binominal form explained only 14% (Table 8). The diagnostics showed a lack fit of the NB model to the data with numerous outliers whereas the ZINB diagnostics appeared reasonable (Appendix 14).

Table 8: Results for the CPUE standardisation of mako shark catches in the TLCER Domestic South dataset.

Distribution: Zero-inflated Negative Binomial

Model:

Catch of mako shark ~ year + vessel + target + offset(log(number of hooks)) (counts)

Catch of mako shark ~ year + vessel + target (zeroes)

Significance:	Not available for ZINB (In negative binomial year and target were significant at p<0.001 and vessel was significant at p<0.05)
Collinearity:	Not available for ZINB (In negative binomial all variables <1.59)
Diagnostics:	Poor correlation between observed and predicted values indicates a lack of model fit (Appendix 14)
Percent Null Deviance Explained:	Not available for ZINB (In negative binomial 14%)

The number of sets in the TLCER domestic south dataset with zero catches of mako shark varied considerably year-by-year from a low of about 30% to a high of about 80% (Figure 23, left). The nominal and standardised abundance indices both show peak catches in 2011 but the confidence intervals on the predictions are relatively large. Therefore, aside from a clearly higher catch rate in 2011 compared to recent years, there is no clear trend over time (Figure 23, centre and right).

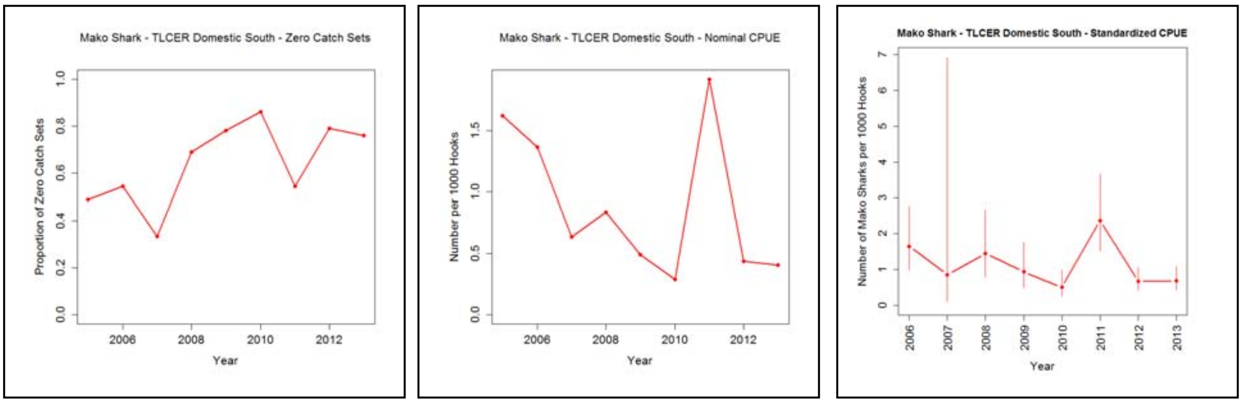

Figure 23: Proportion of sets in the TLCER Domestic South dataset with zero mako sharks recorded by year (left panel), nominal mako shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the ZINB model shown in Table 8 (right panel).

Mako shark abundance indices – TLCER North

As for the TLCER Domestic South dataset, negative binomial and ZINB models were run for the TLCER North dataset with variables suggested by the regression tree analysis. However, due to the large number of vessels (n=96) and areas (n=25) in the dataset, the regression trees could not be estimated with these variables included. The explanatory variables suggested by the regression tree were thus year and month only, but through model selection (as described above), vessel and area factors were added to the model. As the number of records is large the model could compute the coefficients for vessel and area for the negative binomial but not for the ZINB. Rather than sacrifice the predictive power of vessel and area factors, the negative binomial model was chosen.

Appendix 15 shows the model diagnostics for the negative binomial fit to the TLCER North dataset and suggests there are patterns in the residuals, a poor correspondence between observed and predicted values and deviations from the model assumptions at high and low ranges of the observations. The model explains 26% of the deviance in the data and all parameters are statistically significant and not collinear (Table 9). Coefficient-distribution-influence (CDI) plots for the explanatory variables are shown in Appendices 44–46.

Table 9: Results for the CPUE standardisation of mako shark catches in the TLCER north dataset.

Distribution:	Negative Binomial
Model:	

Catch of mako shark ~ year + month + vessel + area + offset(log(number of hooks))

Significance:	All variables were significant at p<0.001
Collinearity:	All variables <1.08
Diagnostics:	Patterns in residuals and poor correlation between observed and predicted values indicates a lack of fit of the model to the data (Appendix 15)
Percent Null Deviance Explained:	26%

The number of sets in the TLCER North dataset with zero catches of mako shark declined slightly year-by-year from about 70% to below 60% (Figure 24, left). The nominal and standardised indices are similar in trend: both increase over the time series (the standardised index significantly), have peaks in 2012 and local maxima in 2008 (Figure 24, centre and right). The relatively small confidence intervals on the annual coefficient estimates reflect the large sample size of this dataset (n more than 1500 in each year). It is likely that the large sample sizes in conjunction with a lack of relevant information to standardise catch rates contributes to the mirroring of the patterns in the observed (Figure 24, centre) and modelled (Figure 24, right) catch rates. Plots of model selection indicate that vessel and area effects increase the predicted catch rates and accentuate the apparent trend in the standardised index (Appendix 27).

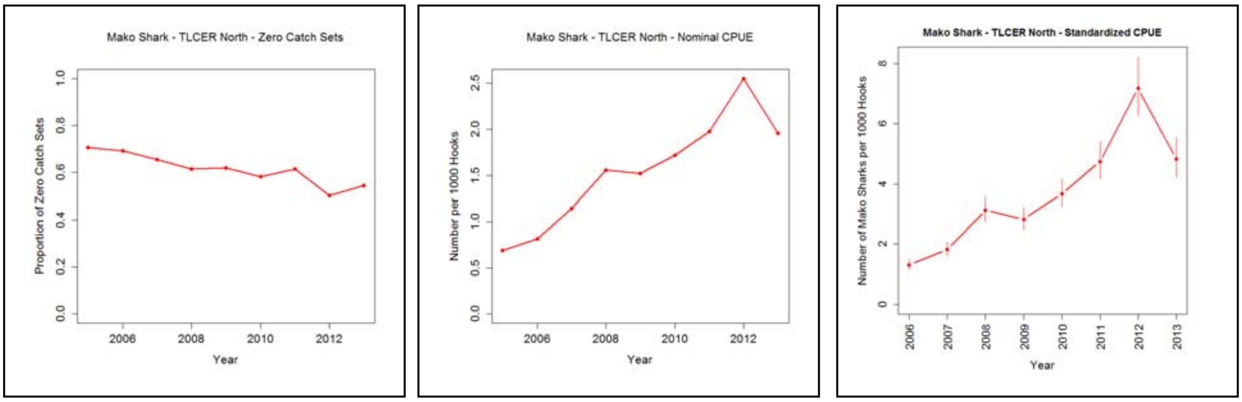

Figure 24: Proportion of sets in the TLCER North dataset with zero mako sharks recorded by year (left panel), nominal mako shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the negative binomial model shown in Table 9 (right panel).

Mako shark abundance indices – Observer

As for most of the mako datasets, the large number of zero catches and the high variance in the counts suggested that the most promising models of the mako catches recorded in the observer dataset would be the negative binomial and the ZINB models. Variables suggested by the regression tree model, i.e. year, month, area, bait type and SST, were used to estimate a negative binomial model. The explanatory power of a vessel factor could not be evaluated using regression tree models because of the large number of vessels in the dataset. A ZINB model could not be estimated with the factors suggested by the regression tree model (or with a vessel factor), whereas the negative binomial model could accommodate all of these factors plus a vessel effect. However, when included in the negative binomial model, the vessel effect caused estimation problems due to the small sample size for some vessels. Therefore, due to practical estimation issues rather than theory *per se*, the negative binomial model without a vessel variable was chosen. This model was not further simplified or elaborated using the criteria of a statistically significant likelihood test and >1% improvement in the AIC value (Table 10).

All explanatory variables in the model were statistically significant and none showed collinearity (Table 10). Model diagnostics appear reasonable and support the model's explanation of a high percentage of the deviance (60%; Appendix 16). Coefficient-distribution-influence (CDI) plots for the explanatory variables are shown in Appendices 47–50.

Table 10: Results for the CPUE standardisation of mako shark catches in the observer dataset.

Distribution:	Negative Binomial
Model:	

Catch of mako shark ~ year + month + area + bait type + SST + offset(log(number of hooks))

Significance:	All variables were significant at $p<0.001$ except for SST which was significant at $p<0.05$.
Collinearity:	All variables <1.86
Diagnostics:	Apparent patterns in the residuals and deviations from model assumptions (Appendix 16)
Percent Null Deviance Explained:	55%

The number of sets in the observer dataset with zero catches of mako shark varied year to year from about 40% to above 80% with no clear trend (Figure 25, left). It is noted that this variation may reflect actual changes in mako abundance and/or changes in mako distribution and its overlap with observed fishing operations. The standardised index (Figure 25, right) is smoother and considerably more level than the nominal one (Figure 25, centre), and while it also suggests a small increase in abundance in recent years (note differences in the abscissa between nominal and standardised plots), its confidence intervals are too wide for a trend to be detectable. The variables area, bait type and SST are capable of explaining much of the variation in the nominal catch rates thus reducing the annual variance in the index of abundance (Appendix 28).

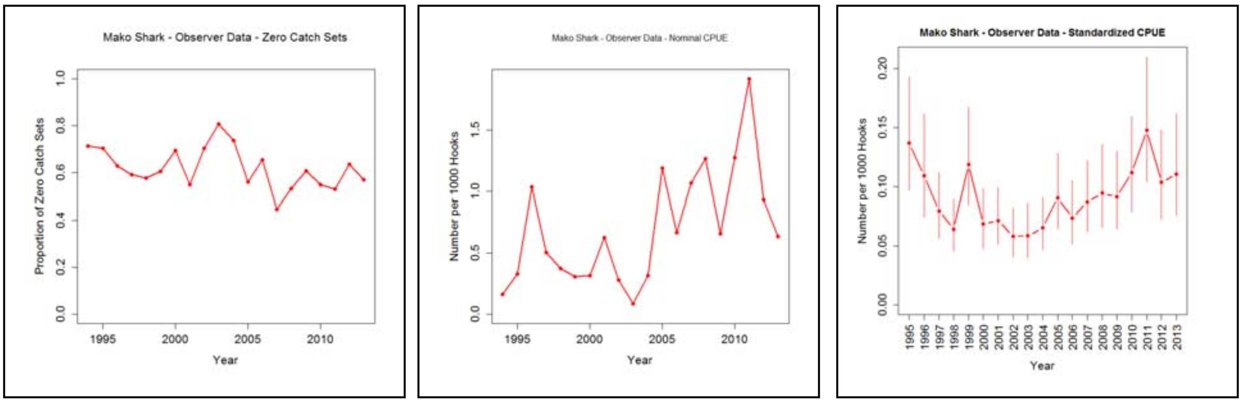

Figure 25: Proportion of sets in the observer dataset with zero mako sharks recorded by year (left panel), nominal mako shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the negative binomial model shown in Table 10 (right panel).

Summary of mako shark results

All of the mako datasets showed an extremely high number of zero catch records, but these proportions were generally stable with the exception of a slight increase in zero catches in the TLCER Domestic South dataset which is outside the mako shark's prime habitat. In all but one case (i.e. the TLCER Japan South dataset), positive catches were overdispersed suggesting that a ZINB might be the most appropriate model to fit. However, in two of the three cases the additional computational requirements of the ZINB led to estimation problems and forced reversion to a more basic negative binomial model. Although it was difficult to determine trends due to wide and overlapping confidence intervals for the models covering the southern fishing grounds (i.e. TLCER Japan South, TLCER Domestic South and approximately two-thirds of the observer data), all datasets indicated peak catches during the period 2011–2013. One of the datasets (i.e. the TLCER North) suggests, on the basis of non-overlapping confidence intervals, that mako catch rates have increased between 2005 and 2012, but then dropped in 2013; however, the 2013 values are higher than values observed in the mid 2000s.

Porbeagle shark

Porbeagle shark data sets and histograms

The datasets used for the porbeagle CPUE standardisations were identical to those used in the previously described analyses for blue and mako sharks. Like the mako shark, the porbeagle shark is relatively rare compared to the blue shark. However, in contrast to the mako shark which is found predominantly in New Zealand’s northern waters, porbeagle catches occur throughout both northern and southern areas. This assists in explaining why the proportions of blue, mako and porbeagle sharks in the TLCER dataset (for which 85% of the sets are in the northern region) are 0.89, 0.06 and 0.04, respectively, whereas for the observer data (which is more representative of the southern fishing grounds) has proportions of 0.89, 0.03 and 0.07, for blue, mako and porbeagle sharks, respectively. As expected, like the mako shark, sets recording zero catches of porbeagle sharks are frequent comprising 49%, 65% and 80% of the records in the TLCER Japan South, Domestic South and North datasets, respectively (Figure 26). The mode of the positive catches was one for the Japan South and North datasets and two for the Domestic South dataset (n=379 for Japan South, n=153 for Domestic South and n=892 for the North dataset).

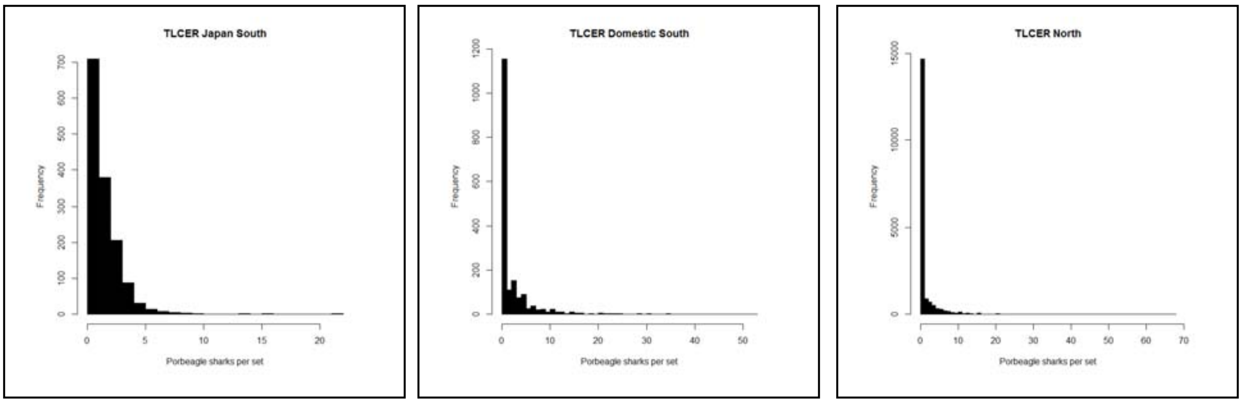

Figure 26: Histograms of porbeagle sharks per set in the TLCER Japan South dataset (left panel, n=1446 of which 710 sets recorded zero porbeagle sharks), the TLCER Domestic South dataset (centre panel, n= 1788 of which 1157 sets recorded zero porbeagle sharks), and the TLCER North data (right panel, n=18 307 of which 14 686 sets recorded zero porbeagle sharks).

The observer dataset recorded zero catches of mako sharks in 40% of its sets (Figure 27). This value is considerably lower than for the TLCER Domestic South and North datasets (65–80%) but similar to the TLCER Japan South proportion of zero catches (49%). As for the mako shark analyses, the high proportion of zero catches in all datasets reduces the information content with regard to estimating abundance trends.

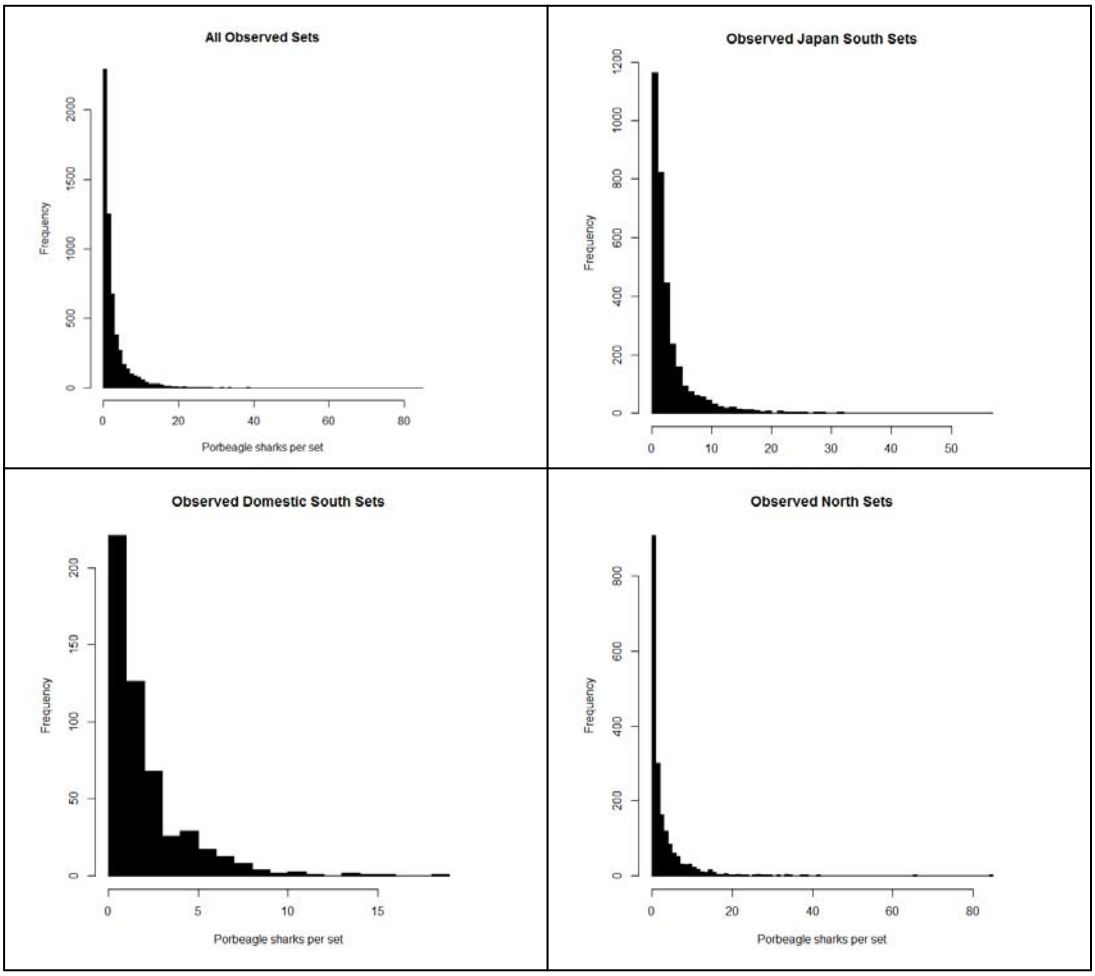

Figure 27: Histogram of porbeagle sharks per set in the observer dataset (n=5783 of which 2295 sets recorded zero porbeagle sharks), and subset by Japan South, Domestic South and North fisheries.

Porbeagle shark model selection

As for the mako shark, the models considered for porbeagle shark, relied heavily on ZINB models to account for the high proportions of zeroes, with a default to negative binomial models if the ZINB parameters could not be estimated.

Porbeagle shark abundance indices – TLCER Japan South

In order to facilitate an unbiased comparison between models with and without bait type for this dataset, 13 sets missing bait type information were excluded from the analysis. Regression tree models for the TLCER Japan south dataset indicated that year, month, vessel and SST are the key variables explaining catches of porbeagle sharks. Negative binomial and ZINB distributions were fitted using a generalised linear model containing all of these variables. Model selection neither simplified nor elaborated the negative binomial model using likelihood ratio testing and a criterion of a 1% improvement in AIC values. However, the ZINB model was simplified by dropping the terms for month and SST from the "zeroes" portion of the model. This reduced ZINB model was slightly preferred to the negative binomial model using AIC values (3788 versus 3791) and a Vuong likelihood test ($p < 0.006$). Regarding model selection, it should be noted that as there is little or no contrast in the TLCER Japan South dataset for factors relating to hook depth, targeting strategy, and bait type, these factors were not included in the model selection process. In comparison to many of the other standardisation models, in this model the variables month, area and SST all have a substantial role in smoothing the year-only index (Appendix 29).

Significance and collinearity cannot be directly assessed for the ZINB model but for the negative binomial model year, month, vessel and SST were significant and not collinear (Table 11). Diagnostics indicate a poor fit of the model to the data with a weak relationship between observed and predicted catches (Appendix 17). The percent deviance explained cannot be assessed for the ZINB but for reference the negative binomial model explains 12%.

Table 11: Results for the CPUE standardisation of porbeagle shark in the TLCER Japan South dataset.

Distribution:	Zero-inflated Negative Binomial
Model:	Catch of porbeagle shark ~ year + month + vessel + SST + offset(log(number of hooks)) (counts) Catch of porbeagle shark ~ year + vessel (zeroes)
Significance:	Not available for ZINB (In negative binomial all variables significant at p<0.001)
Collinearity:	Not available for ZINB (In negative binomial all variables <1.28)
Diagnostics:	Apparent patterns in the residuals and a weak relationship between observed and expected values (Appendix 17)
Percent Null Deviance Explained:	Not available for ZINB (In negative binomial 12%)

The proportion of sets with zero catch of porbeagle sharks varied between about 40 to about 60% from 2005–2013 with no clear trend. Similarly, in both nominal and standardised CPUE series annual means and their confidence intervals do not indicate any significant change in porbeagle abundance despite high estimates in both series for the years 2007 and 2013 (Figure 28, centre and right).

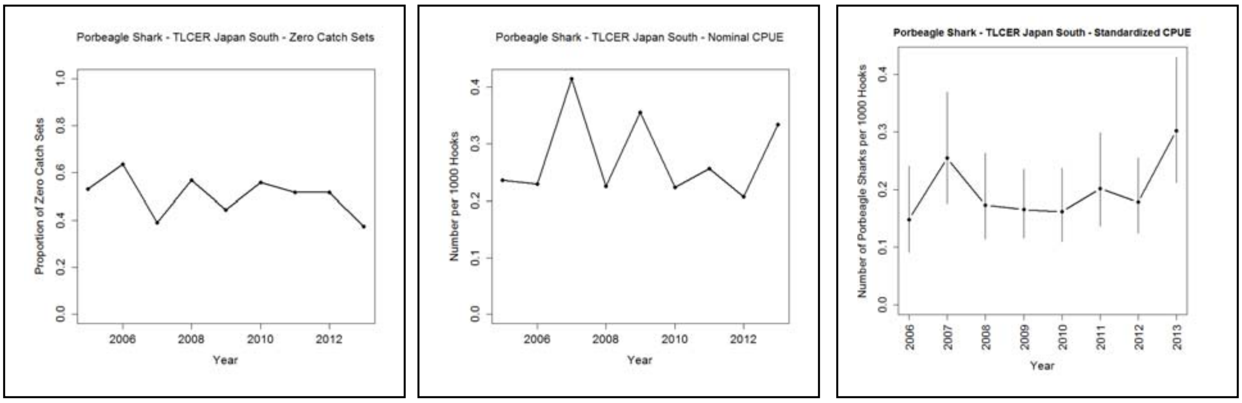

Figure 28: Proportion of sets in the TLCER Japan South dataset with zero porbeagle sharks recorded by year (left panel), nominal porbeagle shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the zero-inflated negative binomial model shown in Table 11 (right panel).

Porbeagle shark abundance indices – TLCER Domestic South

Porbeagle shark catches in the TLCER Domestic South fishery had a slightly greater proportion of zero catch sets and a higher variance in the catches of positive sets. Negative binomial and ZINB models were fitted starting with variables identified as important by the regression tree models: year, month, vessel and bait type. To improve estimation individual vessel identifiers were aggregated into two groups suggested by the regression tree model. Three sets with missing values of SST were removed before testing whether the initial models could be elaborated or reduced from the four starting variables. Neither model changed using selection criteria of statistical significance in a likelihood ratio test and a 1% improvement in AIC value. Sequential plotting of model selection results indicates that bait type has a major role in explaining the peak catch rates observed in 2006, 2009 and 2012 (Appendix 30).

AIC values (5341 versus 5176) and a Vuong test with a p-value<0.001 indicated that the ZINB model better fit the data. None of the explanatory variables in the negative binomial model showed collinearity as measured by variance inflation factors (note: this cannot be calculated for ZINB) and all were statistically significant. It is not possible to assess the percent deviance explained for a ZINB model but for reference the negative binominal form explained only 16% (Table 12). The diagnostics for both negative binomial and ZINB models showed a lack fit to the data with numerous outliers (Appendix 18).

Table 12: Results for the CPUE standardisation of porbeagle shark catches in the TLCER Domestic South dataset.

Distribution: Zero-inflated Negative Binomial

Model:

Catch of porbeagle shark ~ year + month + vessel + bait type + offset(log(number of hooks)) (counts)

Catch of porbeagle shark ~ year + month + vessel + bait type (zeroes)

Significance:	Not available for ZINB (In negative binomial year and month were significant at p<0.001, vessel was significant at p<0.01 and bait type was significant at p<0.05)
Collinearity:	Not available for ZINB (In negative binomial all variables <1.09)
Diagnostics:	Poor correlation between observed and predicted values indicates a lack of model fit (Appendix 18)
Percent Null Deviance Explained:	Not available for ZINB (In negative binomial 16%)

The proportion of sets in the TLCER Domestic South dataset with zero catches of porbeagle shark varied year-by-year between about 50% and about 80% (Figure 29, left). Both nominal and standardised abundance indices showed higher catch rates in 2006, 2009 and 2012 with low catch rates in other years (Figure 29, centre and right). The standardisation model was unable to account completely for this wide variation. It placed wide confidence intervals on the high estimated values indicating uncertainty in the actual magnitude of difference between the low abundance and high abundance years (Figure 29, right). Given that such extreme annual variation is unlikely in a biological sense, it is not recommended that any conclusions should be drawn from this analysis regarding trends in abundance.

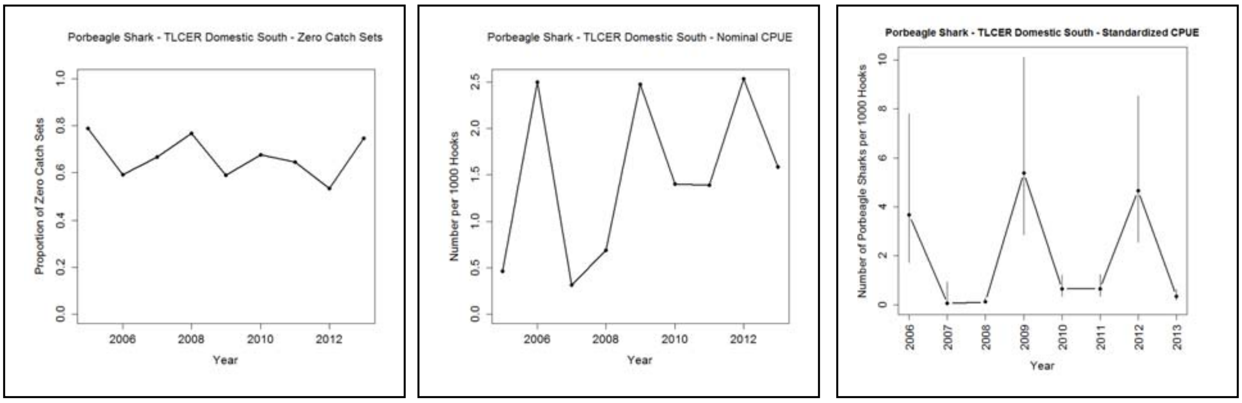

Figure 29: Proportion of sets in the TLCER Domestic South dataset with zero porbeagle sharks recorded by year (left panel), nominal porbeagle shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the ZINB model shown in Table 12 (right panel).

Porbeagle shark abundance indices – TLCER North

As for the TLCER Domestic South dataset, negative binomial and ZINB models were run for the TLCER North dataset with variables suggested by the regression tree analysis. However, due to the large number of vessels (n=96) and areas (n=25) in the dataset, the regression trees could not be run with these variables included. The explanatory variables suggested by the regression tree were thus year and targeting strategy only, but through model selection (as described above), vessel and SST were added to the model. As the number of records is large the model could compute the coefficients for vessel for the negative binomial but not for the ZINB. Rather than sacrifice the predictive power of vessel factors, the negative binomial model was chosen.

Appendix 19 shows the model diagnostics for the negative binomial fit to the TLCER North dataset for porbeagle catches. Although the model explains 40% of the variance in the data (Table 13), the diagnostics show a poor correspondence between observed and predicted value and suggest the model has difficulties fitting the high positive catches (e.g. 15 porbeagle sharks in one set in 2005). Year, target strategy, vessel and SST are all statistically significant and do not demonstrate collinearity. Both target and SST variables have a strong influence on the year-only coefficients and thus play a major role in shaping the resulting index (Appendix 31). Coefficient-distribution-influence (CDI) plots for the explanatory variables are shown in Appendices 51–53.

Table 13: Results for the CPUE standardisation of porbeagle shark catches in the TLCER domestic North dataset.

Distribution: Negative Binomial

Model:
Catch of porbeagle shark ~ year + target strategy + vessel + SST + offset(log(number of hooks))

Significance: All variables were significant at p<0.001

Collinearity: All variables <1.22

Diagnostics: Patterns in residuals. Model has difficulties with fitting high catches (Appendix 19).

Percent Null Deviance Explained: 40%

The proportion of sets in the TLCER North dataset with zero catches of porbeagle sharks has remained high (over 70%) since 2005 (Figure 30, left). There is no evidence for an increase in zero catch sets in this dataset. The nominal and standardised indices both suggest that catch rates have increased since 2007 (Figure 30, centre and right), but the substantial (four-fold) increase in the standardised index between 2007 and 2008 seems too large to reflect a real increase in abundance. The confidence intervals on the estimates caution against concluding that there has been any trend in abundance in recent years (Figure 30, right).

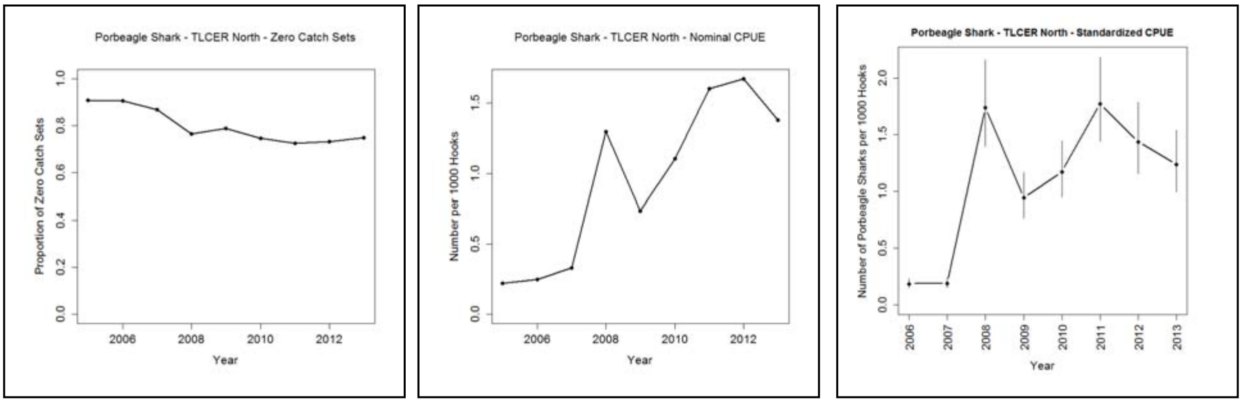

Figure 30: Proportion of sets in the TLCER North dataset with zero porbeagle sharks recorded by year (left panel), nominal porbeagle shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the negative binomial model shown in Table 13 (right panel).

Porbeagle shark abundance indices – Observer

As for all of the porbeagle datasets the proportion of zero catch sets was high, suggesting that a ZINB might be the most appropriate model. However, as for other analyses described above, the higher information requirements for the ZINB could not always be met by the available data. Using regression tree models to explore which variables best explained porbeagle catches, year, month, area, targeting strategy, bait type, SST and catch of southern bluefin tuna were identified.

A negative binomial model with all of the variables suggested by the regression tree model was fitted to the porbeagle data. As described above for the analysis of mako shark catch rates in the observer dataset, a vessel factor could not be tested in the regression tree models but was added to the negative binomial model during model selection and improved the fit significantly. Once the vessel factor was added, targeting strategy was found not to contribute significantly and so was dropped. A vessel factor could not be added to the ZINB model due to estimation errors. The initial ZINB model (year, month, area, target, bait type, SST and catch of southern bluefin tuna) was simplified through model selection procedures only by dropping the bait type variable from the zero catch component of the model. According to AIC values (20 003 compared to 20 576) and a Vuong likelihood ratio test ($p<0.001$) the negative binomial model including the vessel effect performed better than the ZINB model (without the vessel effect). Sequential plotting of model selection results suggests that while year, month and area factors do little to smooth the nominal catch rates in the early part of the time series, after the early 2000s, accounting for vessel effects can explain much of the variance (Appendix 32, Figure 31).

All explanatory variables in the model were statistically significant and none showed collinearity (Table 14). Model diagnostics indicate problems with the model's fit to the data, largely attributable to outliers (Appendix 20), despite explaining a relatively high percentage of the deviance (49%). Coefficient-distribution-influence (CDI) plots for the explanatory variables are shown in Appendices 54–59.

Table 14: Results for the CPUE standardisation of porbeagle shark catches in the observer dataset.

Distribution: Negative Binomial

Model:
Catch of porbeagle shark ~ year + month + area + vessel + bait type + SST + catch of southern bluefin tuna + offset(log(number of hooks))

Significance: All variables were significant at $p<0.001$)

Collinearity: All variables <1.97

Diagnostics: Apparent patterns in the residuals and deviations from model assumptions (Appendix 20).

Percent Null Deviance Explained: 49%

The percentage of sets in the observer dataset with zero catches of porbeagle shark increased from less than 40% before 2002 to about 50% thereafter (Figure 31, left). While this change is not large in magnitude, an increase in zero catches could indicate a reduction in abundance. Nominal catch rates showed large fluctuations in annual values in 1995–2000, with similar variance but lower levels in the late 2000s (Figure 31, centre). Standardisation did little to smooth the catch rate variation in the early part of the time series, but it modulated the variability in nominal catch rates in the later portion of the time series, mainly through accounting for vessel effects (Figure 31, right). The results suggest that while catch rates for porbeagle sharks are at present considerably lower than at some times in the late 1990s, they are no lower and perhaps slightly higher than they were in the early 2000s. Therefore while the proportion of zero catches may have increased, a parallel signal of decreasing abundance in the catch rates is not apparent.

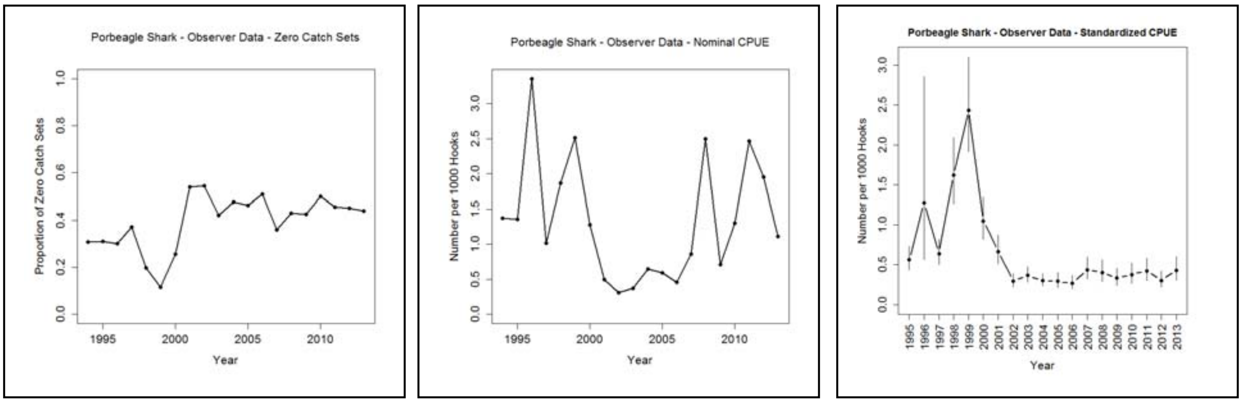

Figure 31: Proportion of sets in the observer dataset with zero porbeagle sharks recorded by year (left panel), nominal porbeagle shark CPUE computed as number caught per 1000 hooks fished per year (centre panel), and year coefficients and their 95% confidence intervals produced using the negative binomial model shown in Table 14 (right panel).

Summary of porbeagle shark results

As for the mako sharks, the catch records for porbeagle sharks suffered from a high proportion of zero catches and a high variation in positive catch records. It is expected that the wider distribution of porbeagle sharks over the various fishing grounds, and particularly in the fishing grounds better covered by observers (i.e. southern areas), has facilitated its analysis as compared to the mako sharks. Nevertheless, it is difficult to draw any conclusions on porbeagle catch rates recorded in the TLCER datasets as there is either no apparent trend and/or the confidence intervals are relatively wide and overlapping. The observer dataset may provide the best indicator of porbeagle catch rates but even this dataset is characterized by high variance in catch rates in the early part of the time series and an apparently sharp decrease in the early years of the 2000s. The fluctuations before 2002, both up and down, appear to be too extreme and occurring over too short a timeframe to accurately reflect changes in stock abundance. They may instead be an artefact of low and unrepresentative observer coverage, or variable availability of porbeagles. If the lower catch rates and reduced uncertainty (as indicated by the standardisation model's narrower confidence intervals) in the more recent years of the time series is real, it appears that there is no evidence for a decrease in abundance in porbeagle sharks over the past decade despite a potentially slight increase in the proportion of zero catch sets since 2000.

5.4 CONCLUSIONS

This analysis has examined catch records for three shark species in New Zealand waters with the objective of producing abundance indices that represent stock status. While it is important to remove potential biases due to changes in fishing conditions or operations through standardisation, the modelling required can be tedious and the results may vary depending on what assumptions are made. This analysis has attempted to thoroughly explore the available data and i) determine which datasets and methods are best used to standardise CPUE as an indicator of stock status; and ii) produce findings on the stock status of blue, mako and porbeagle sharks. Although this study tested many alternatives in terms of datasets, data formatting, model distributions and variables, there are inevitably other approaches that could be attempted. Nevertheless, a number of general conclusions can be drawn with regard to the data sources, the stock status of the three species, and the analytical techniques that have been explored.

Fishing grounds and datasets

Indicator analyses are ideally based on datasets which are both consistent and representative of the stock being assessed. In this sense, of the four datasets available for this analysis, the TLCER Japan South dataset comprised the most consistent sampling for shark abundance given a nearly constant set of operational parameters such as hook depth, bait type and soak time as well as a limited and largely unvarying fishing ground. This consistency suggests that the TLCER Japan South dataset is the closest approximation of fisheries-independent sampling for SLL fisheries in New Zealand waters. The disadvantage of relying heavily on this dataset to assess New Zealand sharks is that Japan vessels fish mainly in southern and often offshore fishing grounds and thus the data are not necessarily representative of sharks' stock status in other waters.

The observer dataset is the most accurate record of shark catches over the longest timeframe (since 1994). Nevertheless, this dataset is preferentially focused on foreign-flagged vessels (i.e. the Japan-flagged fleet) such that the foreign fleet has had 78% observer coverage compared to less than 10% coverage achieved for the domestic fleet (Griggs & Baird 2013). This bias toward foreign-flagged vessels implies that the observer dataset is, like the TLCER Japan South dataset, biased toward southern offshore waters. This is particularly a concern when assessing mako sharks which are more commonly encountered in New Zealand's northern waters.

It thus appears important to assess indicators for northern waters, particularly when considering the status of mako sharks. Most of the catch rates for northern waters are however from the TLCER North dataset and when working with commercial fisheries data there is often the risk that fishing (i.e. sampling) effort is biased by targeting strategies. While the occurrence of shark targeting is not known specifically for the northern domestic fleet, the southern domestic fleet is known to have been supplying a market for blue shark meat on the west coast of the South Island from 2010–2012 (Clarke et al. 2013). This may have influenced fishing operational practices, catch reporting practices or both.

Given these considerations a focus on the TLCER Japan South and observer datasets is recommended when assessing the status of blue and porbeagle sharks. For mako sharks which are not encountered frequently in the fishing grounds represented in these datasets, the TLCER North dataset should be the focus of the analyses, but appropriate caution should be exercised when interpreting results due to potential targeting or other operational biases including under-reporting.

Species

Each of the three species assessed has special characteristics which shaped the analytical approach. Blue shark are commonly encountered in all of the fishing grounds and thus the catch rate data were both copious (i.e. not skewed by high zero catches) and representative of a range of potential explanatory variables in the standardisation models. This allowed the blue shark models to estimate a wider range of coefficients with more power than was possible for the rarer mako and porbeagle sharks where the majority of catch records were zeroes. In addition to the high proportion of zero catches, mako and porbeagle shark datasets were characterized by rare, extremely high catch rates of up to 100 sharks per 1000 hooks. (Blue sharks also showed extremely high catch rates in some instances but had larger numbers of records between these high catches and zero). Therefore, based on natural frequency of occurrence alone, the blue shark results can be considered more reliable than the results for the other species. Uncertainties in estimating the abundance of rare species, which are compounded when distributions are spatially or temporally aggregated, are expected to persist regardless of advances in statistical techniques.

Blue shark showed an overall increasing trend of abundance in three of the four datasets examined (TLCER Japan South, observer and TLCER North). In the fourth dataset, i.e. the TLCER Domestic South dataset, the trend increased until 2011 but decreased slightly in 2012 and 2013 to levels similar to those observed in years prior to 2011. As a result of many zero catch records, the lack of information in the catch data for mako and porbeagle sharks resulted in wide confidence intervals on the annual estimates. In most cases, including the observer data, there was no apparent trend in abundance demonstrated for either species in recent years. For some of the domestic fisheries (e.g. mako sharks in the TLCER Domestic South and North datasets, and porbeagle in the TLCER Domestic South dataset) catch rates in 2011–2012 were highest in recent years. An increase in the proportion of zero catches was noted only for blue and mako sharks in the TLCER Domestic South dataset. In the case of blue sharks this may be related to the decrease in catch rates observed in 2012–2013, possibly due to the decline in the market for blue shark meat (Clarke et al. 2013). In the case of mako sharks, the variability in zero catches in the south may be related to the fact that they occur less frequently in southern areas. Porbeagle sharks showed a slight decline in the proportion of zero catch sets in the northern area since 2005 and a slight increase in zero catch sets in the observer data set since the early 2000s. This increase in zero catch sets in the observer data corresponds to a sharp decline in both nominal and standardised observer data catch rates for porbeagle since 1999 but it is noted that standardised catch rates have shown little variation on a slight trend of increase since 2002. In summary, on the basis of this analysis there is no evidence of a decrease in abundance for any of these species in New Zealand waters in the past decade.

Analytical techniques

This study has made progress toward identifying streamlined and repeatable methods for standardising shark catch rates as an indicator of stock status. For all species-dataset combinations analysed, either the negative binomial or ZINB distribution was preferred for the standardisation models. These results demonstrated in some cases that even though the number of zero-catch sets was very high, a negative binomial model was preferred over a ZINB. This may have been due to the higher information requirements in the ZINB models (i.e. more coefficients to be estimated) and a low, or unbalanced, amount of information in the datasets which contained mostly zero catches. Use of the negative binomial model was thus sometimes selected by default, but was easier to evaluate in terms of model performance and diagnostics. The Poisson distribution, though not preferred in any of these analyses, would have similar ease of operation to the negative binomial and may be considered when catches are small. These results have highlighted the importance of considering the trade-off between the advantages and disadvantages of more complex models such as the ZINB.

The data grooming, subsetting and exploration necessary for catch rate standardisation can be time consuming, and even if the methods recommended in this study are repeated for subsequent analyses, circumstances may change with time and may require re-evaluation. If a full-scale standardisation study is not possible each time the indicators are updated, it may be worthwhile to compute simple, nominal catch rate indices as an initial screening tool. These results could then be compared to past nominal and standardised catch rate indices to gauge the appropriate level of concern. Where standardisation confirms any alarming trends, this result in combination with other indicators may prompt a more detailed analysis of population dynamics, such as a stock assessment.

6. MEDIAN SIZE AND SEX RATIO INDICATOR ANALYSES

6.1 INTRODUCTION

Exploitation of a fish population may lead to a reduction in the mean age of individuals in the population, and this in turn can lead to a shift in the length distribution towards smaller size classes (Goodyear 2003). Consequently, trends in fish size can be a useful indicator of population status (Clarke et al. 2011), and may even provide information on the level of exploitation that a fish stock is experiencing (Francis & Smith 1995). Clarke et al. (2011) examined trends in median length of five species of sharks in tropical waters north of New Zealand, including blue and mako sharks. They found significant declines in most combinations of spatial strata and sex for blue and mako sharks. As the sizes of sharks differ by sex (females typically grow larger and heavier than males), it is important to examine indicators on a sex-specific basis where possible (Clarke et al. 2011). Length is a better measure of size than weight because the former does not fluctuate with reproductive or other seasonal factors. The median length is preferred over the mean length as the median is less likely to be influenced by outliers.

The sex ratio of a shark population may also be a useful indicator of its status. Heavy exploitation could lead to a preferential loss of females because they tend to be larger and older than males. Thus if the median length in a population declines, it may also impact on the sex ratio. Additionally, male and female sharks often segregate spatially (Mucientes et al. 2009), and this has been reported in HMS sharks in New Zealand waters: in South region, blue shark catches are dominated by females and mako shark catches by males (Francis 2013). If fishing activity is concentrated in areas favoured by one sex, then an imbalance in the sex ratio could be created.

In this section we analyse trends in median length and the proportion of males over time.

6.2 METHODS

Using observer data, Francis (2013) calculated the proportion of males of each of the three shark species in the tuna longline catch, stratified by region, between 1992−93 and 2011−12. That analysis was extended here by adding one more year of observer data to the time series. A new analysis of trends in shark length in the observed catch was also carried out. We calculated and plotted the median and 5th and 95th percentiles of fork length by year, stratified by sex and region.

Length-frequency distributions and sex ratios were calculated for each shark species using data collected by observers aboard SLL vessels. A total of 316 observer trips made between April 1993 and October 2013 were included. For blue shark, 28 observer trips were omitted from length-frequency and proportion mature analyses because their length measurements showed a strong bias towards numbers ending in zero (more than 20% of lengths ending in zero compared with the expected 10%). This indicates either that the sharks were not measured accurately, or that measurements were rounded to 10 cm intervals. Twenty-one further trips by the same observers were also omitted because of uncertainty about the accuracy of their length measurements. Thus 49 observer trips (15.5%) were omitted from blue shark length-frequency analyses (but were included in other analyses such as sex ratio). Measurement bias was not apparent, or at least not detectable, for porbeagle and mako sharks, which were caught in much lower numbers and may therefore have been measured more accurately. Five additional trips (1.7%) were omitted from all analyses because of known species identification problems, or other data quality issues.

Observers measured sharks using one or both of two measurements: fork length (FL) and ‘Length2’. Before 2002, most Length2 measurements were of precaudal length (PCL; tip of snout to the precaudal pit in front of the tail fin). After 2002, most Length2 measurements were of total length (TL). In 2002, some trips used PCL and others used TL. Fork length was adopted as the measurement standard in this study. For sharks having no FL measurement, FL was estimated from Length2 (if recorded) as follows. Time periods of consistent observer behaviour were identified. Plots of FL versus Length2 were generated for every individual trip by species. If Length2 was mostly less than FL, then Length2 was assumed to be PCL for the entire trip; if Length2 was mostly greater than FL, then Length2 was assumed to be TL for the entire trip. Generally it was obvious which measurement had been used, although some outliers existed within trips that were clearly errors, including occasional inadvertent swapping of FL and Length2 between datasheet columns. For blue and porbeagle sharks, trips 598–1633 (except 875) and 30601–31423 (1993– mid 2002) used Length2 = PCL and trips 1757 to 3856 (2003–2013) used Length2 = TL. Some intermediate trips in mid−late 2002 (1636–1686) were omitted from the regressions because of uncertainty during the period of changeover from PCL to TL. For mako shark, individual trips during 1993−2002 used either PCL or TL with no clear temporal pattern, and after 2002, only two mako sharks with missing FL had Length2 (i.e. TL) recorded; consequently no length conversions were done for mako shark. For blue and porbeagle shark, linear regressions of FL versus PCL and TL were generated and used to estimate FL where it was missing in the time periods described above.

When large numbers of sharks (particularly blue sharks) are caught on a longline set, observers may not be able to record data from individual fish. In these cases, observers count (‘tally’) the sharks but do not measure and sex them or record other data such as the time of landing, fate, or processing method. Significant proportions of the blue sharks caught on some trips may be tallied, or important data may not be collected, leading to likely biases in length-frequency distributions, proportion of males, proportion mature, etc. These biases were considered in detail by Francis (2013). Tallied sharks were necessarily excluded from subsequent analyses.

6.3 RESULTS

The proportion of males in the observed SLL catches showed no clear temporal trends for any of the three shark species (Figure 32). For blue sharks in the North region, there was a slight overall bias towards males (54%) but the sex ratio varied markedly among years, with females being dominant in some years. In the South region, blue shark catches were dominated by females, with only 25% males across all years. North region catches were skewed towards males because of the presence of mature adult males as well as juveniles, and southern catches were dominated by females because of a large number of sub-adults (Francis 2013).

The proportion of male porbeagle sharks in the North region was generally higher in the first half of the time series than in the second half, although the difference between the two periods was small. Overall, there were slightly more males than females in North region (56% males), and about equal numbers of both sexes in South region (51% males). The North region catch was skewed towards males because of the presence there of mature adults as well as juveniles.

The mako shark sex ratio was relatively stable over time in the North and South regions (although the time series of adequate sample sizes was short in South region). There were equal numbers of males and females in the North region (50% males), but there was a strong bias towards males in the South region (81% males).

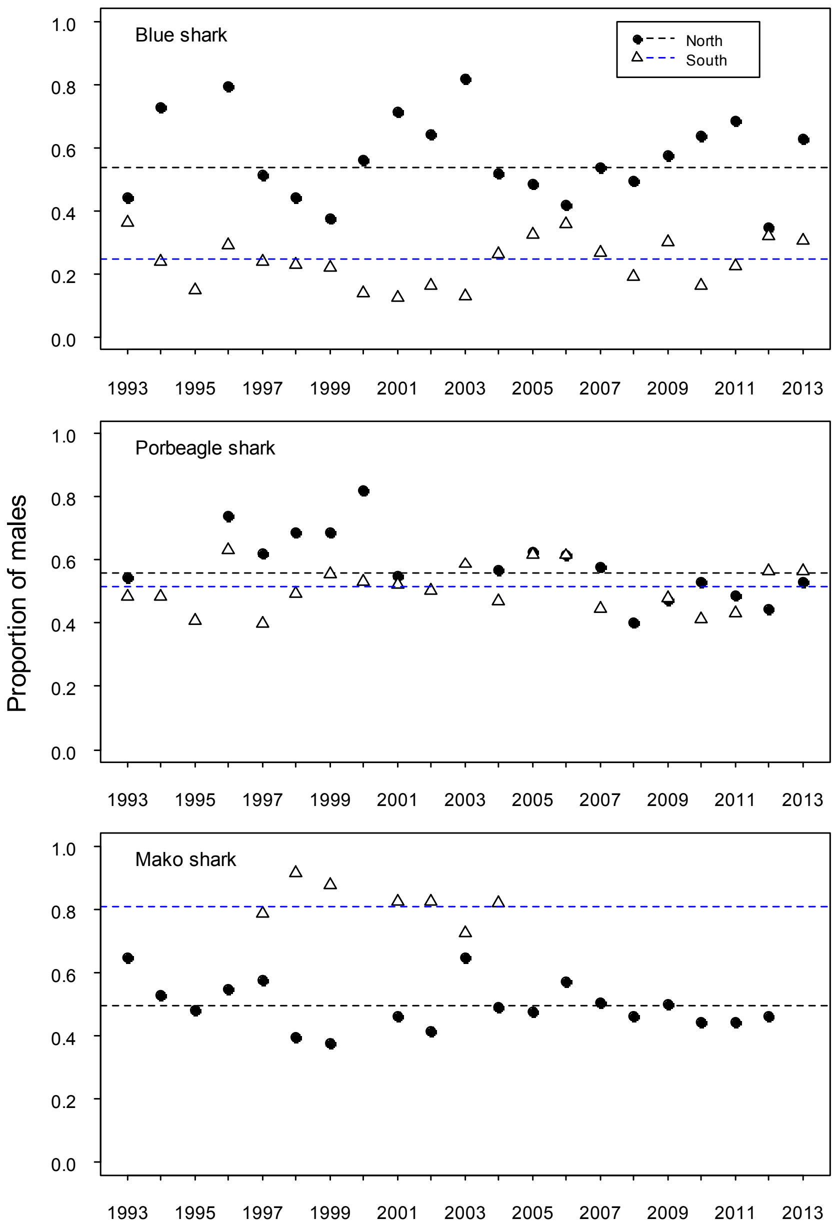

Figure 32: Proportions of male blue, porbeagle and mako sharks by region and year observed on surface longlines, 1993−2013. The horizontal dashed lines indicate the proportions of males for the whole time series in each region. Only year-region combinations with sample sizes greater than 50 are shown.

Trends in median fork length for blue, porbeagle and mako sharks are shown for North and South regions in Figures 33 and 34. Male blue sharks showed considerable inter-annual variability in North region because of varying proportions of adult males in the observed catches (Francis 2013). Male blue sharks in South region, and female blue sharks in both regions, showed much less inter-annual variability (apart from one notable outlier in 2002 for females in North region). There were no apparent trends in blue shark median length for either sex or region.

Male porbeagles in North region showed an early period of relatively high median fork length (about 140 cm from 1996 to 1999) followed by a period of lower median length (75−130 cm from 2004 onwards). The higher early values were the result of a higher proportion of adults than in later years. North region female porbeagles showed no temporal trend in length. In South region, both sexes of porbeagles showed a slow increase from about 100 cm to about 150 cm (males) and 130 cm (females) in 2002, followed by a rapid decline to initial levels of about 100 cm. These trends correspond with an initial increase in the proportion of adults followed by length distributions dominated by juveniles (Francis 2013).

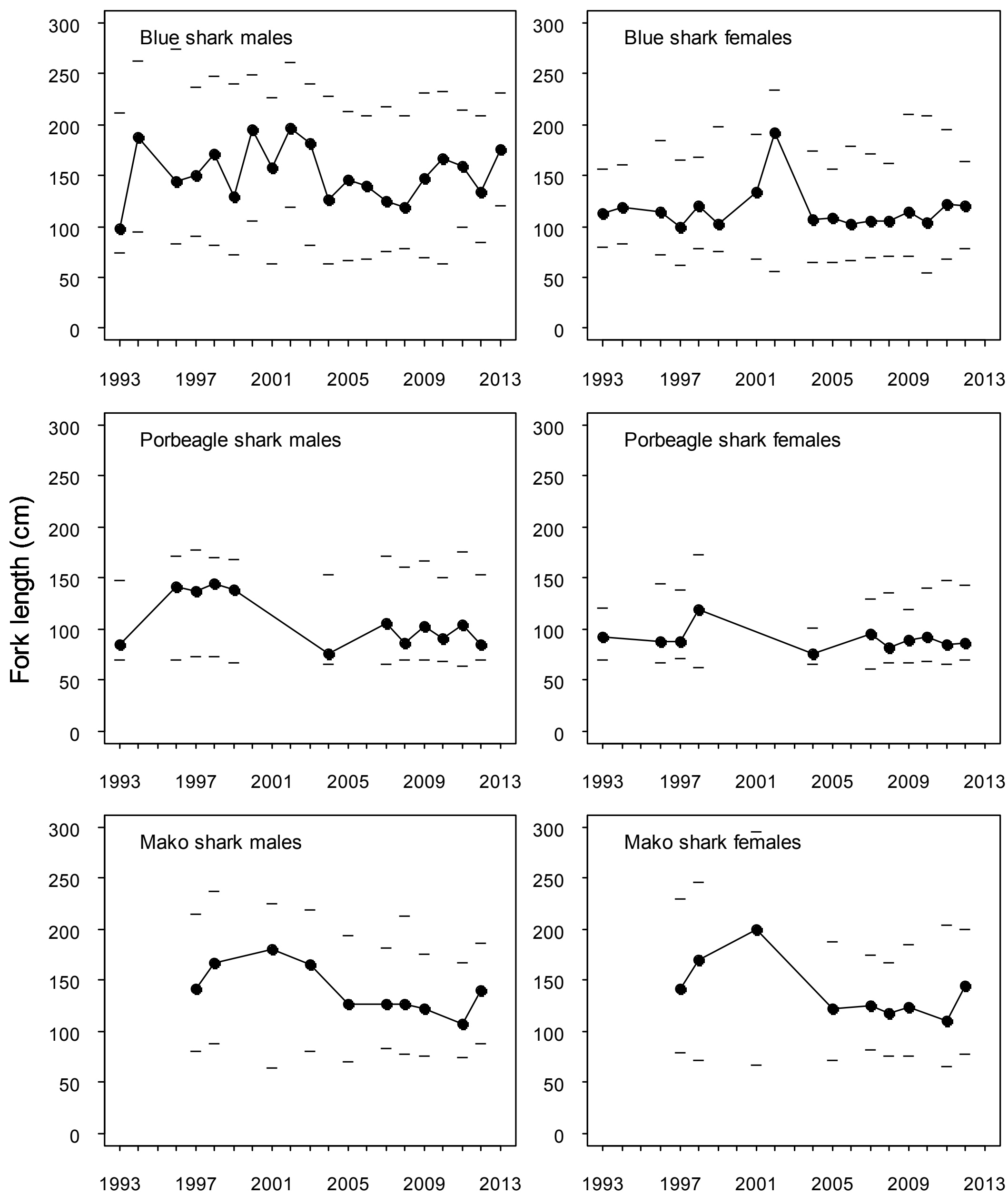

Figure 33: Median fork length of male and female blue, porbeagle and mako sharks in North region by year observed on surface longlines, 1993−2013. The dashes show the 5th and 95th percentiles of the fork length ranges. Only years with sample sizes greater than 50 are shown.

Mako sharks of both sexes in North region showed an early period of relatively high median lengths (140−200 cm in 1997−2003) followed by a period of lower, stable lengths (110−130 cm in 2005−2011) and an upswing in 2012 (140 cm). This pattern was also reflected in the 95th percentile length. There were insufficient data from 2013 to determine whether the 2012 upswing was maintained the following year. There were too few data from South region to identify trends.

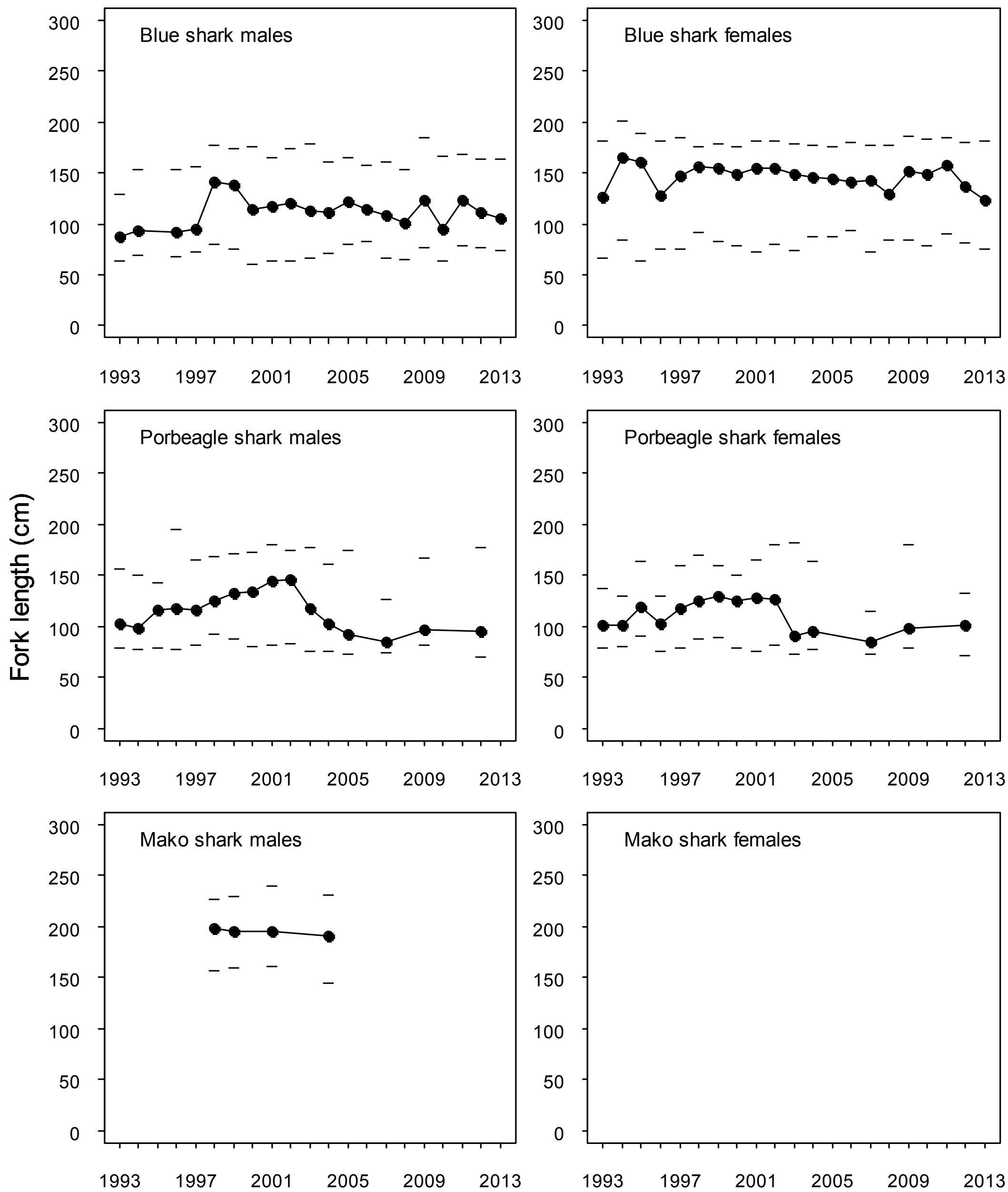

Figure 34: Median fork length of male and female blue, porbeagle and mako sharks in South region by year observed on surface longlines, 1993−2013. The dashes show the 5th and 95th percentiles of the fork length ranges. Only years with sample sizes greater than 50 are shown.

6.4 CONCLUSIONS

There were no clear temporal trends in sex ratio for any combination of species, sex, or region. Sex ratios were close to equality for all three species in the North region (albeit with high inter-annual variation for blue sharks). In the South region, blue shark catches were dominated by females, mako shark catches by males, and porbeagle shark catches had similar proportions of both sexes. In combination, the spatial variation in length composition and sex ratios indicate that blue and mako sharks segregate spatially by size and sex, whereas porbeagles are more uniformly distributed but with a higher proportion of juveniles in the north and subadults in the south. Spatial and sexual segregation are common in sharks, and have been reported for pelagic sharks elsewhere in the Pacific (Nakano et al. 1985; Nakano 1994; Nakano & Nagasawa 1996; Mucientes et al. 2009).

Blue sharks showed no temporal trends in median length in either region. Male porbeagles in both regions and female porbeagles in South region, showed reduced median lengths in the second part of the time series. Similarly, mako sharks of both sexes in North region showed a decline in median length through time. However, the interpretation of shark length-frequency distributions obtained from observer data is unfortunately confounded by trends in fisher and observer practices (Clarke et al. 2013; Francis 2013). Francis (2013) noted: "*Analysis of long time series (1993−2012) of observer data revealed that there has been an increase in the proportion of porbeagle and mako sharks (but not blue shark) discarded by SLL vessels since 1996. Although the proportion of sharks measured by observers showed no long-term trends for blue sharks, and female porbeagle and mako sharks, the annual estimates were often highly variable and there may have been overall declines for male porbeagle and mako sharks. In conjunction with a large decrease in the proportion of discarded sharks that were measured, and a likely bias in measurements of discarded sharks towards small individuals, the declining trends noted in the percentages of mature blue, porbeagle and mako sharks should not be interpreted as real as they are probably biased by changing fisher and observer practices, particularly associated with the introduction of these sharks to the QMS in 2004 and the associated ability to release live sharks under Schedule 6.*" The indicated trends and biases may well have contributed to the apparent declines in some median length datasets, so their utility as valid indicators may have been compromised.

7. DISCUSSION

The period from 2005 to 2013 has the best available data for conducting indicator analyses on blue, porbeagle and mako sharks. Prior to 2005, the three species were not managed under the QMS, so there was less incentive for fishers to accurately report their landed catch. Furthermore, TLCER forms did not have provision for recording discarded and released sharks before 2003. Thus data sourced from commercial fishers before 2005 were not considered for our indicator analyses. We also discounted the TLCER domestic South dataset because of the low and probably unrepresentative fishing effort in that stratum.

A summary of trends in indicators over the period 2005–2013 is shown in Table 15. None of the indicators suggested that any of the shark species were declining in either North or South regions. In fact, most of the distribution and catch composition indicators suggested positive trends for all three species in North region, and some indicators also suggested positive trends for all species in South region. Standardised CPUE indicators suggested increasing abundance of blue shark in both regions, and mako shark in North region. The abundance of mako shark in South region was very low, because of that species' more northern distribution, and this rendered some South region indicators incalculable (because of small sample sizes) or inappropriate.

TLCER data are fishery-dependent and could be biased by operational and reporting issues, especially under-reporting. Many sharks are discarded or released, and these proportions are increasing for porbeagle and mako sharks, but not for blue sharks (Francis 2013). However, the annual sums of the TLCER processed weights closely matched the annual MHR landings for blue shark (see Figure 2), indicating that TLCER reporting of processed blue sharks has been accurate and complete overall since 2005. Mako and porbeagle sharks are also caught by other fisheries in addition to the SLL fishery, so the same comparison could not be made with the data available. But we would not expect reporting to be worse for those two species, and in fact it may be better as they are more likely to be retained as trunks than be finned, as happens to most blue sharks (Griggs & Baird 2013). Furthermore, observer-based CPUE indicators showed the same trends as TLCER-based indicators for five out of six of the species-region strata (the exception being makos in North region, and even then, both indices increased but the increase in the observer index was not significant) (Table 15). TLCER data are therefore considered to be generally reliable for indicator analyses.

Table 15: Summary of trends identified in abundance indicators since the 2005 fishing year based on both TLCER and observer data sets. The CPUE-Obs indicator was calculated for both North and South regions combined. For the CPUE-TLCER indicator in South region, only the Japan dataset indicator is shown (the TLCER Domestic South dataset was small and probably unrepresentative). Green cells show indicators that suggest positive trends in stock size. Note that a downward trend in 'proportion-zeroes' is considered a positive stock trend. NA = indicator not applicable because of small sample size.

		North region			South region		
Indicator class	Indicator	Blue	Porbeagle	Mako	Blue	Porbeagle	Mako
Distribution	High-CPUE	Up	Up	Up	Up	Up	NA
Distribution	Proportion-zeroes	Nil	Down	Down	Nil	Nil	Down
Catch composition	GM index total catch - TLCER	Up (all species)			Up (all species)		
Catch composition	GM index total catch - Obs	Up (all species)			Nil (all species)		
Catch composition	GM index HMS shark catch - TLCER	Up (all species)			Up (all species)		
Catch composition	GM index HMS shark catch - Obs	Up (all species)			Nil (all species)		
Standardised CPUE	CPUE - TLCER	Up	Nil	Up	Up	Nil	Nil
Standardised CPUE	CPUE - Obs	Up	Nil	Nil	Up	Nil	Nil
Sex ratio	Proportion males	Nil	Nil	Nil	Nil	Nil	NA
Size composition	Median length - Males	Nil	Nil	Nil	Nil	Nil	NA
Size composition	Median length - Females	Nil	Nil	Nil	Nil	Nil	NA

We conclude that there is no evidence that the stocks of blue, porbeagle and mako sharks in New Zealand waters have been adversely affected by fishing at the levels experienced since 2005, and that there are good signs that they are increasing. We caution, however, that there are a number of important caveats associated with our indicator analyses, especially relating to data quality and availability, and goodness of model fit in the CPUE analyses, as detailed in the previous sections. Furthermore, all the indicators used in this study would be affected by increased shark targeting, although we have no indication that that has occurred.

The observer dataset spans a considerably longer period (1993–2013) than the TLCER dataset, and therefore provides a useful extended perspective. However the observer dataset suffers from some important limitations, notably low coverage rate (especially in the domestic North fishery which accounted for most of the SLL fishing effort in the last 15 years) (Griggs & Baird 2013; Ministry for Primary Industries 2013), unrepresentative spatial and temporal distribution (Francis 2013), and increased discard/release rates for porbeagle and mako sharks that have potentially led to biases in the size range of sharks measured (Francis 2013). Indicators based on observer data therefore need to be interpreted cautiously. For blue and mako sharks, standardised observer CPUE generally declined from 1995 or 1996 to 2003, before increasing again to peak in the last 2–4 years (2010–2013). A similar down-then-up pattern was apparent in the North region catch composition geometric mean indices for these two species, although the South region indices were more stable. The median length and sex ratio indicators showed no trends for blue sharks over the longer time series, but median length of North region mako sharks declined during the early 2000s. These results suggest that blue and mako shark abundance may have declined during the late 1990s and early 2000s, and then increased since the mid 2000s, an interpretation that is consistent with the indicators based on more recent TLCER data. We note, however, that trends in observer CPUE indices appear to be negatively correlated with trends in longline fishing effort (Ministry for Primary Industries 2013), and caution that CPUE changes may reflect local abundance patterns and gear competition in areas where effort is concentrated rather than trends in a wider population.

Observer data show a different pattern for porbeagle shark. Standardised CPUE for both regions showed a variable period of generally high catch rates in 1995–1999, followed by a steep decline to low levels by 2002, with little change since then. However, the decline may have been an artefact of data problems or model fitting difficulties. Nevertheless, this decline coincided with a rapid increase in domestic (and total) fishing effort during the late 1990s that peaked in 2002 (Griggs & Baird 2013), and an increase in porbeagle landings that peaked at 240 t in 1999 before dropping rapidly to below 75 t by 2004 (Ministry for Primary Industries 2013). The median length for male and female porbeagles in South region and male porbeagles in North region dropped abruptly in 2003 (male and female mako sharks in North region showed a similar drop at about the same time). While we hesitate to draw strong conclusions from the observer data because of the limitations mentioned above, these results in combination suggest that porbeagle abundance may have declined rapidly in the late 1990s before stabilising at a relatively low level, or increasing as indicated by the trend in the TLCER North CPUE index. Further work on the porbeagle observer CPUE model is required to explore whether the year effects are reasonable, or are driven by other factors such as changes in the fishery, the environment or the availability of porbeagles. There may also be signals in the other indicators for porbeagle that can provide further ideas to be explored in future updates of this indicator analysis.

The indicators presented here cover only the most recent portion of a longer fishing history that was characterised by greater effort levels. SLL fishing effort in the New Zealand EEZ was high in the 1980s and early 1990s, when many foreign fishing vessels held licences. The SLL fleet set 10–25 million hooks per year over that period, compared with fewer than 10 million hooks per year since 1993, and 4 million hooks since 2005 (Griggs & Baird 2013; Ministry for Primary Industries 2013). There is no information on the effect of the high fishing effort of the 1980s and early 1990s, and there are no shark catch data from that period, nor effort data from before 1980.

Blue, porbeagle and mako sharks are generally regarded as wide-ranging, mobile oceanic species. While this may be true of blue sharks, recent electronic tagging of porbeagle and mako sharks in New Zealand waters has shown that juveniles[7] at least are partly residential in the New Zealand EEZ. Tagged porbeagles make seasonal north-south movements within the EEZ (some also move outside the EEZ), being found further north in winter and further south in summer (M. Francis and J. Holsdworth, unpubl. data). Similarly, tagged juvenile mako sharks have spent 64–100% of their time inside the EEZ during deployments of 7–15 months (M. Francis, unpubl. data).

Blue shark populations and, to a presumably lesser extent, mako and porbeagle shark populations inside the EEZ may have been affected by fishing effort outside the EEZ but the extent of any impact is unknown. Foreign effort outside the EEZ has not been quantified but has been substantial. Japanese research drift net data from the South Pacific Ocean between New Zealand and Chile showed no trend in standardised porbeagle CPUE between 1982 and 1990 (Semba et al. 2013). However, Japanese commercial longline porbeagle CPUE data from much of the Southern Hemisphere showed a decline between 1994 and 2004, followed by an increase to a higher level in 2007–2010 (Semba et al. 2013). Clarke et al. (2012) analysed tuna longline CPUE data for the South Pacific Ocean (including the New Zealand observer data that we analysed in the present study) and found no significant trends for blue

[7] Most female porbeagle and mako sharks and many of the males of both species that are caught in the SLL fishery are immature (Francis 2013).

shark or mako sharks[8] between 1996 and 2010, although the CPUE plots were U-shaped with minima in the early 2000s, as we found here. In order to understand trends in the wider HMS shark stocks of the South Pacific, and to quantify their status in relation to management reference points, regional stock assessments are now required.

8. RECOMMENDATIONS FOR FUTURE INDICATOR ANALYSES

The present study sought to develop and interpret indicators of stock abundance for three HMS shark species in New Zealand waters. This study is envisaged as the first in a series of similar studies that will be used to regularly monitor the stock abundance of these species. Indicator studies are generally conceived as rapid assessments that use data that may be limited in quantity and quality to produce indicative stock size trends. The CPUE indices developed in this study go well beyond the scope of an indicator analysis. Developing and testing multiple models with different error structures and explanatory variables was very time-consuming and more appropriate to a detailed research study than an indicator analysis. For that reason, we did not explore all possible avenues for generating the best possible CPUE models, and some of these might be worth attempting in future studies. We regard the models developed here as an important and valuable first attempt, but it may be possible to improve upon them with further work. Suggestions for potential improvements to CPUE models that could be explored include:

- Remove or modify explanatory variables with low predictive power; for example, removal of vessels that made few longline sets may improve models that incorporate a vessel factor, and allow fitting of ZINB models in place of NB models
- Explore the utility of alternative diagnostic tests for NB and ZINB models (Hoyle et al. 2014)
- Investigate the observer and TLCER North CPUE models for porbeagle sharks to understand the cause of, and to correct if possible, the large and implausible fluctuations in year indices
- Omit species catch as an indicator variable, and investigate other approaches for accounting for the effects of fishing strategy/targeting
- Fit continuous variables such as month and % squid bait with smoothers rather than categorical variables
- Discontinue the domestic South CPUE series. This series had small sample sizes leading to large confidence intervals. It provided little useful information in the present study, and this is not expected to change in future
- Consider combining all TLCER datasets to produce a New Zealand wide index of abundance (as was done for the observer data).

9. MANAGEMENT IMPLICATIONS

Our indicator analyses suggest that blue, porbeagle and mako shark populations in the New Zealand EEZ have not been declining under recent fishing pressure, and may have been increasing since 2005. These changes are presumably in response to a decline in SLL fishing effort since 2002 (Griggs & Baird 2013), and declines in annual landings since peaks in 2001 for blue and mako sharks, and since 1999 for porbeagle sharks (Ministry for Primary Industries 2013). Observer data from 1995 suggest that blue and mako sharks may have undergone a down-then-up trajectory. Porbeagle shark abundance may have declined rapidly in the late 1990s before stabilising at a relatively low level, or increasing as indicated by the trend in the TLCER North CPUE index. The quality of observer data and model fits means that these interpretations are uncertain. The stock status of porbeagle sharks remains uncertain, but is potentially low, whereas blue and mako sharks may be recovering. Conclusive determinations of stock status will require regional (i.e. South Pacific) stock assessments.

[8] Two mako species (shortfin and longfin) were combined. The longfin mako shark does not occur in New Zealand waters.

10. ACKNOWLEDGMENTS

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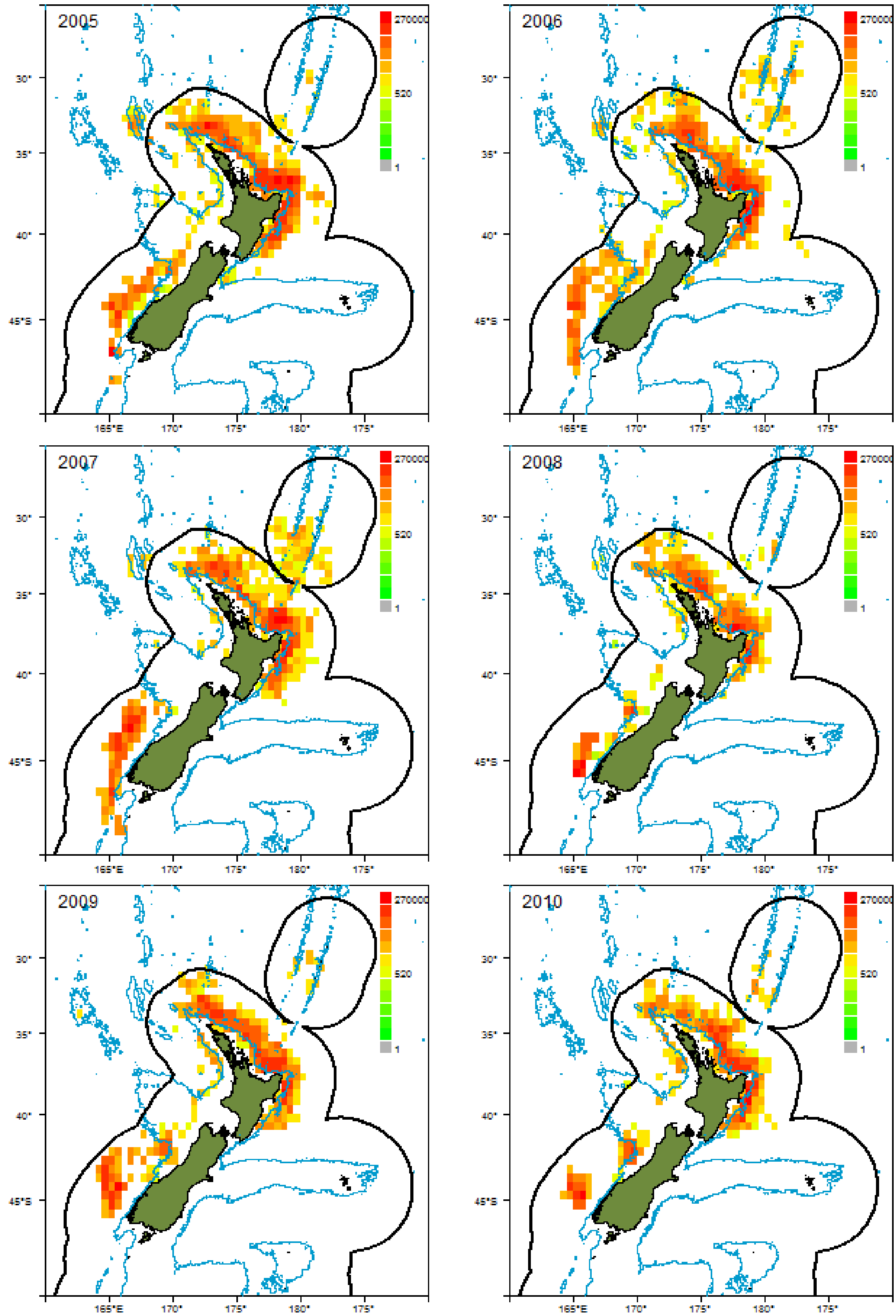
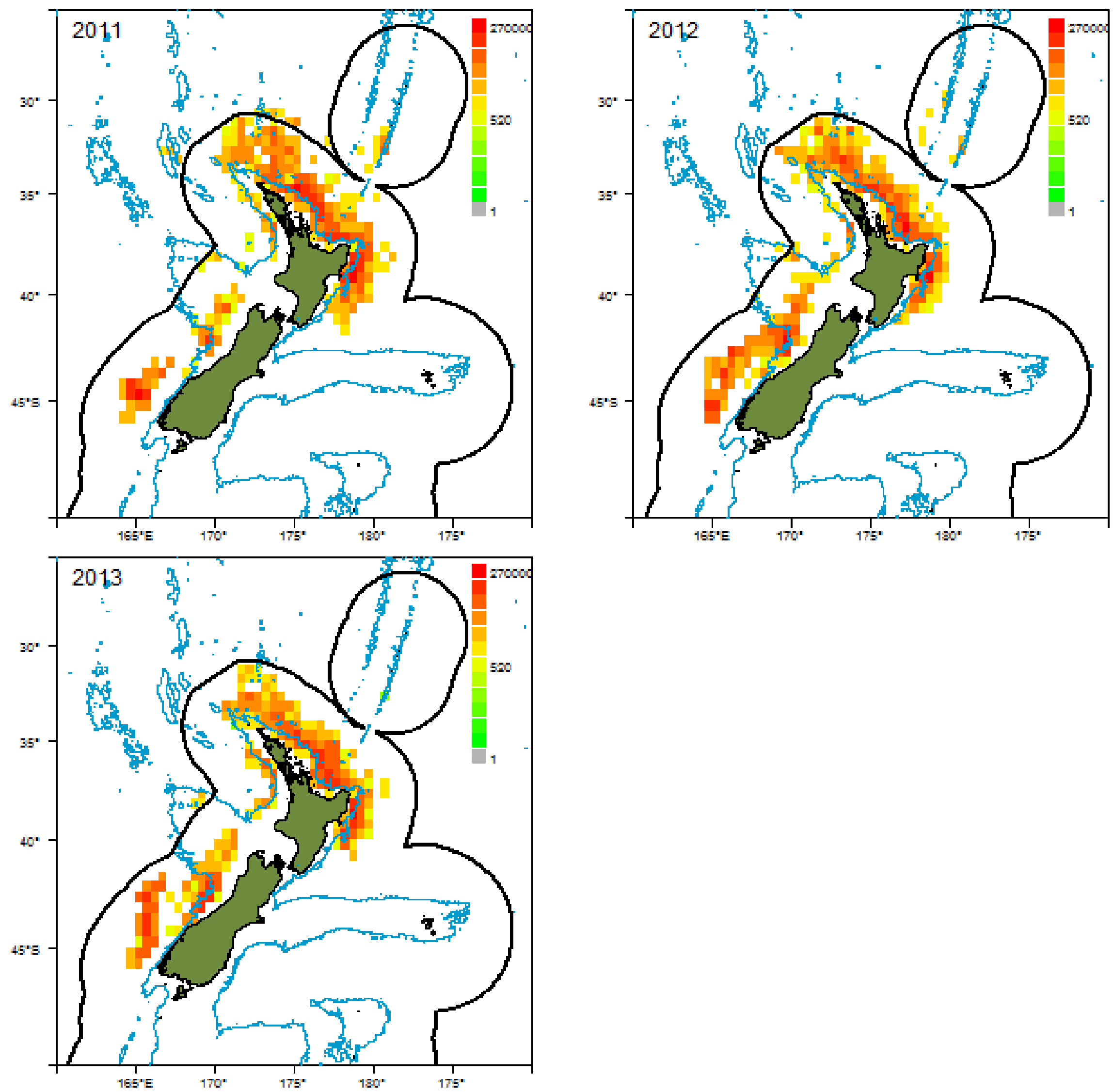
APPENDICES

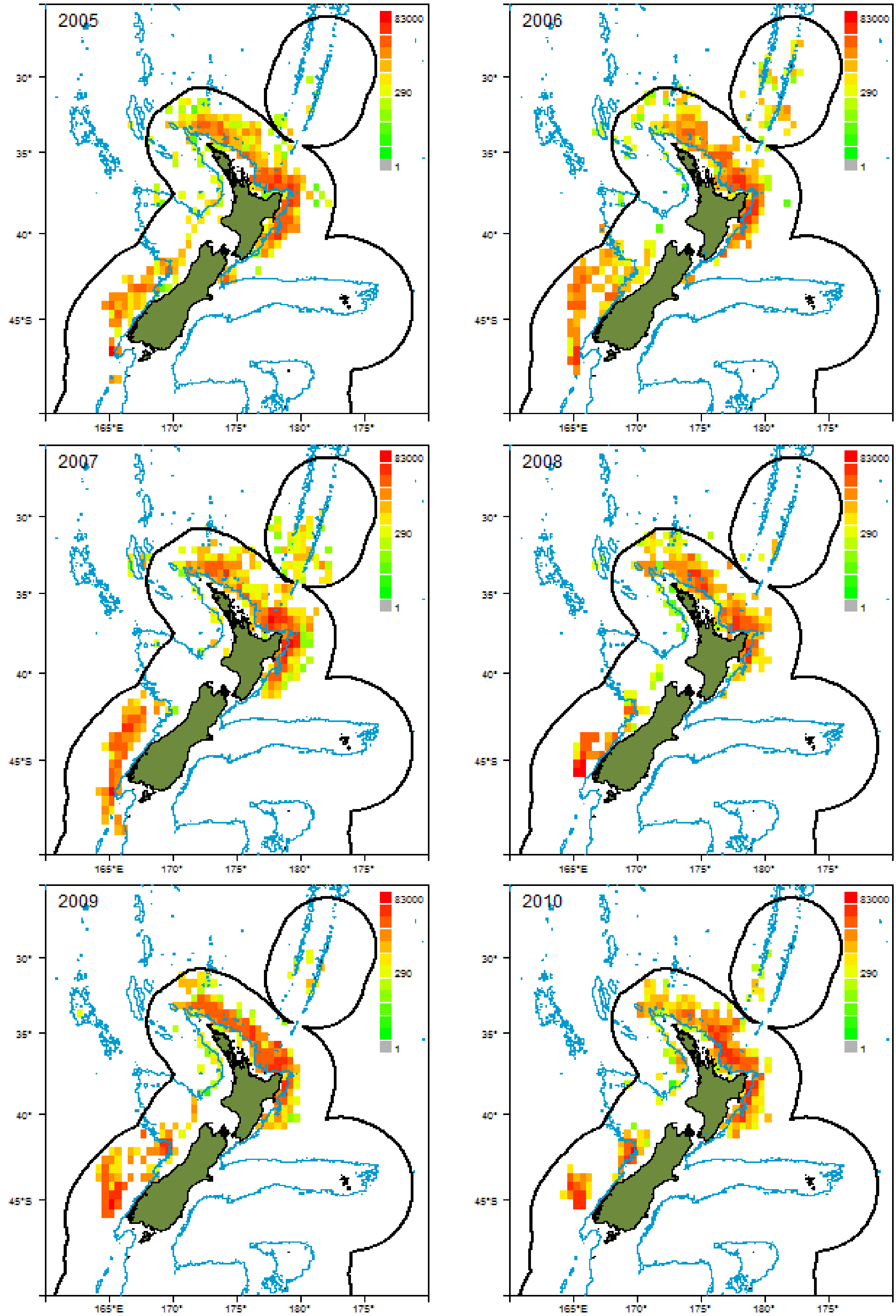
Appendix 1: Number of hooks set by the surface longline fishery in 0.5 degree rectangles by fishing year. Note the log scale used for the colour palette. Depth contour = 1000 m.



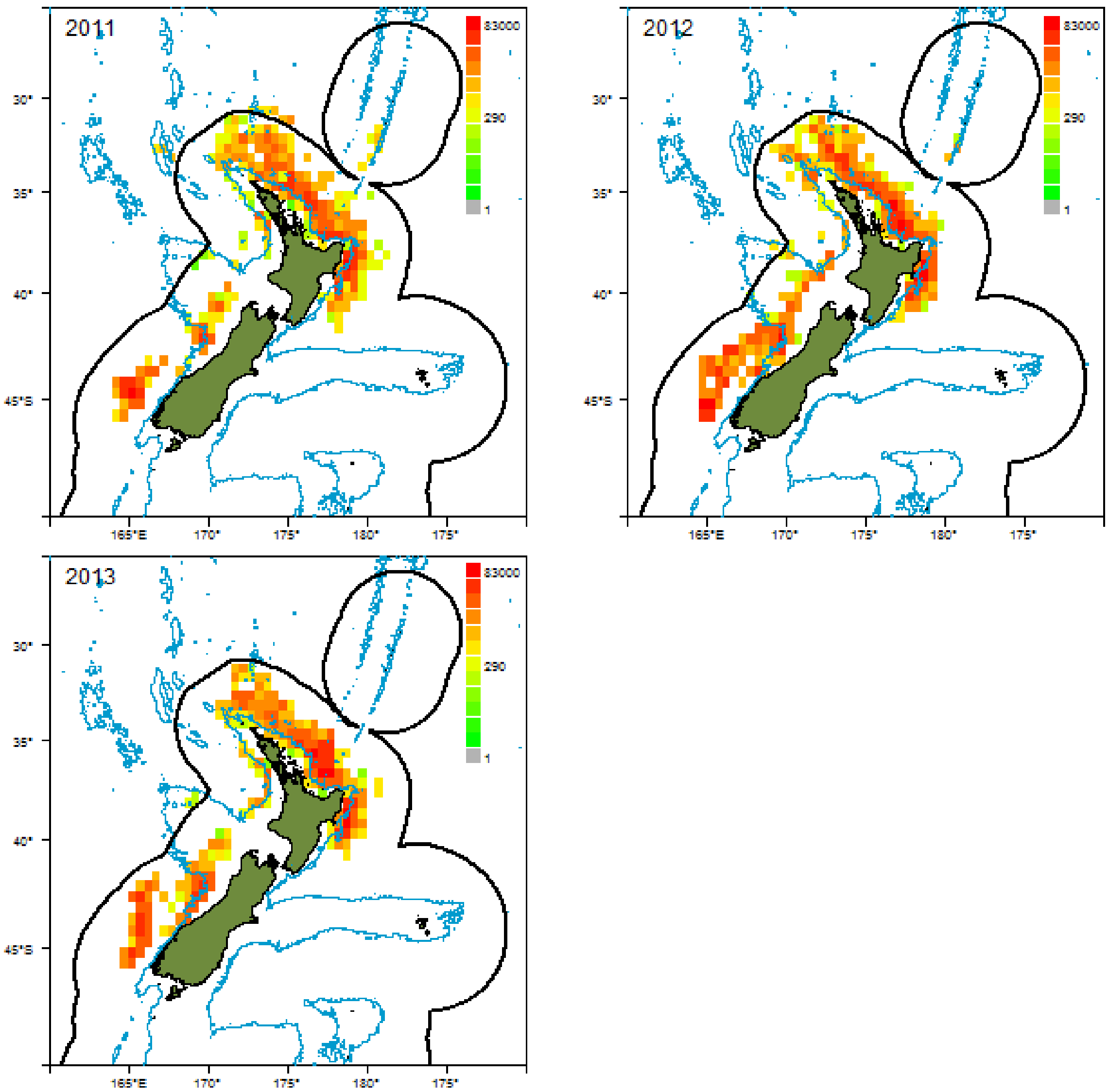
Appendix 1: continued



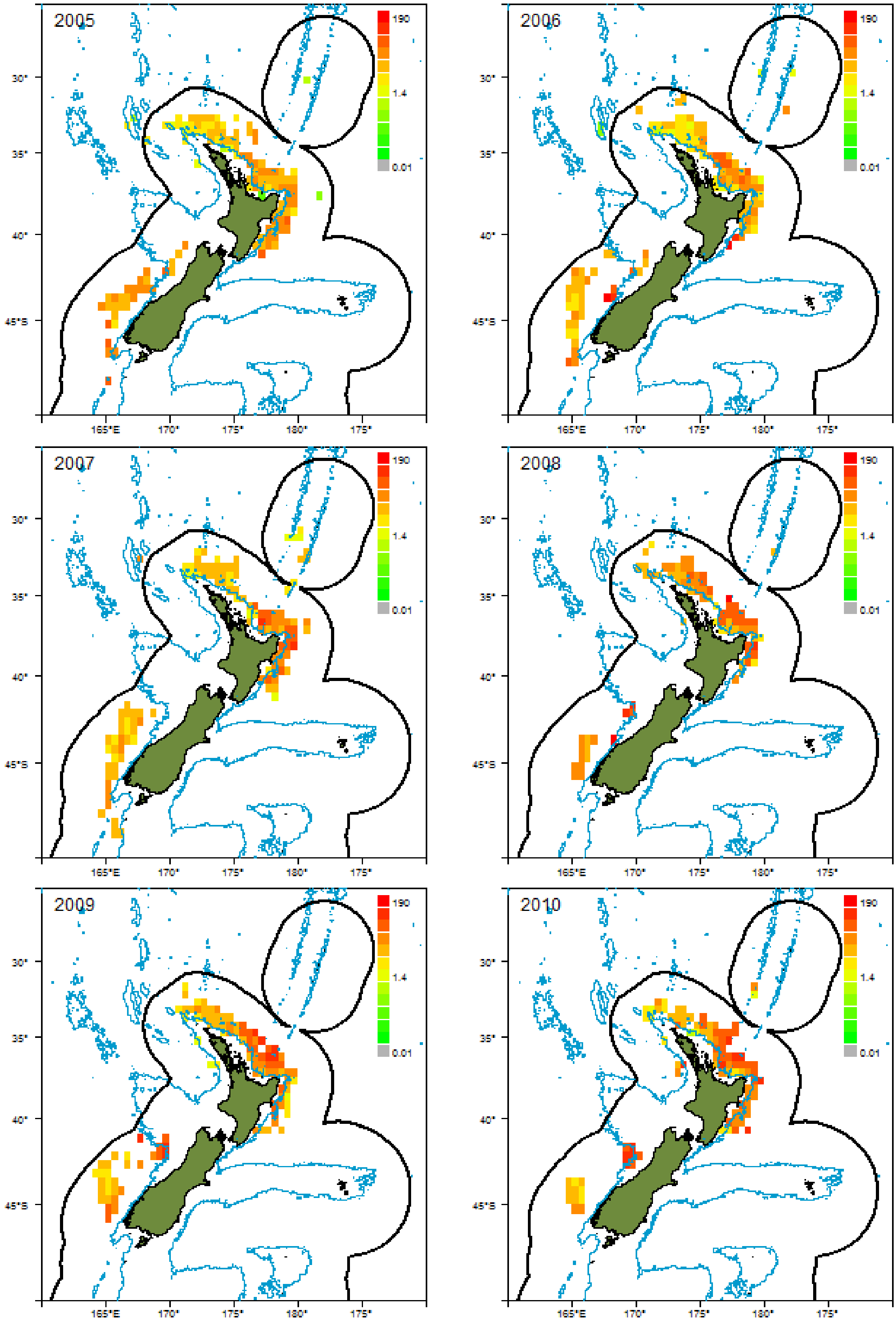
Appendix 2: Blue shark catches (kg) by the surface longline fishery in 0.5 degree rectangles by fishing year. Note the log scale used for the colour palette. Depth contour = 1000 m.



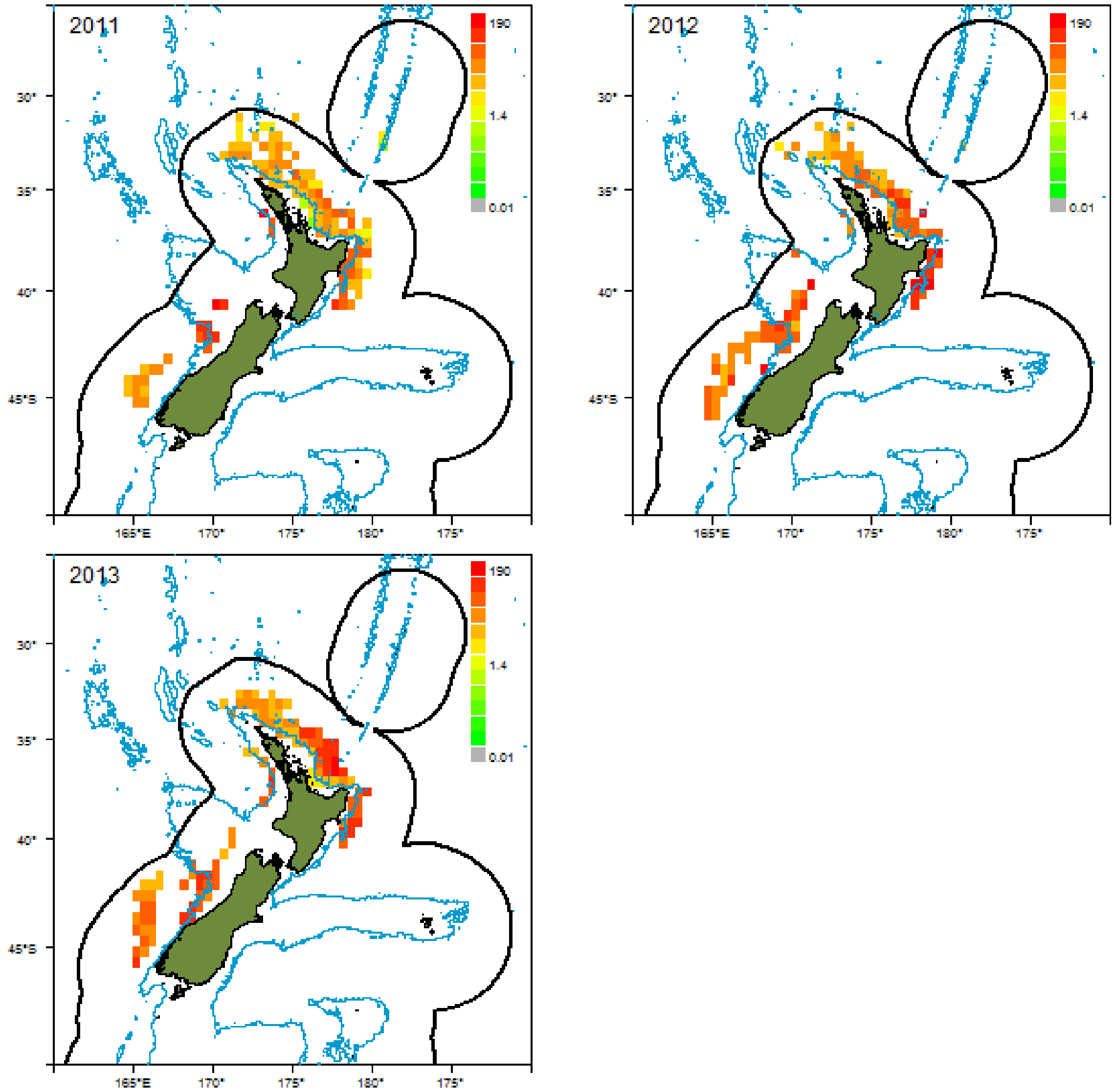
Appendix 2: continued



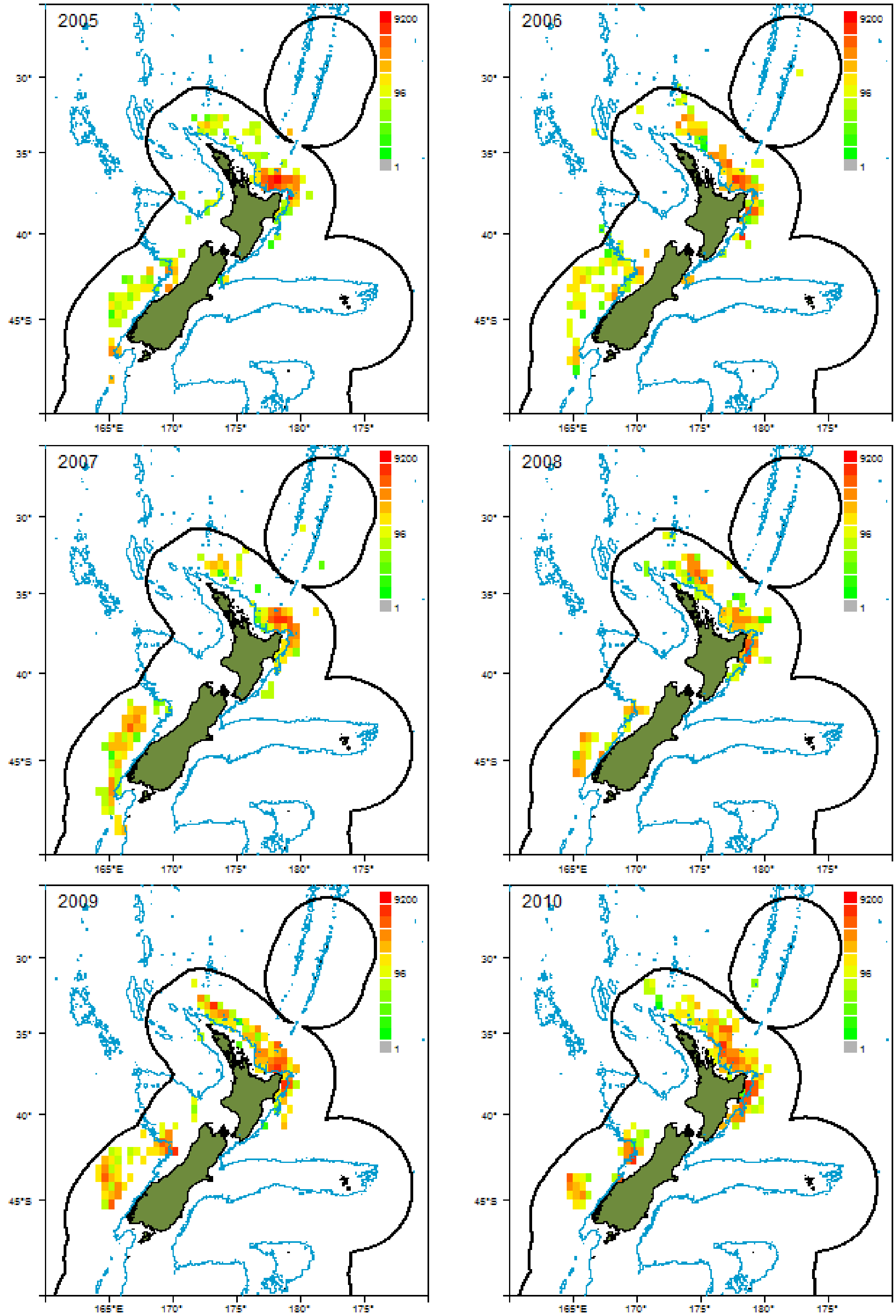
Appendix 3: Blue shark catch rates (number per 1000 hooks) by the surface longline fishery in 0.5 degree rectangles by fishing year. Note the log scale used for the colour palette. Depth contour = 1000 m.



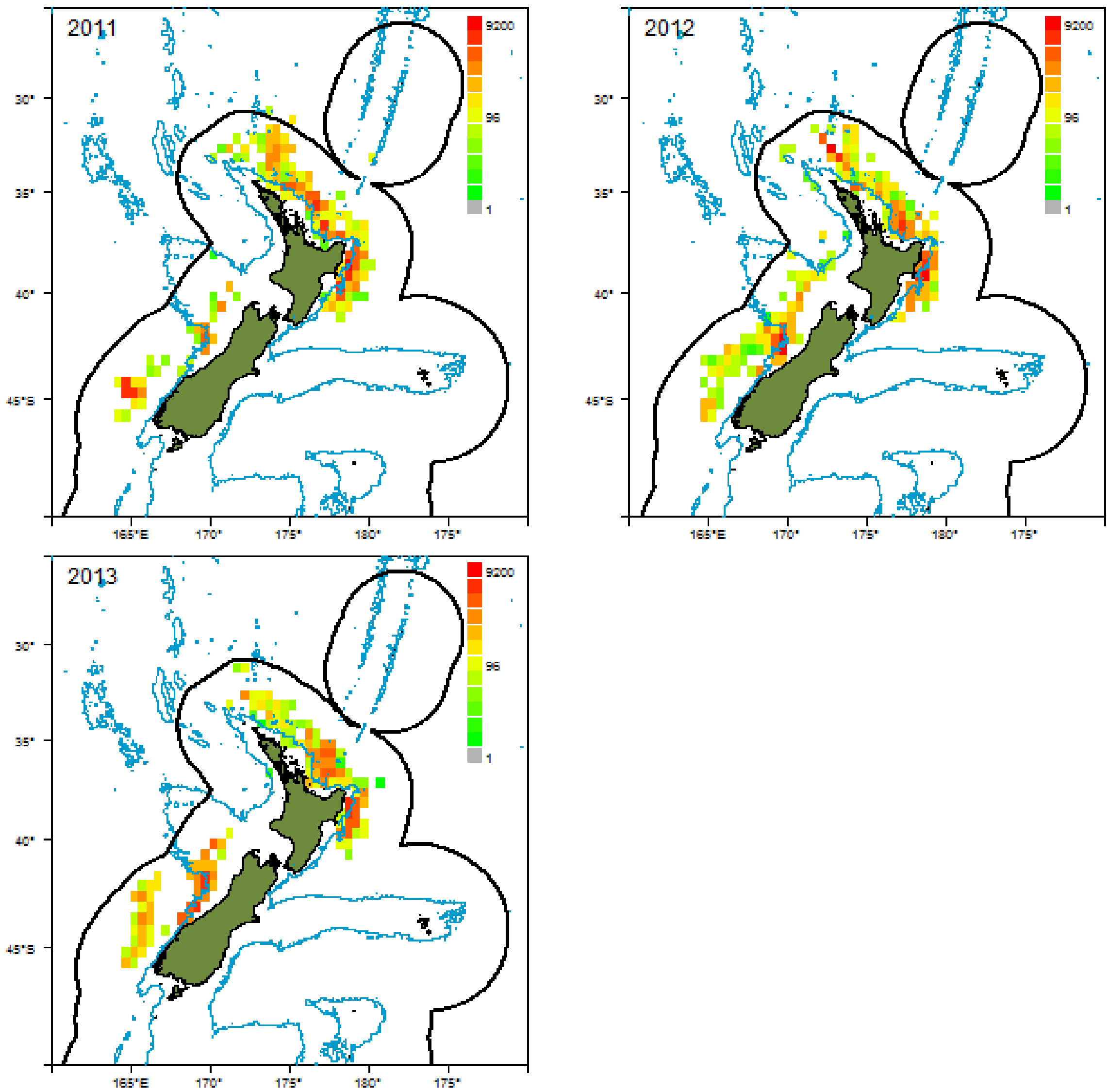
Appendix 3: continued



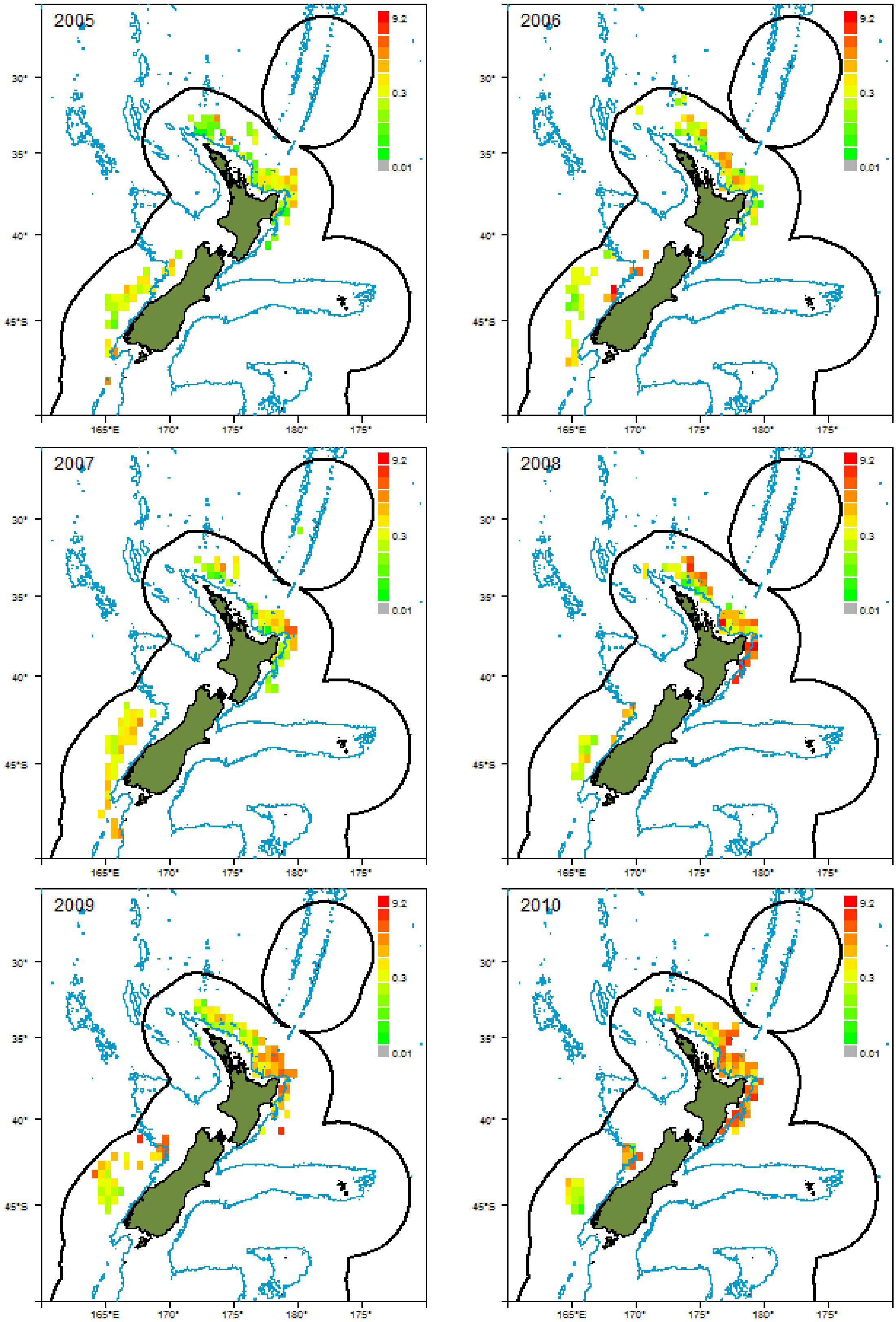
Appendix 4: Porbeagle shark catches (kg) by the surface longline fishery in 0.5 degree rectangles by fishing year. Note the log scale used for the colour palette. Depth contour = 1000 m.



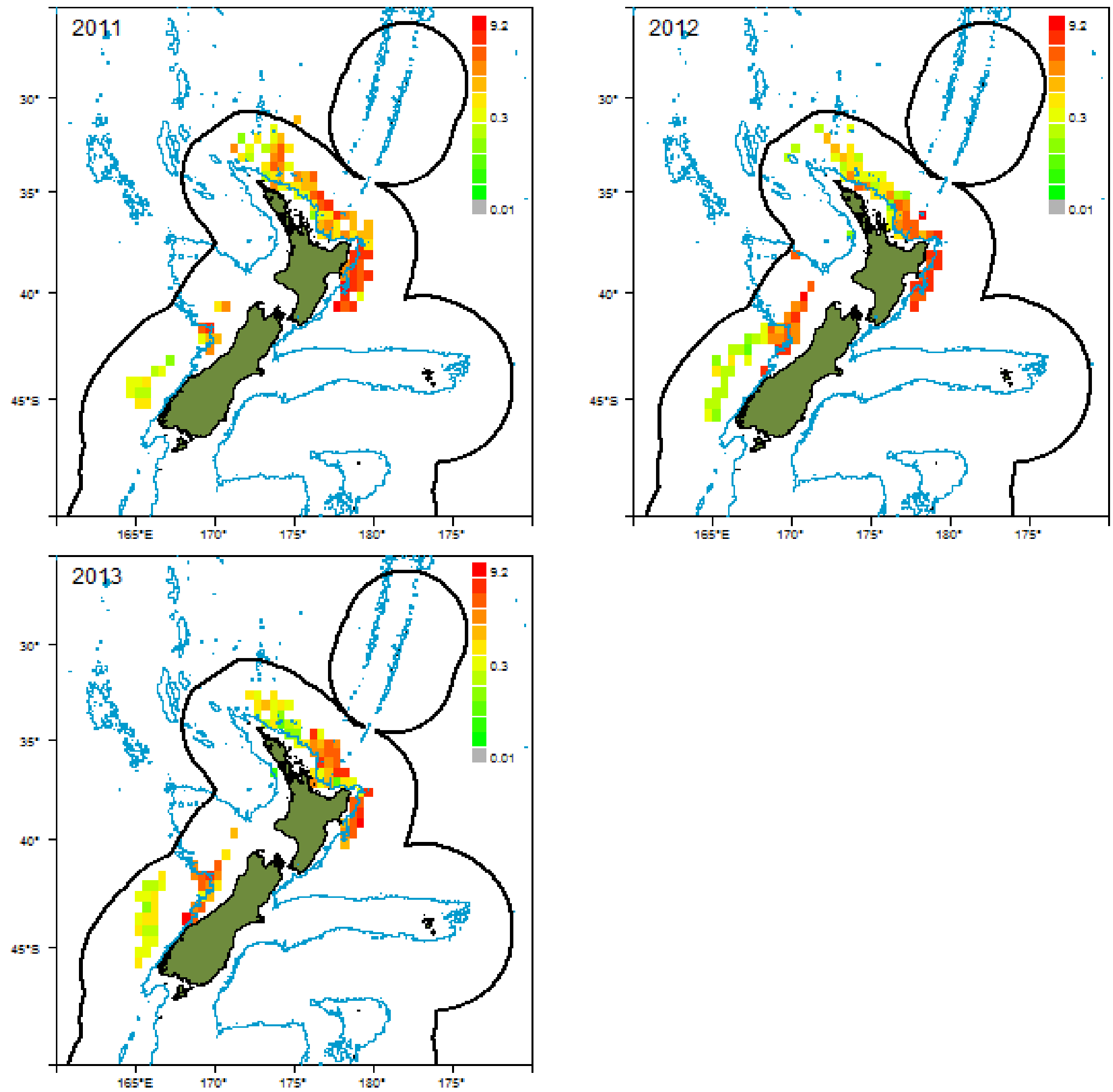
Appendix 4: continued



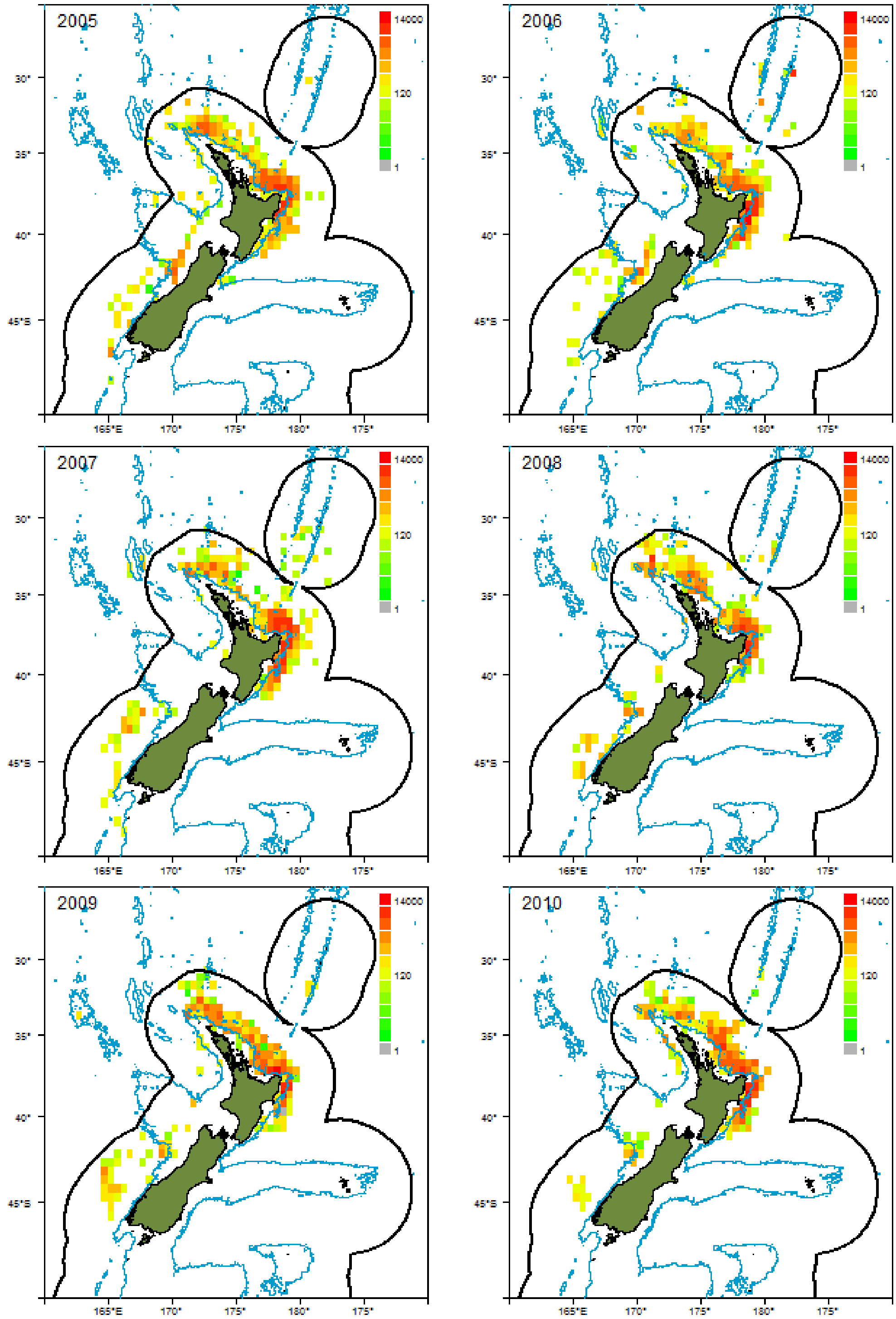
Appendix 5: Porbeagle shark catch rates (number per 1000 hooks) by the surface longline fishery in 0.5 degree rectangles by fishing year. Note the log scale used for the colour palette. Depth contour = 1000 m.



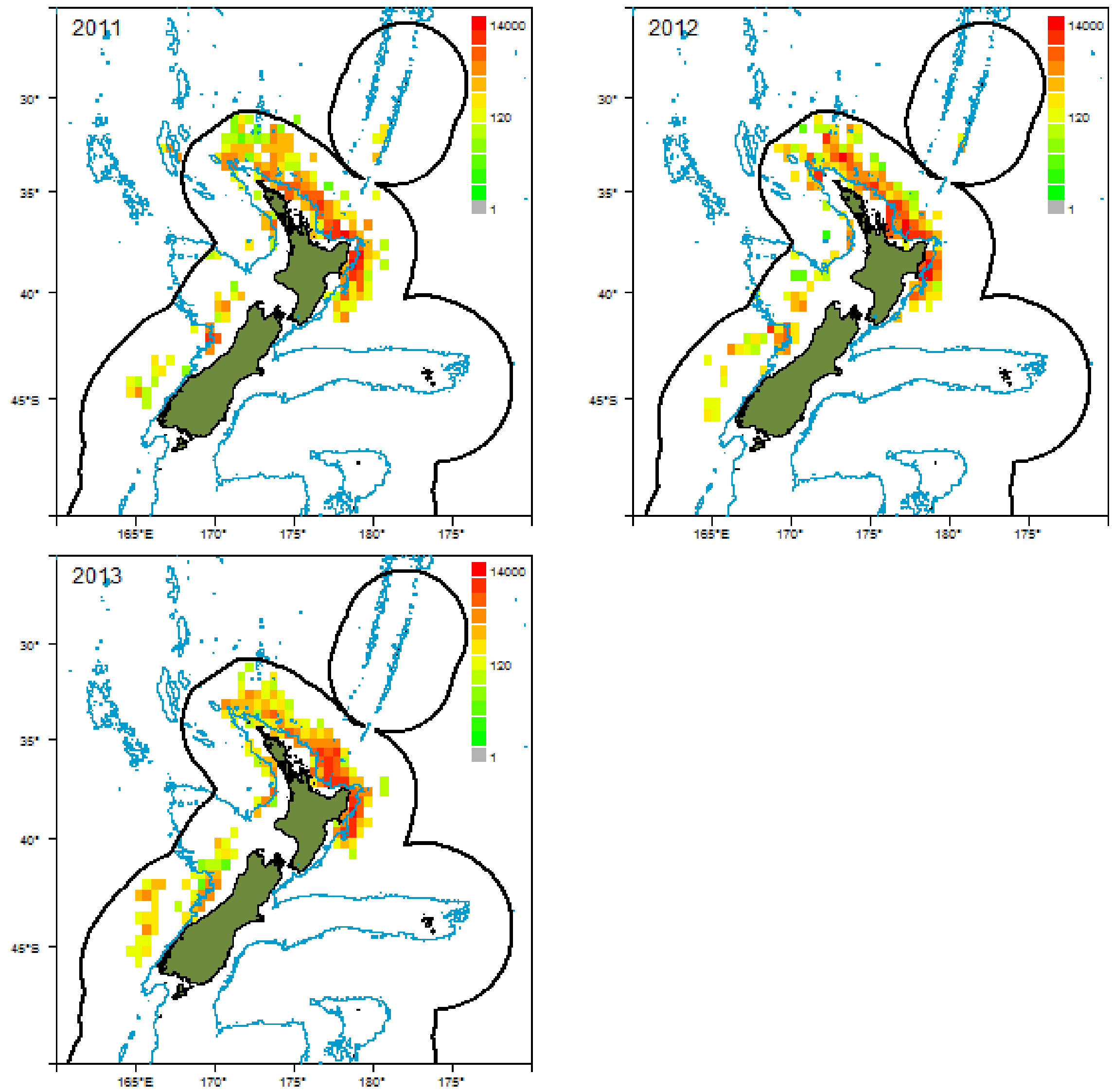
Appendix 5: continued



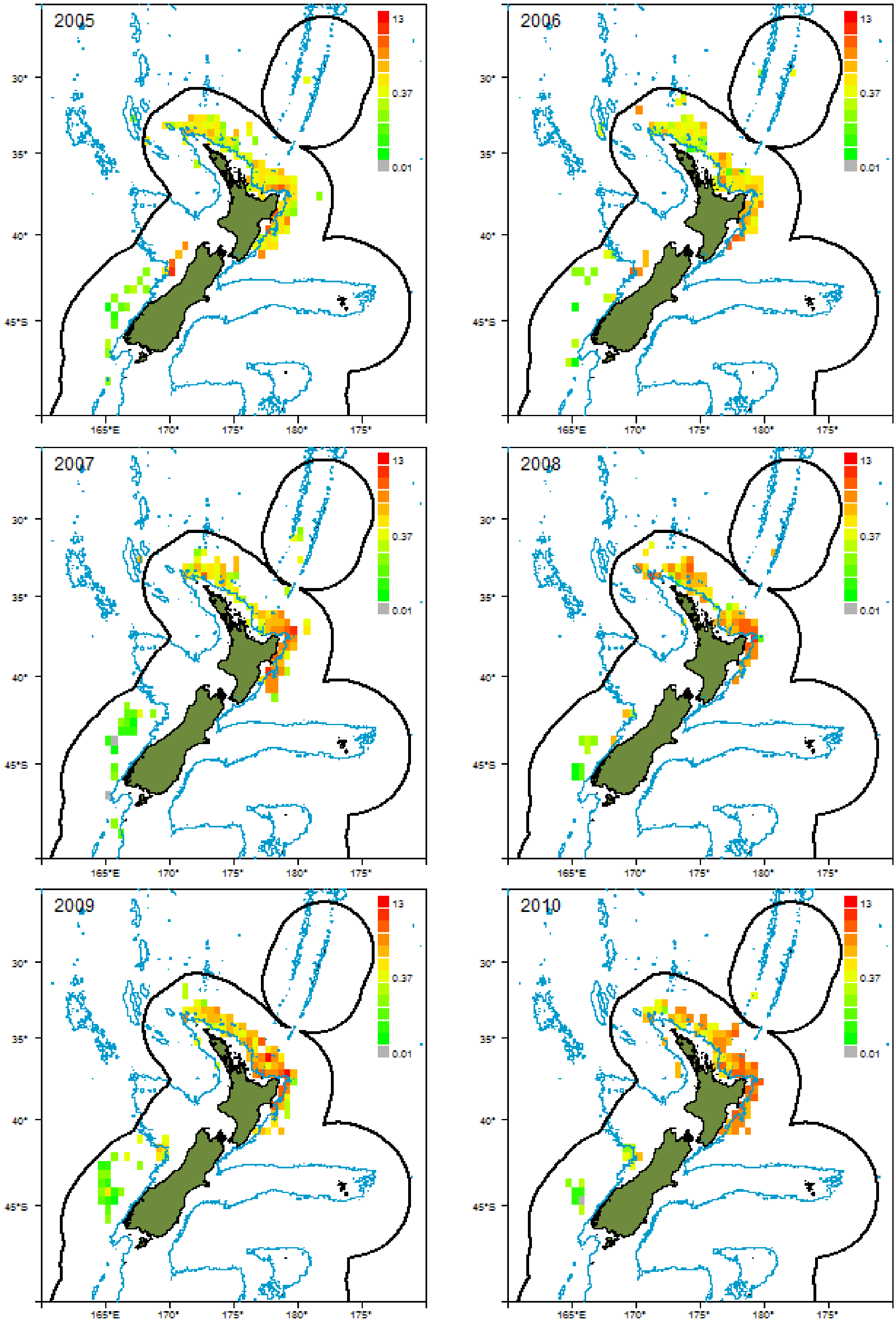
Appendix 6: Mako shark catches (kg) by the surface longline fishery in 0.5 degree rectangles by fishing year. Note the log scale used for the colour palette. Depth contour = 1000 m.



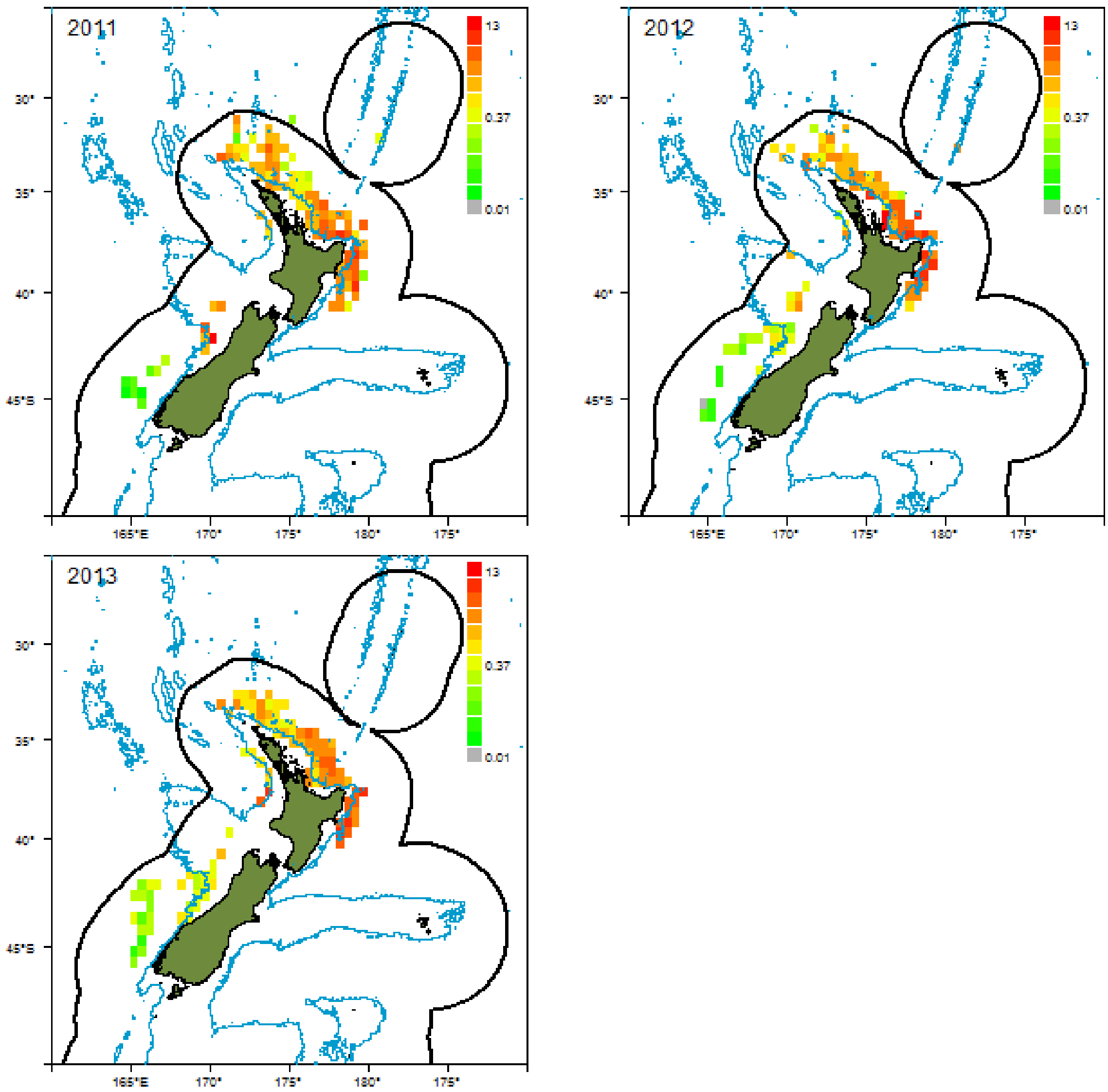
Appendix 6: continued



Appendix 7: Mako shark catch rates (number per 1000 hooks) by the surface longline fishery in 0.5 degree rectangles by fishing year. Note the log scale used for the colour palette. Depth contour = 1000 m.



Appendix 7: continued



Appendix 8: Tables of catch proportions

Table A1: Proportion of the catch by each fleet in each year (2005-2013) comprised of blue, mako and porbeagle sharks, other sharks (all chondrichthyan fishes besides the three aforementioned species) and other catch (teleost fishes, both target and non-target, and other non-target species). Due to rounding, proportions may not tally exactly to 1.

	2005	2006	2007	2008	2009	2010	2011	2012	2013
									TLCER Japan South
Blue	0.64	0.54	0.50	0.54	0.55	0.40	0.54	0.62	0.63
Mako	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.01
Porbeagle	0.02	0.02	0.03	0.01	0.02	0.01	0.01	0.01	0.01
Other Sharks	0.04	0.18	0.06	0.05	0.05	0.05	0.06	0.06	0.06
Other Catch	0.30	0.26	0.40	0.39	0.37	0.53	0.39	0.31	0.29
									TLCER Domestic South
Blue	0.73	0.81	0.93	0.81	0.76	0.74	0.73	0.65	0.58
Mako	0.07	0.03	0.02	0.01	0.01	0.01	0.02	0.01	0.01
Porbeagle	0.02	0.05	0.01	0.01	0.04	0.03	0.02	0.04	0.03
Other Sharks	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Other Catch	0.18	0.11	0.04	0.17	0.19	0.23	0.23	0.30	0.38
									TLCER North
Blue	0.27	0.31	0.42	0.43	0.32	0.36	0.32	0.51	0.49
Mako	0.02	0.03	0.03	0.04	0.03	0.03	0.05	0.05	0.03
Porbeagle	0.01	0.01	0.01	0.03	0.02	0.02	0.04	0.03	0.02
Other Sharks	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Other Catch	0.70	0.66	0.53	0.5	0.63	0.58	0.59	0.41	0.45

Appendix 8: continued

Table A2: Proportion of the catch in the observer dataset by each fleet in each year (2005–2013) comprised of blue sharks, mako sharks, porbeagle sharks, other sharks (all chondrichthyan fishes besides the three aforementioned species) and other catch (teleost fishes, both target and non-target, and other non-target species). Due to rounding, proportions may not tally exactly to 1. NA = no data available.

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Observer Japan South																								
Blue	0.53	0.36	0.14	0.35	0.18	0.22	NA	0.45	0.42	0.36	0.37	0.44	0.30	0.29	0.31	0.34	0.26	0.24	0.29	0.32	0.19	0.20	0.43	0.38
Mako	0.01	0.02	0.03	0.00	0.00	0.01	NA	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Porbeagle	0.02	0.01	0.06	0.08	0.03	0.07	NA	0.02	0.09	0.11	0.06	0.03	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Other Sharks	0.03	0.01	0.09	0.08	0.03	0.11	NA	0.04	0.06	0.08	0.05	0.02	0.03	0.04	0.05	0.04	0.06	0.04	0.03	0.04	0.03	0.03	0.04	0.04
Other Catch	0.42	0.59	0.68	0.49	0.75	0.59	NA	0.48	0.44	0.44	0.53	0.50	0.65	0.65	0.63	0.62	0.67	0.71	0.67	0.63	0.77	0.76	0.52	0.57
Observer Domestic South																								
Blue	NA	NA	NA	NA	NA	0.17	0.62	NA	NA	NA	NA	NA	NA	NA	0.22	0.62	0.06	NA	NA	0.42	0.68	0.25	0.63	0.66
Mako	NA	NA	NA	NA	NA	<0.01	<0.01	NA	NA	NA	NA	NA	NA	NA	0.01	<0.01	0.02	NA	NA	0.01	0.01	0.04	<0.01	0.01
Porbeagle	NA	NA	NA	NA	NA	0.02	0.04	NA	NA	NA	NA	NA	NA	NA	0.06	0.03	0.01	NA	NA	0.02	0.02	<0.01	0.03	0.10
Other Sharks	NA	NA	NA	NA	NA	0.03	0.03	NA	NA	NA	NA	NA	NA	NA	0.02	<0.01	0.01	NA	NA	0.01	<0.01	0.08	<0.01	<0.01
Other Catch	NA	NA	NA	NA	NA	0.77	0.3	NA	NA	NA	NA	NA	NA	NA	0.70	0.35	0.91	NA	NA	0.54	0.30	0.62	0.34	0.23
Observer North																								
Blue	0.16	0.22	0.34	0.64	0.75	0.88	0.17	0.51	0.30	0.29	0.30	0.17	0.33	0.13	0.23	0.31	0.43	0.53	0.63	0.53	0.58	0.32	0.64	0.54
Mako	0.01	0.04	0.03	0.01	0.01	0.00	0.02	0.02	0.01	0.02	0.01	0.02	0.02	0.01	0.02	0.04	0.03	0.04	0.03	0.03	0.03	0.05	0.02	0.01
Porbeagle	0.07	0.02	0.04	0.07	0.04	0.04	0.06	0.03	0.02	0.07	0.03	0.01	0.01	0.01	0.04	0.02	0.02	0.03	0.05	0.03	0.05	0.06	0.04	0.02
Other Sharks	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.03	0.01	0.01	0.04	0.01	0.02	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01
Other Catch	0.75	0.72	0.58	0.27	0.20	0.08	0.72	0.44	0.65	0.61	0.63	0.79	0.64	0.81	0.70	0.61	0.51	0.40	0.28	0.41	0.34	0.55	0.30	0.42

Appendix 8: continued

Table A3: Proportion of the catch by each fleet in the TLCER dataset in each year (2005-2013) comprised of blue, mako and porbeagle sharks. Due to rounding, proportions may not tally exactly to 1.

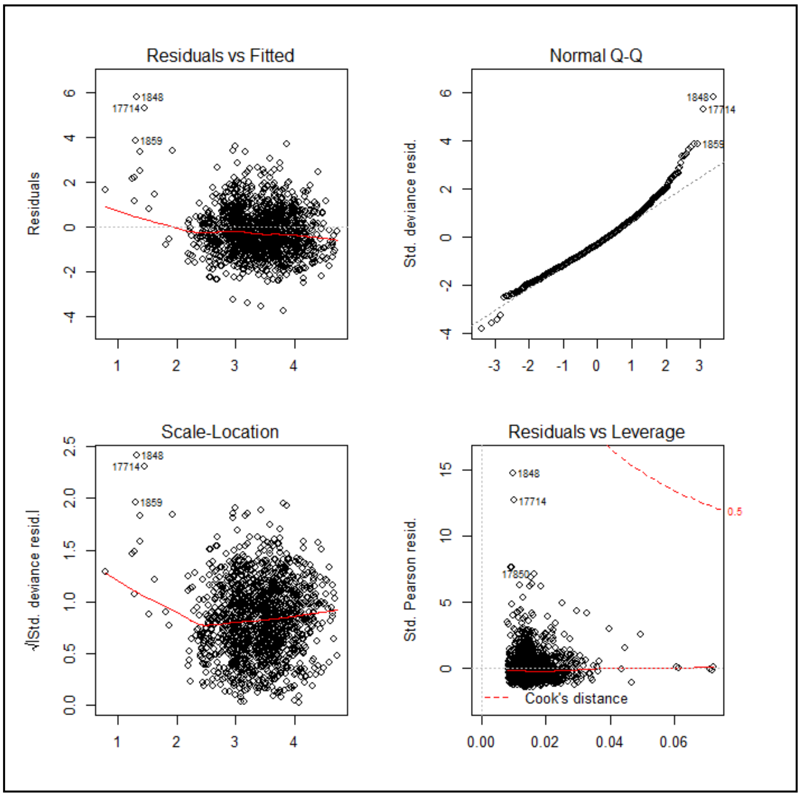
	2005	2006	2007	2008	2009	2010	2011	2012	2013
									TLCER Japan South
Blue	0.97	0.96	0.93	0.98	0.95	0.96	0.97	0.98	0.97
Mako	0.01	<0.01	0.01	0.01	0.01	0.01	0.01	<0.01	0.01
Porbeagle	0.02	0.04	0.06	0.02	0.04	0.03	0.03	0.01	0.02
									TLCER Domestic South
Blue	0.90	0.91	0.97	0.97	0.94	0.96	0.95	0.93	0.94
Mako	0.08	0.03	0.02	0.01	0.01	0.01	0.03	0.01	0.01
Porbeagle	0.02	0.06	0.01	0.01	0.05	0.03	0.02	0.06	0.05
									TLCER North
Blue	0.90	0.90	0.91	0.87	0.86	0.87	0.79	0.87	0.89
Mako	0.08	0.07	0.07	0.07	0.09	0.08	0.11	0.08	0.06
Porbeagle	0.02	0.02	0.02	0.06	0.05	0.05	0.09	0.05	0.04

Appendix 8: continued

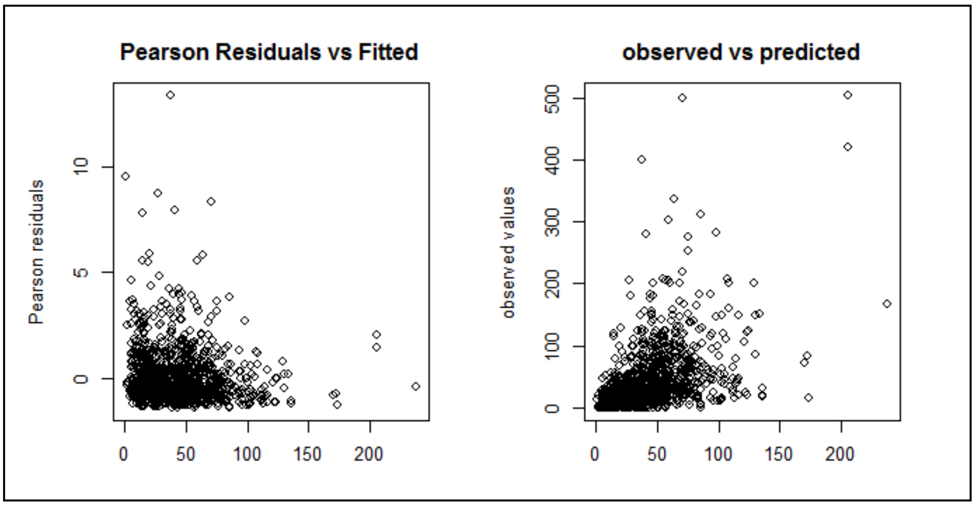
Table A4: Proportion of the catch in the observer dataset by each fleet in each year (2005-2013) comprised of blue, mako and porbeagle sharks. Due to rounding, proportions may not tally exactly to 1. NA = no data available.

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Observer Japan South																								
Blue	0.96	0.92	0.63	0.8	0.84	0.73	NA	0.94	0.82	0.76	0.86	0.93	0.94	0.93	0.95	0.97	0.96	0.93	0.98	0.95	0.96	0.96	0.98	0.97
Mako	0.01	0.05	0.12	0.01	0.02	0.04	NA	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	<0.01	0.01	0.01	0.01	0.01	0.01	<0.01	0.01
Porbeagle	0.03	0.03	0.25	0.19	0.14	0.23	NA	0.05	0.18	0.23	0.14	0.06	0.05	0.06	0.04	0.02	0.04	0.06	0.02	0.04	0.03	0.03	0.01	0.02
Observer Domestic South																								
Blue	NA	NA	NA	NA	NA	0.89	0.93	NA	NA	NA	NA	NA	NA	NA	0.78	0.95	0.70	NA	NA	0.93	0.97	0.86	0.94	0.86
Mako	NA	NA	NA	NA	NA	<0.01	<0.01	NA	NA	NA	NA	NA	NA	NA	0.03	<0.01	0.20	NA	NA	0.03	0.01	0.14	0.01	0.01
Porbeagle	NA	NA	NA	NA	NA	0.11	0.06	NA	NA	NA	NA	NA	NA	NA	0.19	0.04	0.11	NA	NA	0.04	0.02	0	0.05	0.13
Observer North																								
Blue	0.64	0.78	0.81	0.89	0.94	0.96	0.67	0.92	0.91	0.77	0.88	0.85	0.92	0.88	0.81	0.84	0.90	0.89	0.89	0.90	0.88	0.73	0.92	0.94
Mako	0.05	0.15	0.08	0.01	0.01	<0.01	0.09	0.03	0.03	0.05	0.03	0.09	0.05	0.08	0.06	0.10	0.06	0.07	0.04	0.04	0.05	0.13	0.03	0.03
Porbeagle	0.31	0.07	0.10	0.09	0.05	0.04	0.24	0.05	0.06	0.18	0.09	0.06	0.02	0.04	0.13	0.06	0.03	0.04	0.06	0.05	0.07	0.15	0.06	0.03

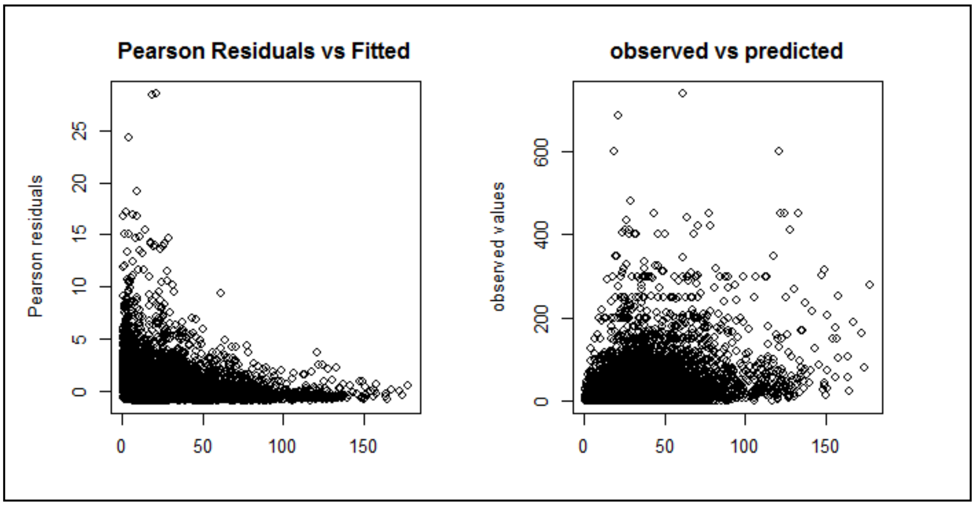
Appendix 9: Model diagnostics for negative binomial model fit to blue shark catches recorded in the TLCER Japan South dataset.



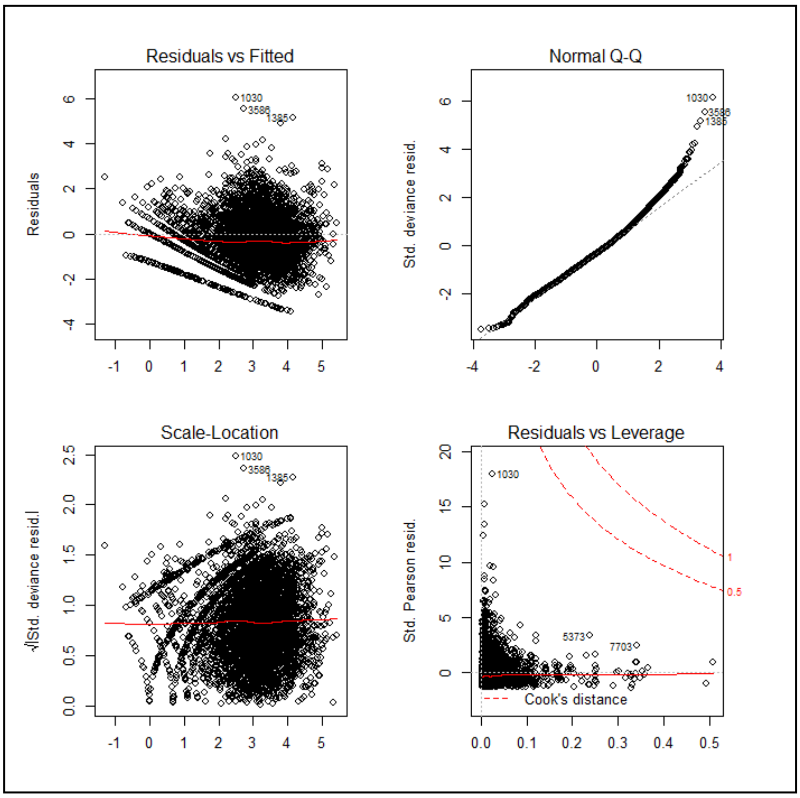
Appendix 10: Model diagnostics for zero-inflated negative binomial model fit to blue shark catches recorded in the TLCER Domestic South dataset.



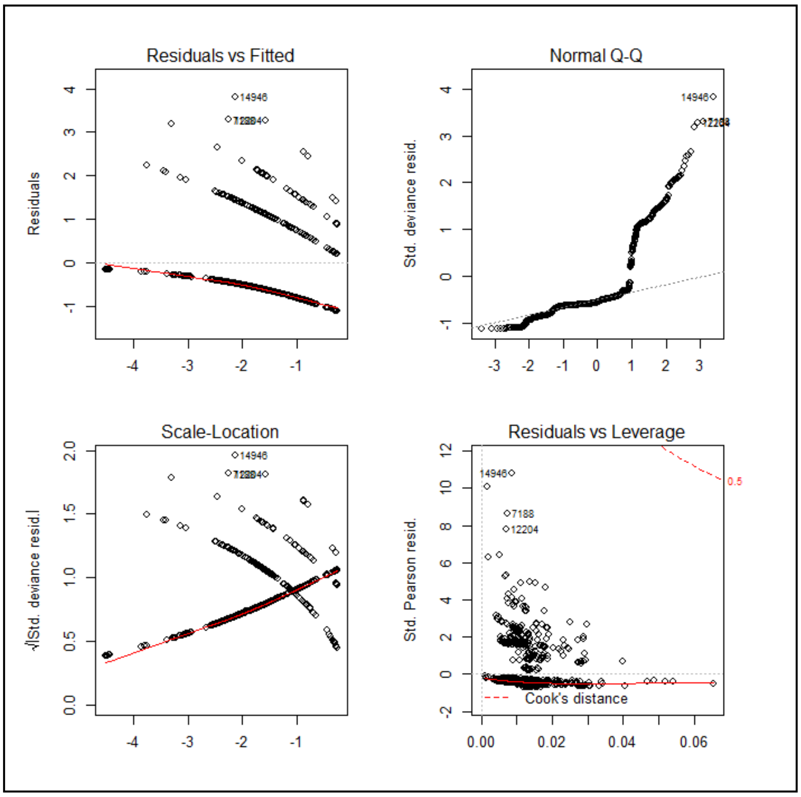
Appendix 11: Model diagnostics for zero-inflated negative binomial model fit to blue shark catches recorded in the TLCER North dataset.



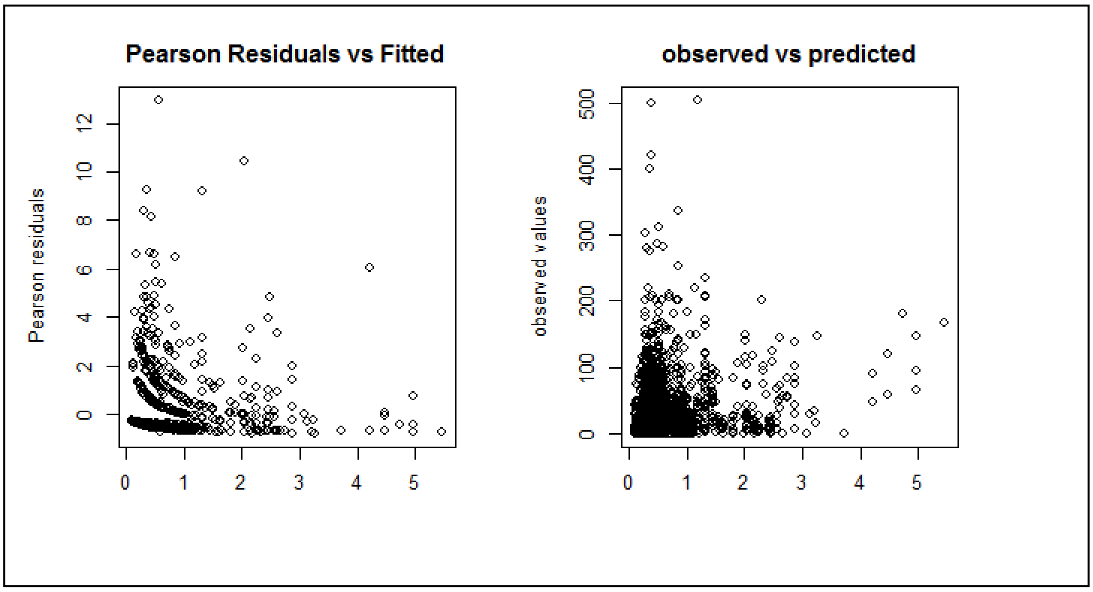
Appendix 12: Model diagnostics for negative binomial model fit to blue shark catches recorded in the observer dataset.



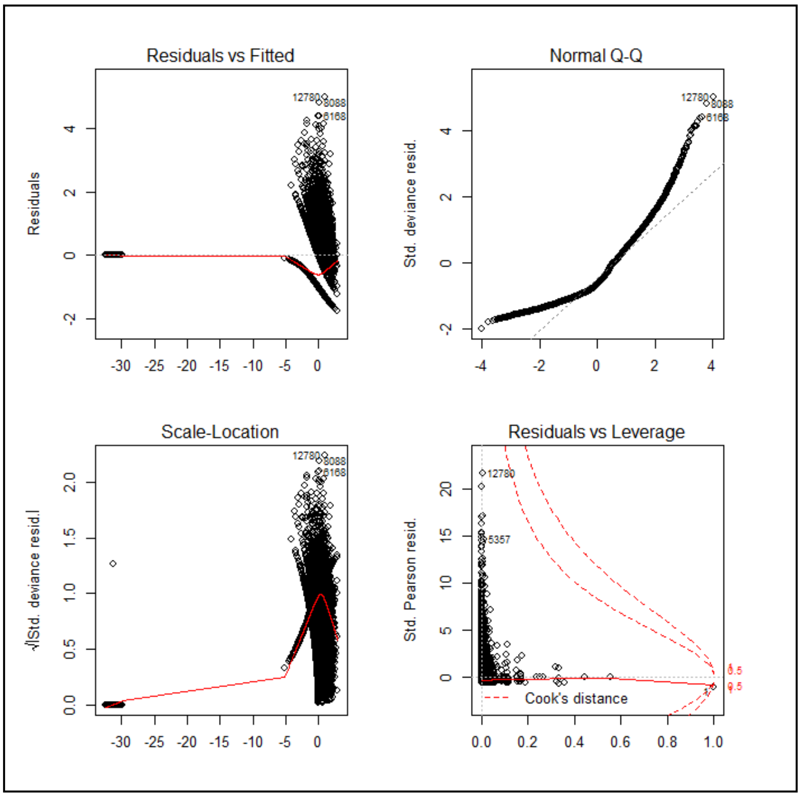
Appendix 13: Model diagnostics for negative binomial model fit to mako shark catches recorded in the TLCER Japan South dataset.



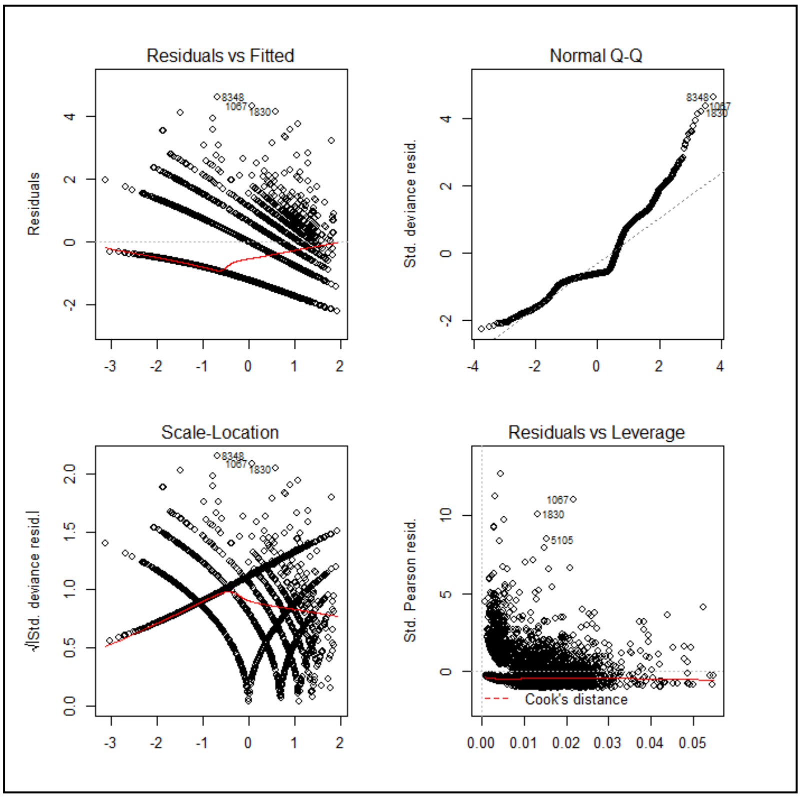
Appendix 14: Model diagnostics for zero-inflated negative binomial model fit to mako shark catches recorded in the TLCER Domestic South dataset.



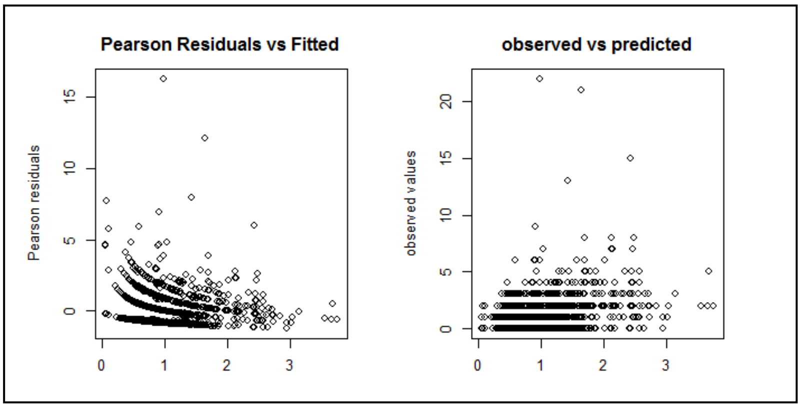
Appendix 15: Model diagnostics for negative binomial model fit to mako shark catches recorded in the TLCER North dataset.



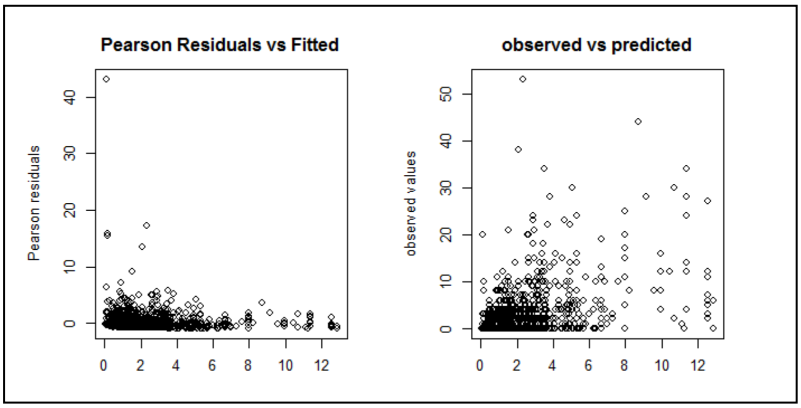
Appendix 16: Model diagnostics for negative binomial model fit to mako shark catches recorded in the observer dataset.



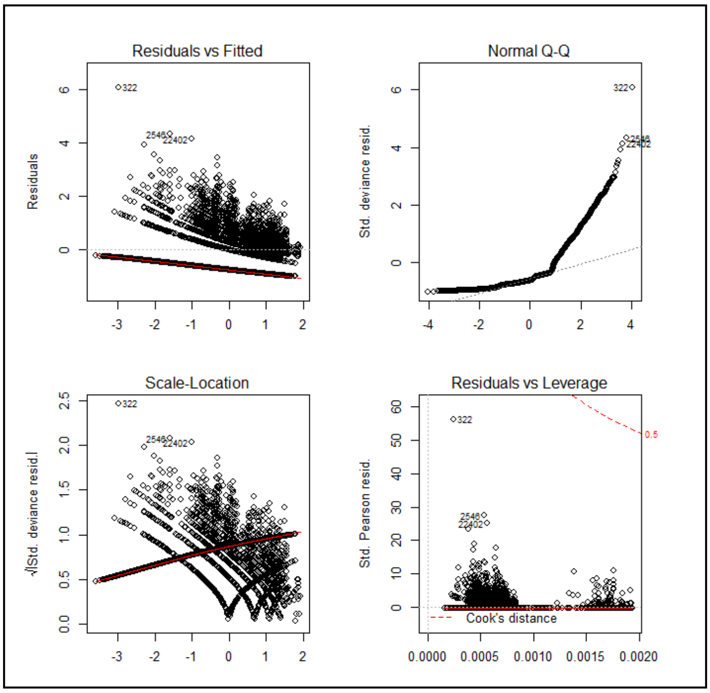
Appendix 17: Model diagnostics for zero-inflated negative binomial model fit to porbeagle shark catches recorded in the TLCER Japan South dataset.



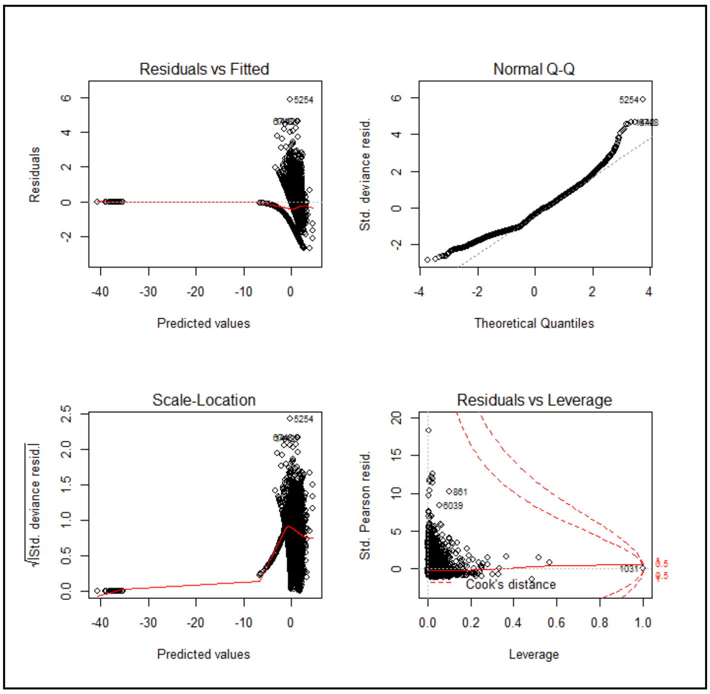
Appendix 18: Model diagnostics for zero-inflated negative binomial model fit to porbeagle shark catches recorded in the TLCER Domestic South dataset.



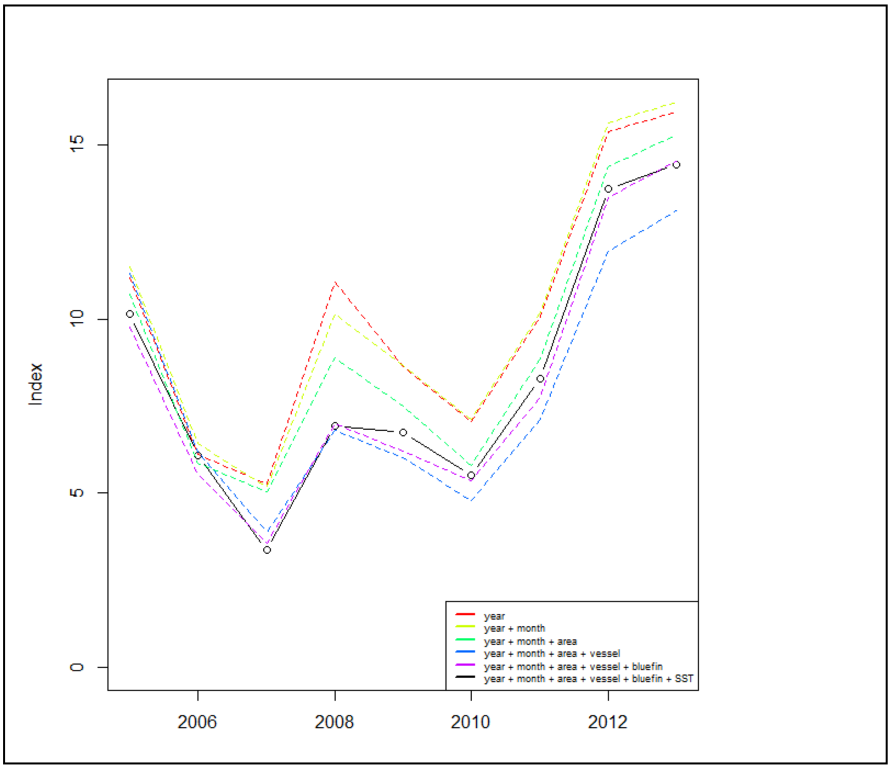
Appendix 19: Model diagnostics for negative binomial model fit to porbeagle shark catches recorded in the TLCER North dataset.



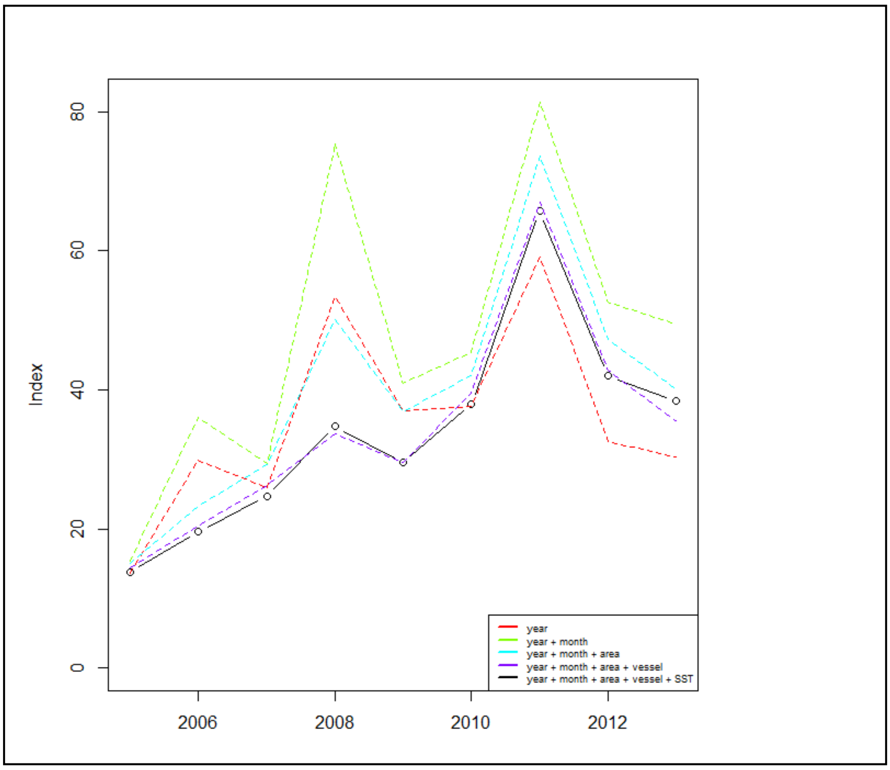
Appendix 20: Model diagnostics for negative binomial model fit to porbeagle shark catches recorded in the observer dataset.



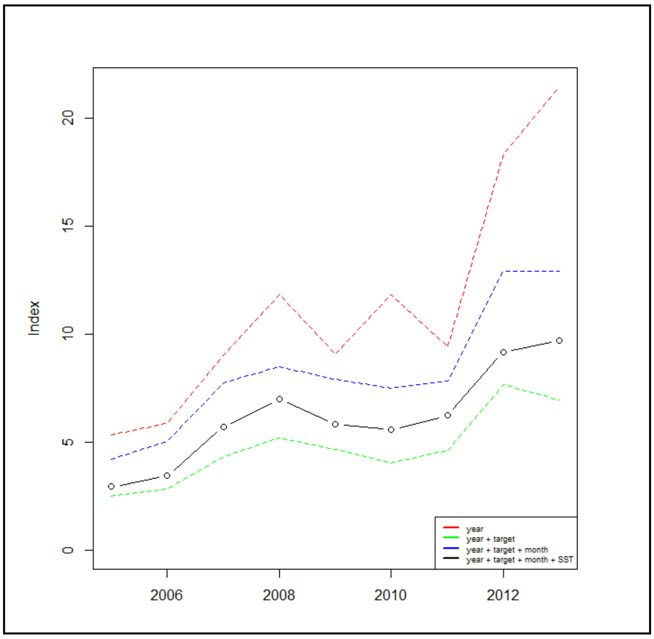
Appendix 21: CPUE standardised for year effects and other sequentially added variables for TLCER Japan South blue shark model. The final model is shown by the black solid line with points.



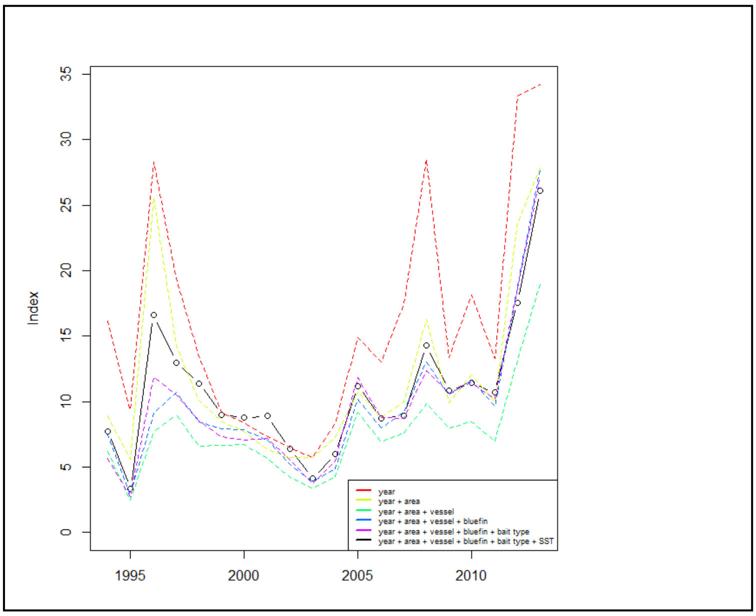
Appendix 22: CPUE standardised for year effects and other sequentially added variables for TLCER Domestic South blue shark model. The final model is shown by the black solid line with points.



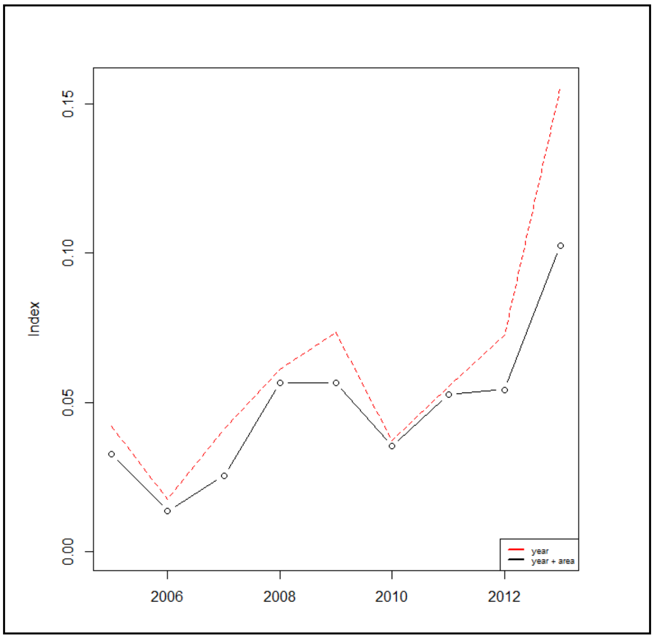
Appendix 23: CPUE standardised for year effects and other sequentially added variables for TLCER North blue shark model. The final model is shown by the black solid line with points.



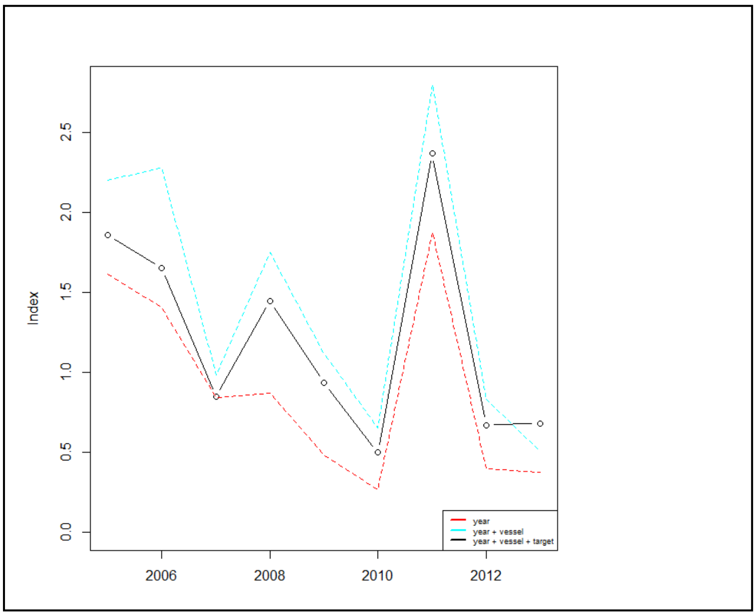
Appendix 24: CPUE standardised for year effects and other sequentially added variables for observer blue shark model. The final model is shown by the black solid line with points.



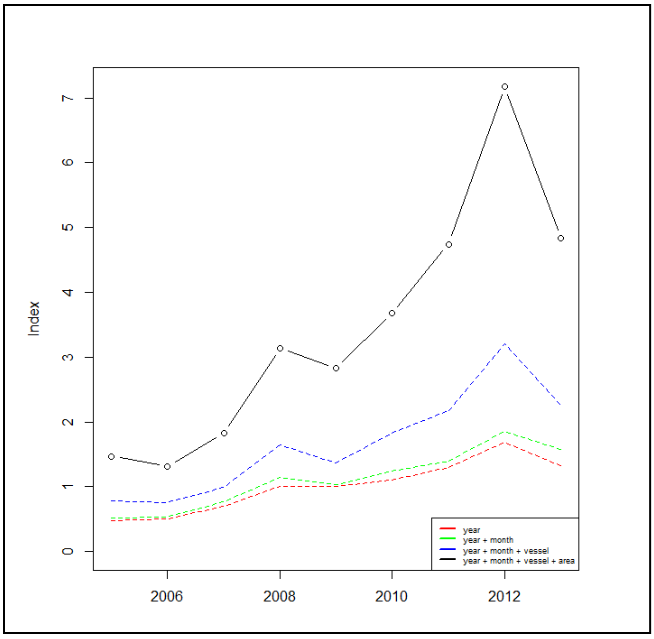
Appendix 25: CPUE standardised for year effects and other sequentially added variables for TLCER Japan South mako shark model. The final model is shown by the black solid line with points.



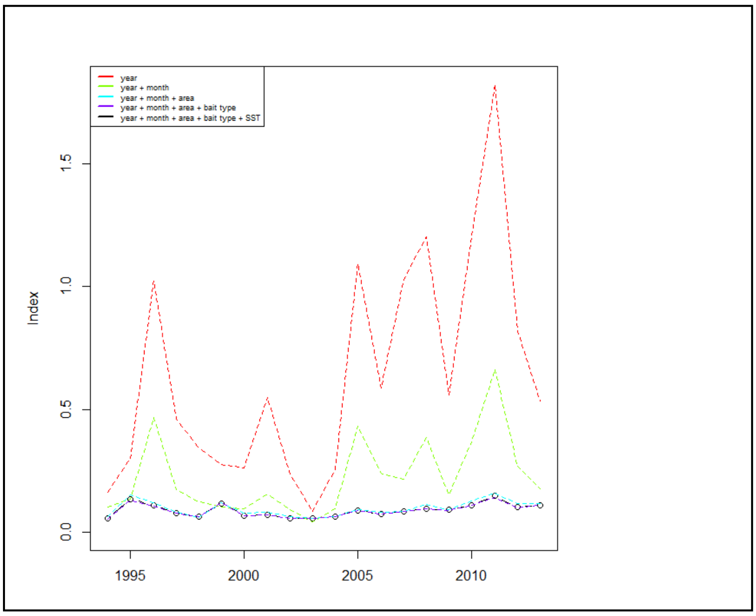
Appendix 26: CPUE standardised for year effects and other sequentially added variables for TLCER Domestic South mako shark model. The final model is shown by the black solid line with points.



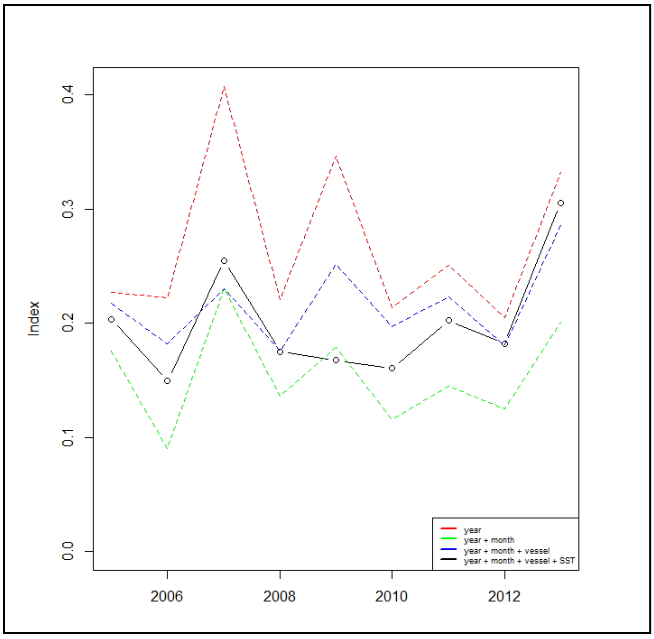
Appendix 27: CPUE standardised for year effects and other sequentially added variables for TLCER North mako shark model. The final model is shown by the black solid line with points.



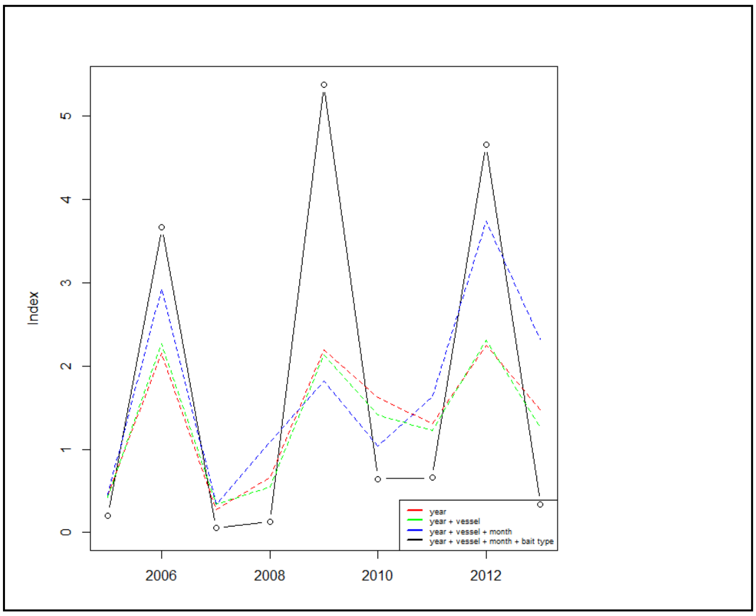
Appendix 28: CPUE standardised for year effects and other sequentially added variables for observer mako shark model. The final model is shown by the black solid line with points.



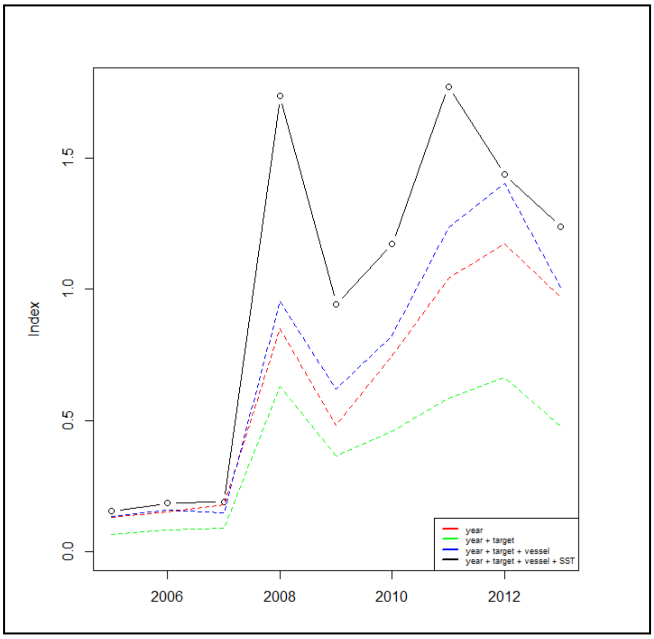
Appendix 29: CPUE standardised for year effects and other sequentially added variables for TLCER Japan South porbeagle shark model. The final model is shown by the black solid line with points.



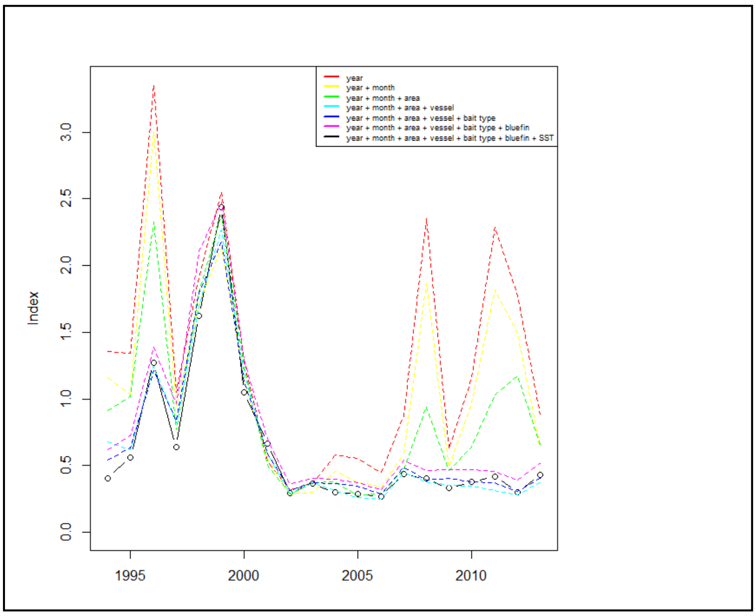
Appendix 30: CPUE standardised for year effects and other sequentially added variables for TLCER Domestic South porbeagle shark model. The final model is shown by the black solid line with points.



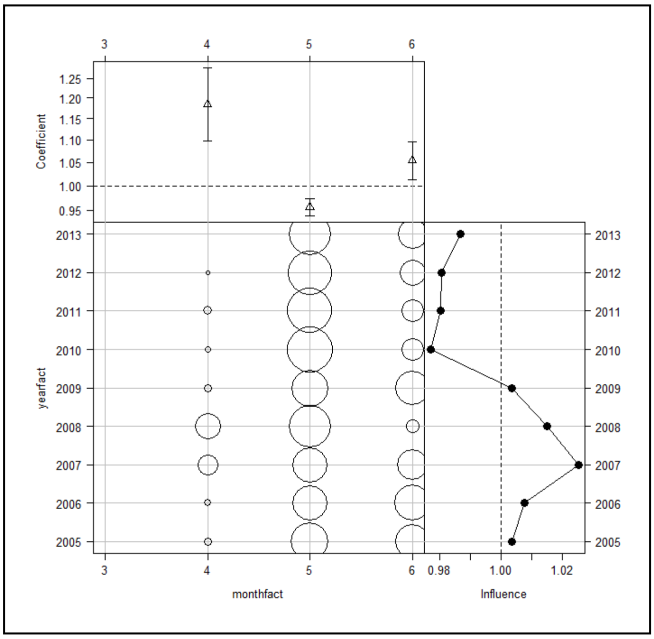
Appendix 31: CPUE standardised for year effects and other sequentially added variables for TLCER North porbeagle shark model. The final model is shown by the black solid line with points.



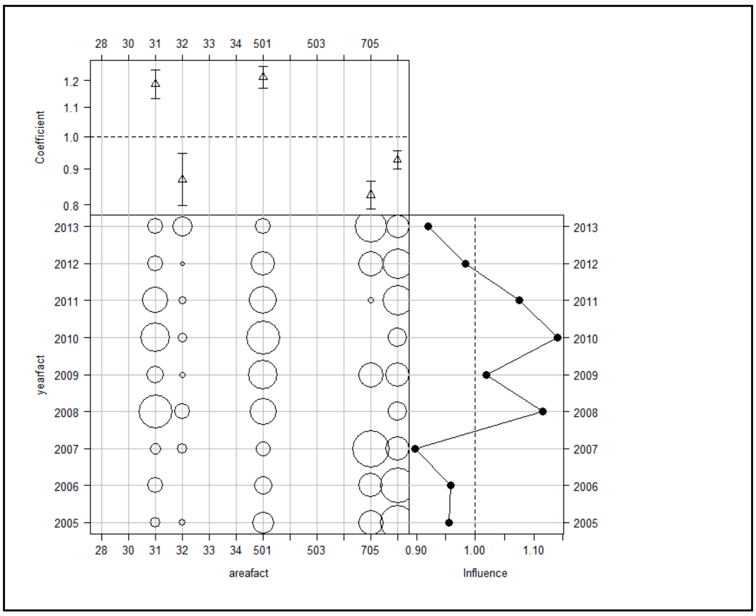
Appendix 32: CPUE standardised for year effects and other sequentially added variables for observer porbeagle shark model. The final model is shown by the black solid line with points.



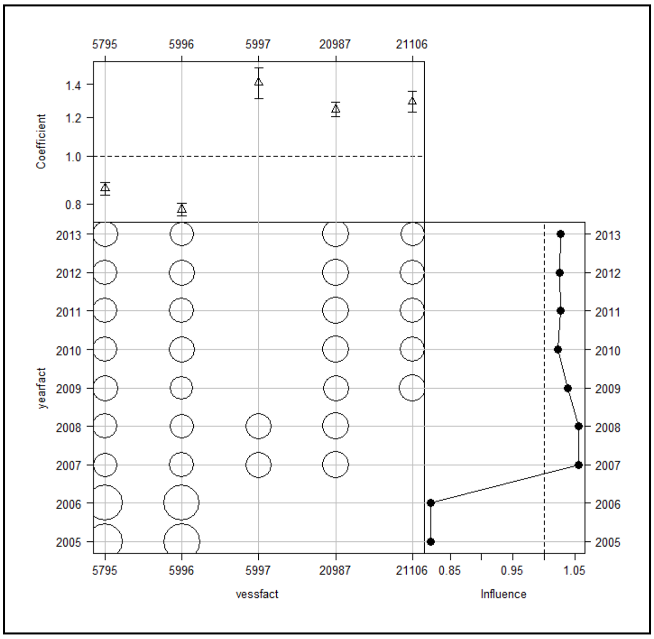
Appendix 33: Influence plot for the explanatory variable "month" in the negative binomial model of blue shark CPUE for the TLCER Japan South dataset



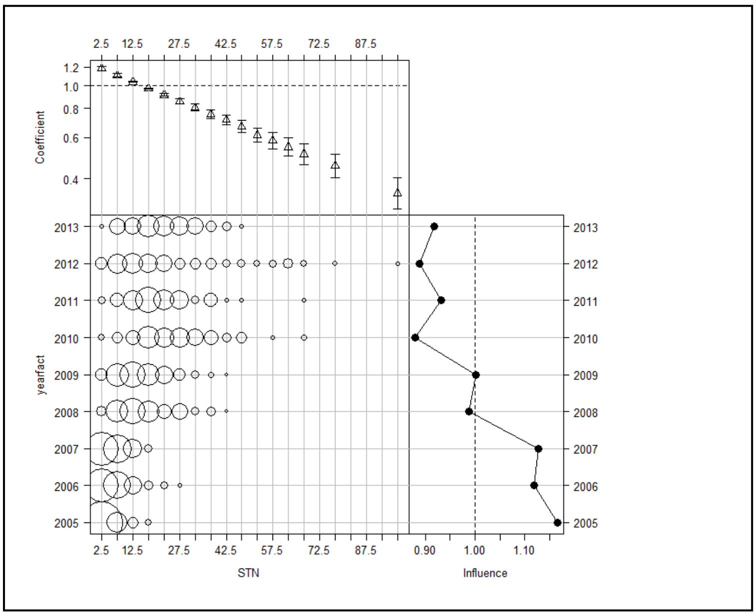
Appendix 34: Influence plot for the explanatory variable "area" (as New Zealand General Statistical Area) in the negative binomial model of blue shark CPUE for the TLCER Japan South dataset



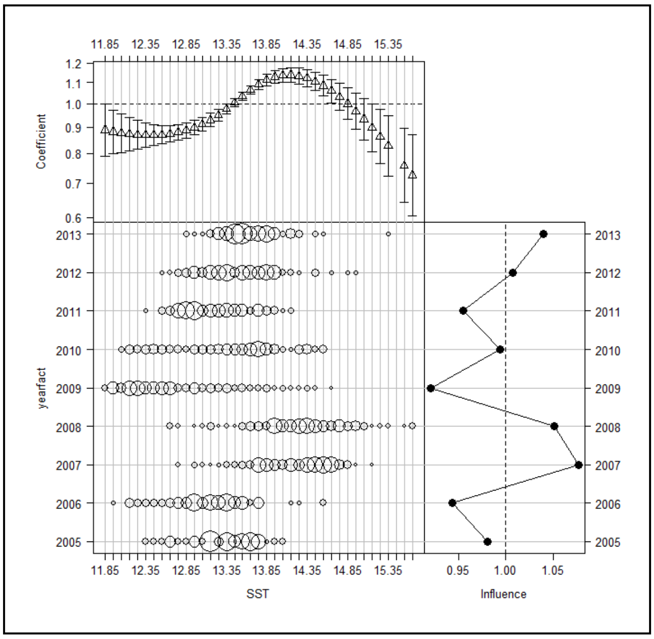
Appendix 35: Influence plot for the explanatory variable "vessel" in the negative binomial model of blue shark CPUE for the TLCER Japan South dataset



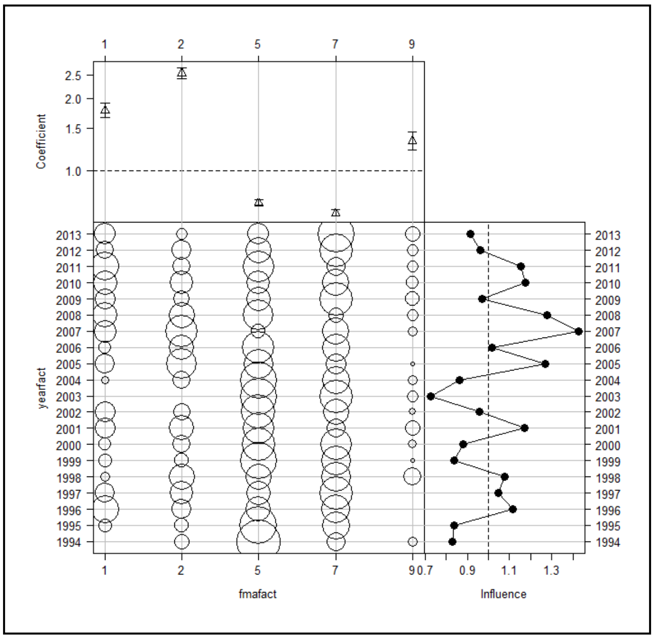
Appendix 36: Influence plot for the explanatory variable "catch of southern bluefin tuna (STN)" in the negative binomial model of blue shark CPUE for the TLCER Japan South dataset



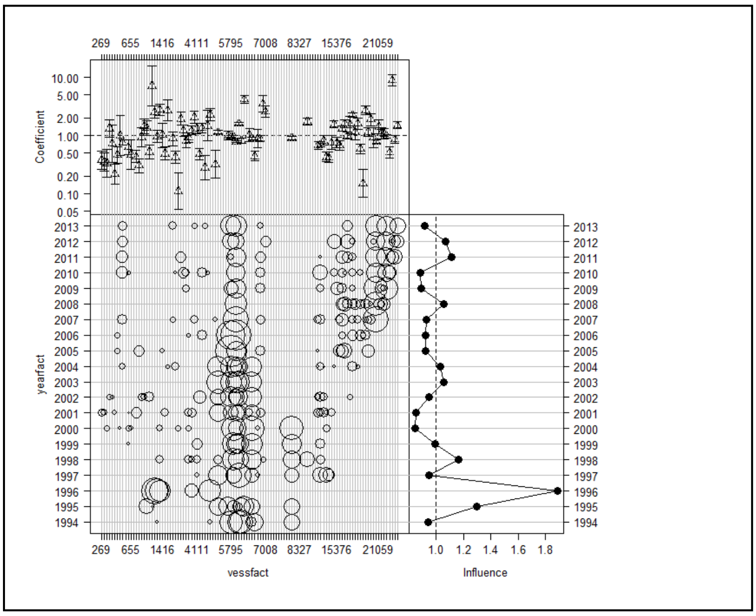
Appendix 37: Influence plot for the explanatory variable “sea surface temperature” in the negative binomial model of blue shark CPUE for the TLCER Japan South dataset



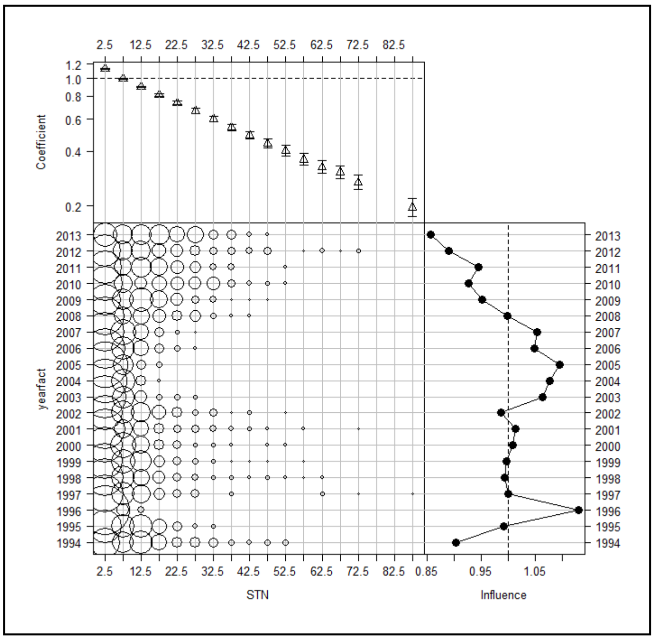
Appendix 38: Influence plot for the explanatory variable “area” (as FMA area) in the negative binomial model of blue shark CPUE for the observer dataset



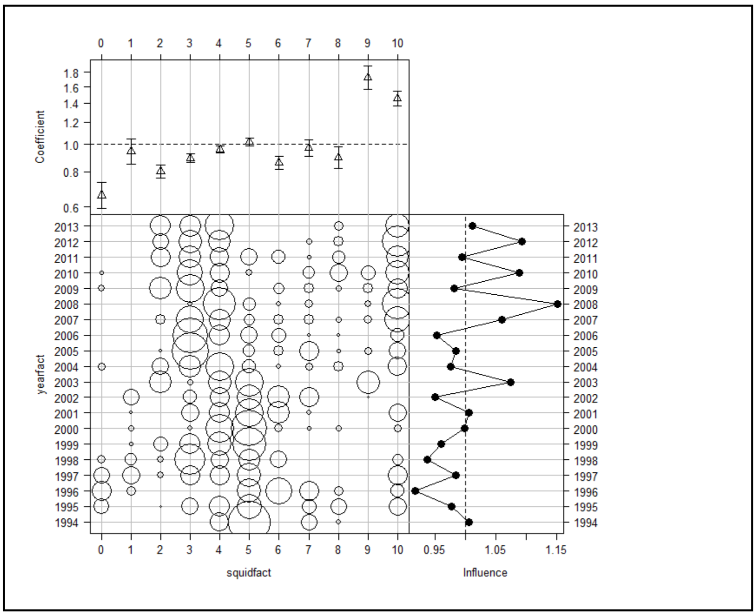
Appendix 39: Influence plot for the explanatory variable "vessel" in the negative binomial model of blue shark CPUE for the observer dataset.



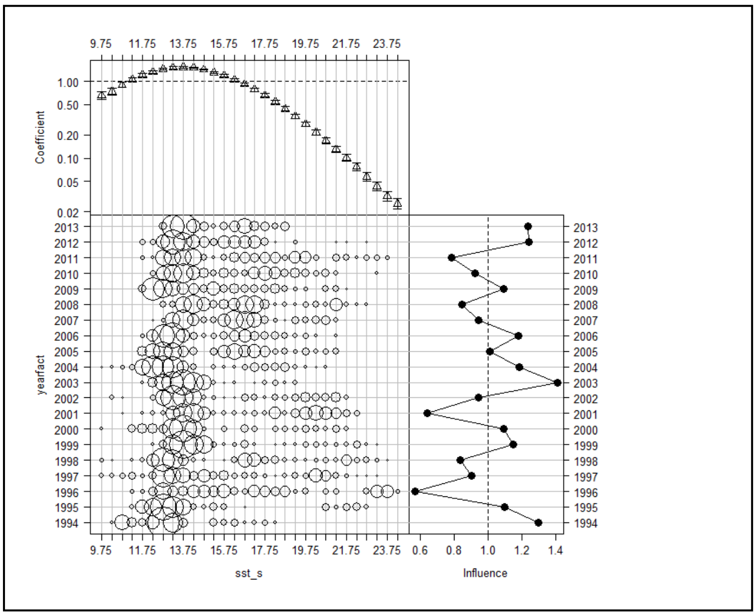
Appendix 40: Influence plot for the explanatory variable "catch of southern bluefin tuna (STN)" in the negative binomial model of blue shark CPUE for the observer dataset.



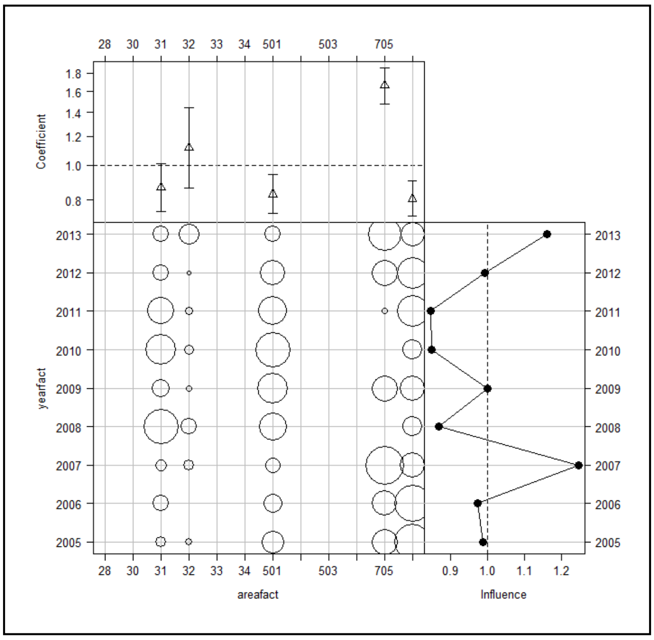
Appendix 41: Influence plot for the explanatory variable "percentage squid bait" (in intervals of 10%) in the negative binomial model of blue shark CPUE for the observer dataset.



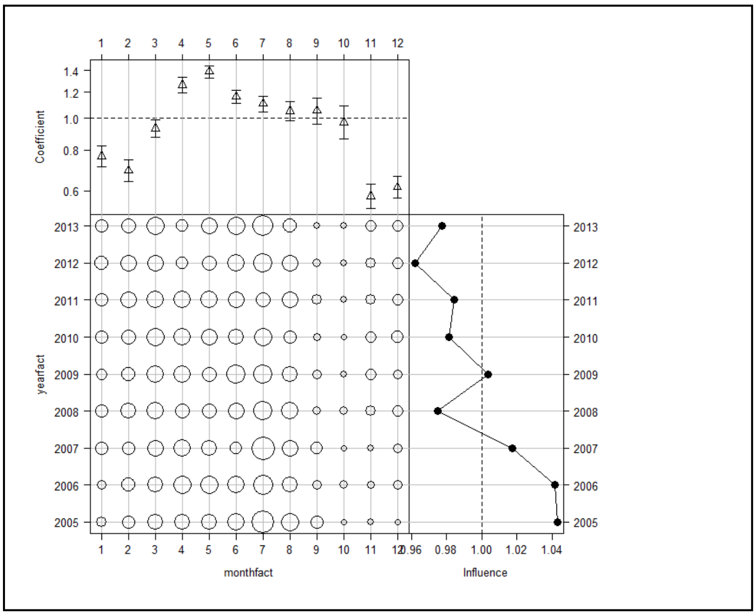
Appendix 42: Influence plot for the explanatory variable "sea surface temperature" in the negative binomial model of blue shark CPUE for the observer dataset.



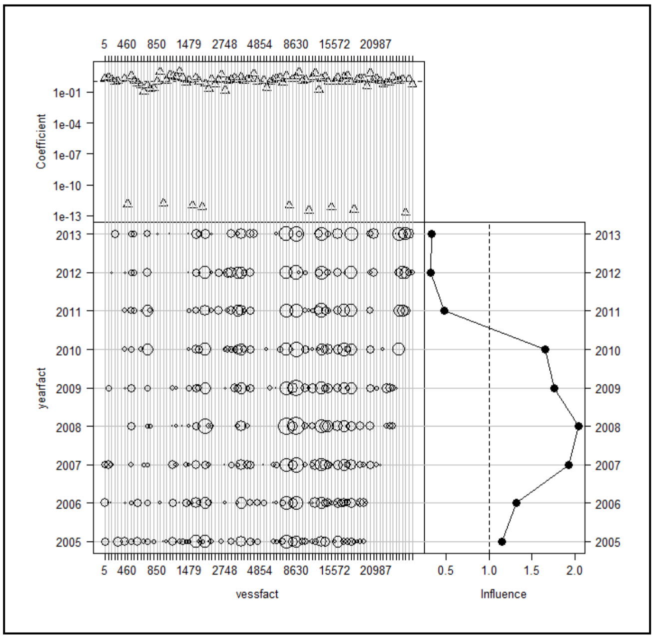
Appendix 43: Influence plot for the explanatory variable "area" (as New Zealand General Statistical Area) in the negative binomial model of mako shark CPUE for the TLCER Japan South dataset. Areas included in the model were only those with sufficient sampling coverage (five areas only).



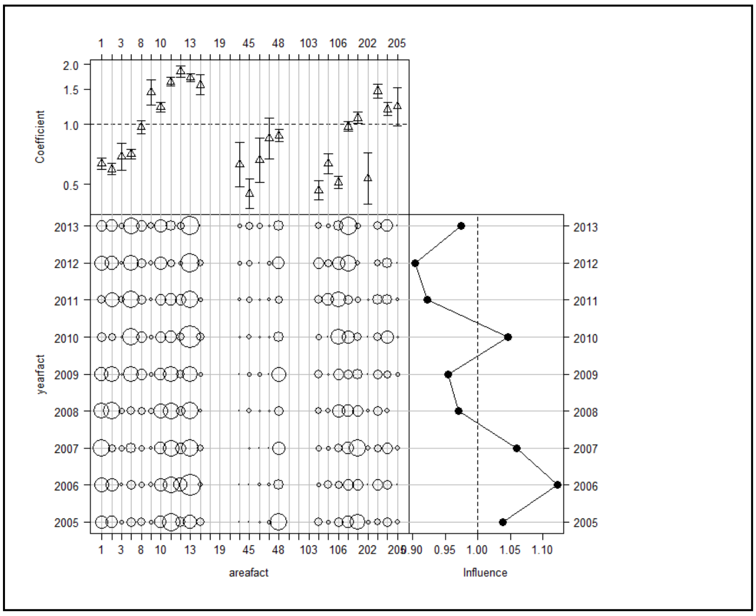
Appendix 44: Influence plot for the explanatory variable "month" in the negative binomial model of mako shark CPUE for the TLCER North dataset



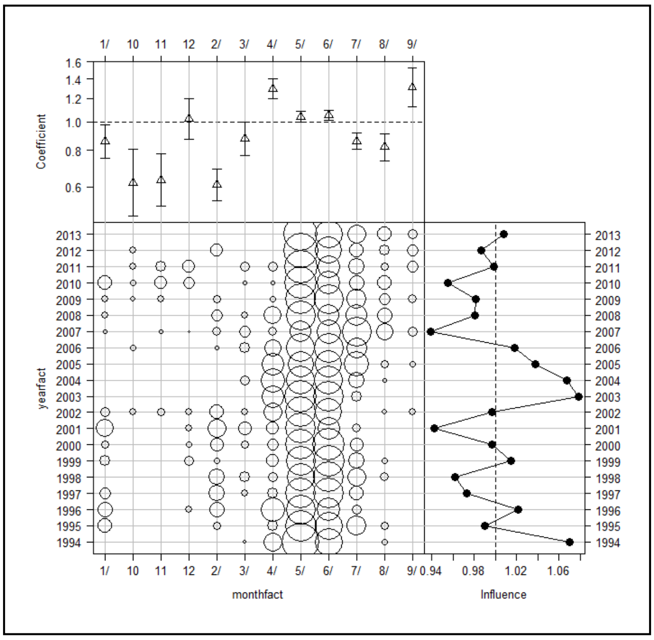
Appendix 45: Influence plot for the explanatory variable “vessel” in the negative binomial model of mako shark CPUE for the TLCER North dataset



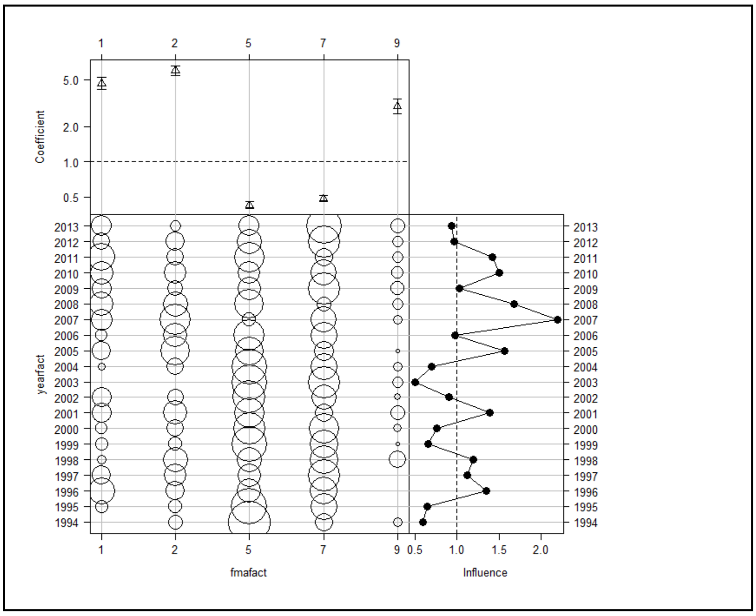
Appendix 46: Influence plot for the explanatory variable “area” (as New Zealand General Statistical Area) in the negative binomial model of mako shark CPUE for the TLCER North dataset



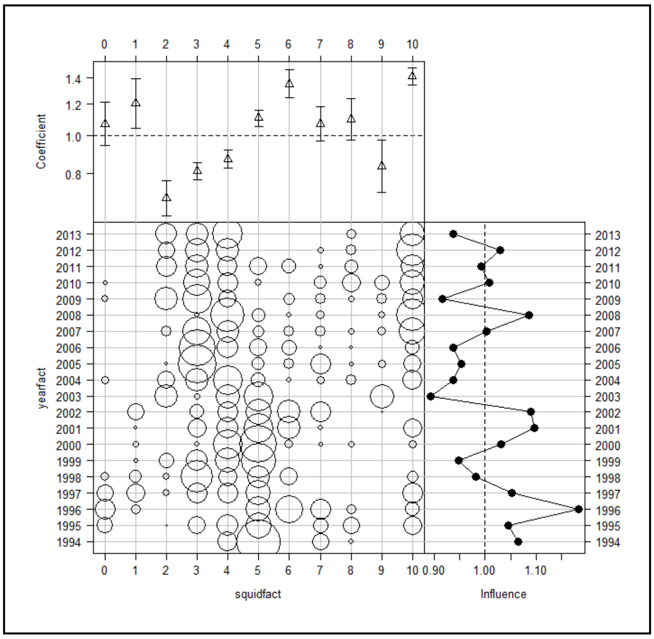
Appendix 47: Influence plot for the explanatory variable “month” in the negative binomial model of mako shark CPUE for the observer dataset. Note: The months are not displayed in chronological order because of software coding issues.



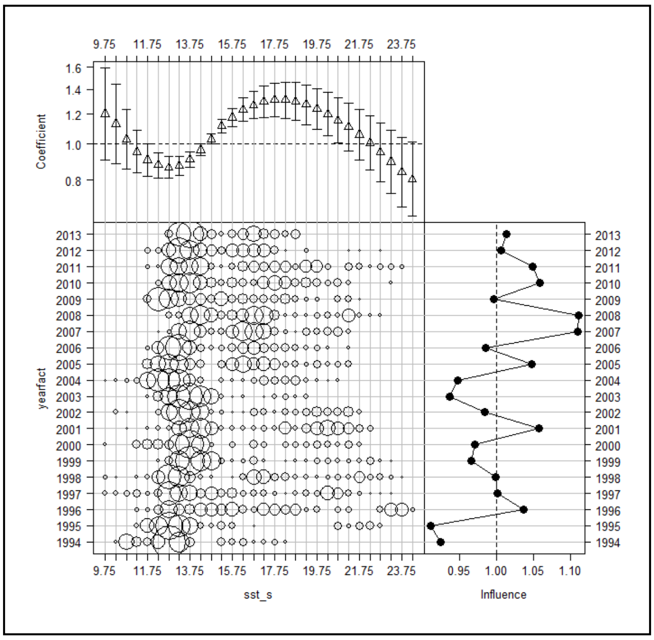
Appendix 48: Influence plot for the explanatory variable “area” (as FMA area) in the negative binomial model of mako shark CPUE for the observer dataset.



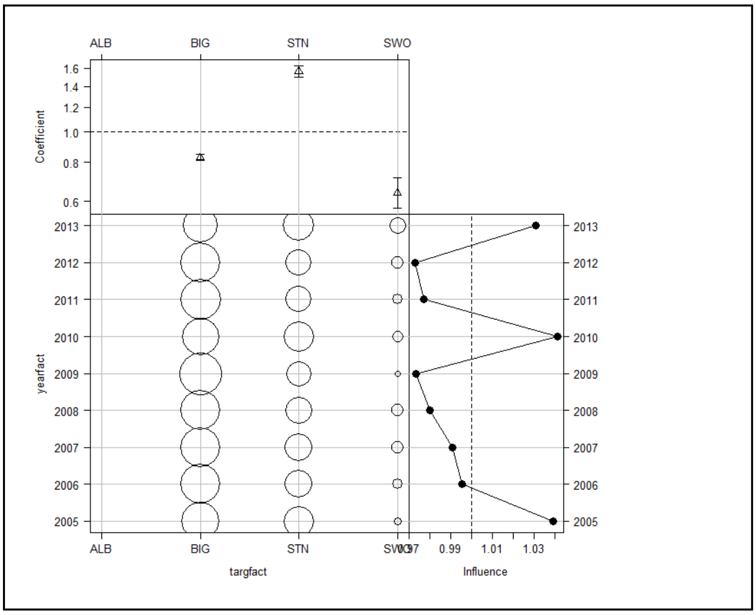
Appendix 49: Influence plot for the explanatory variable “percentage squid bait” (in intervals of 10%) in the negative binomial model of mako shark CPUE for the observer dataset.



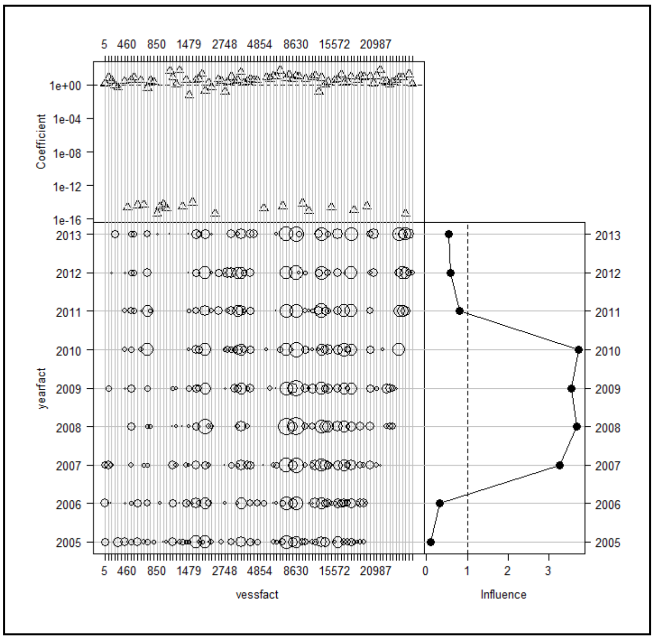
Appendix 50: Influence plot for the explanatory variable “sea surface temperature” in the negative binomial model of mako shark CPUE for the observer dataset.



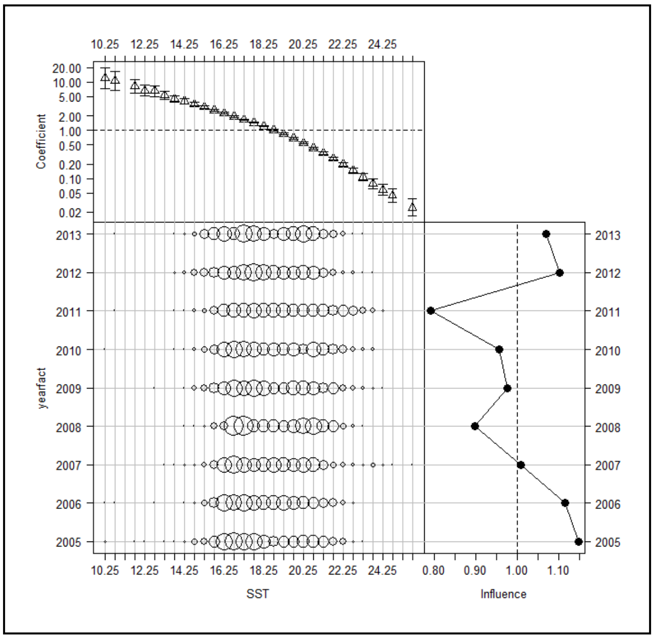
Appendix 51: Influence plot for the explanatory variable "target strategy" in the negative binomial model of porbeagle shark CPUE for the TLCER North dataset. (Sets targeting albacore (ALB) were not included in the analysis).



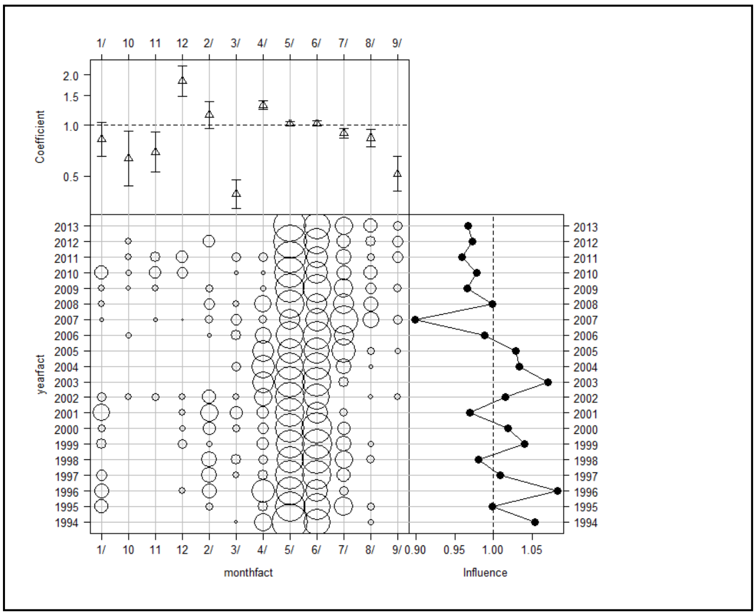
Appendix 52: Influence plot for the explanatory variable "vessel" in the negative binomial model of porbeagle shark CPUE for the TLCER North dataset.



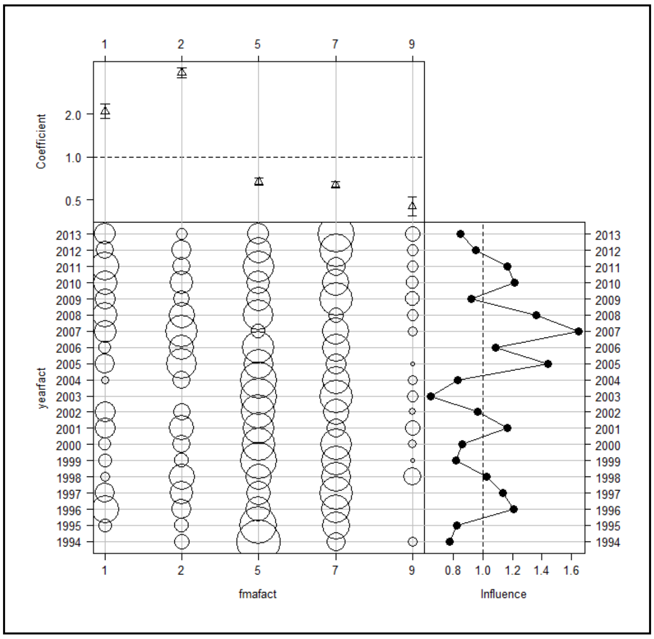
Appendix 53: Influence plot for the explanatory variable "sea surface temperature" in the negative binomial model of porbeagle shark CPUE for the TLCER North dataset.



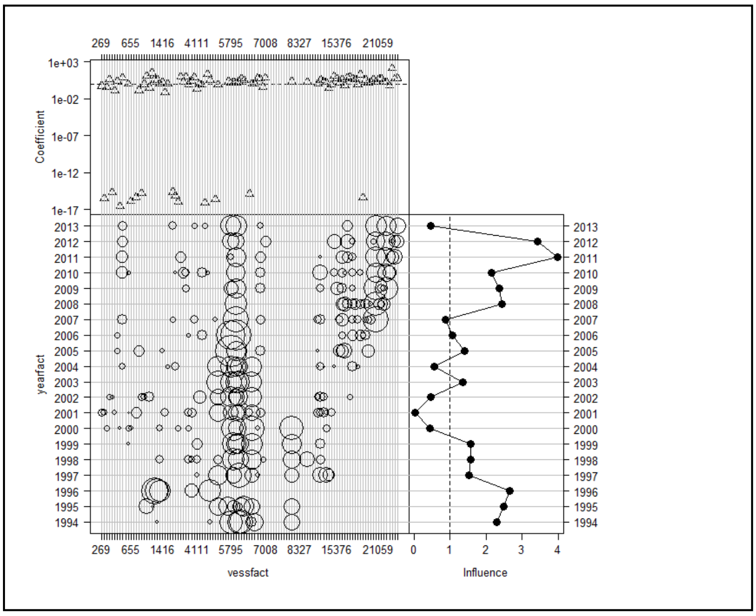
Appendix 54: Influence plot for the explanatory variable "month" in the negative binomial model of porbeagle shark CPUE for the observer dataset. Note: The months are not displayed in chronological order because of software coding issues.



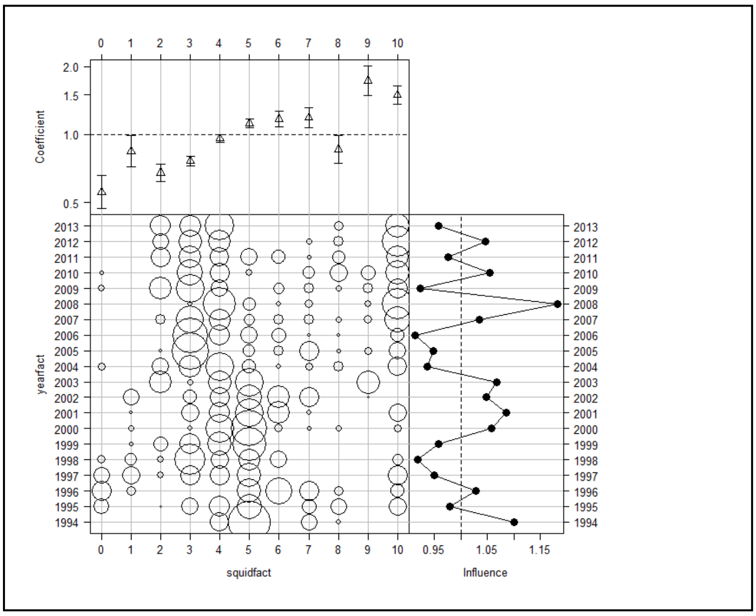
Appendix 55: Influence plot for the explanatory variable "area" (as FMA area) in the negative binomial model of porbeagle shark CPUE for the observer dataset.



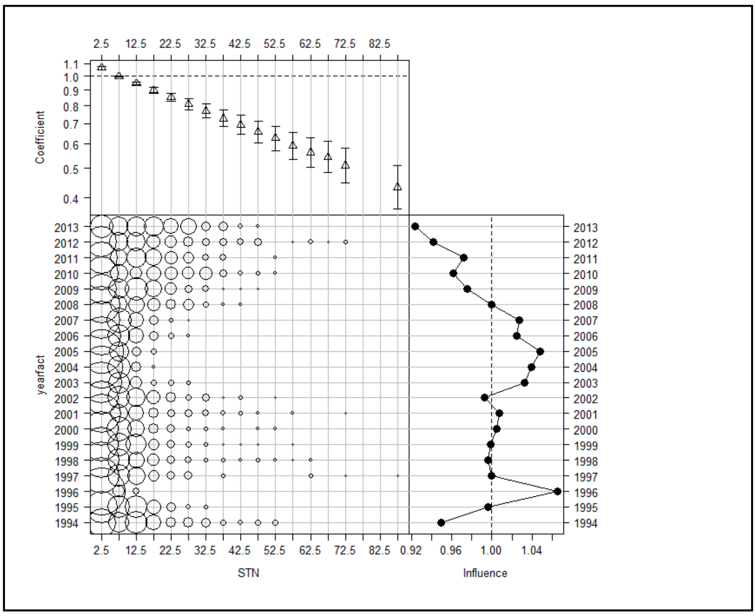
Appendix 56: Influence plot for the explanatory variable "vessel" in the negative binomial model of porbeagle shark CPUE for the observer dataset.



Appendix 57: Influence plot for the explanatory variable "percentage squid bait" (in intervals of 10%) in the negative binomial model of porbeagle shark CPUE for the observer dataset.



Appendix 58: Influence plot for the explanatory variable "catch of southern bluefin tuna (STN)" in the negative binomial model of porbeagle shark CPUE for the observer dataset.



Appendix 59: Influence plot for the explanatory variable "sea surface temperature" in the negative binomial model of porbeagle shark CPUE for the observer dataset.