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Development of Southern Hemisphere porbeagle shark stock abundance indicators using Japanese commercial and survey data

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Japan holds the longest-term and largest spatial extent of porbeagle shark (*Lamna nasus*) catch-effort data from longline fishing in the Southern Hemisphere, and also size and sex composition data collected by observers. The various sets of catch and effort data have previously been analysed, but opportunities were identified for improving the analyses. These include modelling spatial effects at a finer scale, investigating spatial variation in trends, accounting for the effects of targeting behaviour, and accounting for differences in catchability among vessels. Potential to examine reporting reliability was also identified. We considered that improvements may significantly affect the porbeagle stock assessment, because of the crucial nature of the Japanese data. In a collaborative project, New Zealand and Japanese scientists worked together to reanalyse these data. We explored issues related to reporting reliability, analysed the spatial and temporal distribution pattern of different size and sex classes of porbeagles, and modelled catch rates in several different datasets.

In investigating reporting rates, we developed a new method for identifying groups of longline sets that reliably report sharks, given that their reporting rates are similar to those seen in the observer data. The estimated reliability of shark reporting in logbooks before 2008 appeared to be low, but increased sharply in 2008, with the proportions of nonzero shark catches almost reaching the levels in the observer data. The reasons for the 2008 change are unclear, but it will be important to identify them. Increased reporting rates are likely to affect catch per unit effort (CPUE) indices derived from the logbook data, and a large increase in CPUE in 2008 is indeed apparent in previously estimated porbeagle shark CPUE indices. Identifying the cause of this change will help to determine whether other indices may be affected.

Data preparation included identifying a number of different targeting strategies using cluster analysis on the species composition data for well reported tuna and billfish species. This approach assumes that different fishing strategies will catch, on average, different mixtures of species. Species compositions were indeed very distinct between the fishing strategies, with effort targeted at southern bluefin tuna reporting very low catch rates of other tuna and billfish species. Fishing strategies were also spatially and seasonally separated, but the separation was sufficiently complex and variable that categorization based on covariates alone would have resulted in incorrect allocation of sets. There may be other covariates that would reliably differentiate fishing strategies, but if so these have not been recorded, or were not available to the analysts. The strategies that Japanese longline vessels use to target different species have also in some cases changed through time, suggesting that species composition data may be more useful than, or complementary to, operational covariates as an indicator of the intentions of individual vessels. Grouping the data by fishing strategy will affect abundance indices based on catch rate, because different fishing strategies are likely to have different catch rates for the species of interest (porbeagle).

Modelling of the length data suggested that length is strongly associated with sea surface temperature (SST). Smaller sharks were apparent above about 12 °C in a number of datasets. Given the spatial size variation associated with water temperature we grouped the data into two separate fisheries north and south of 40°S for CPUE standardization. We also grouped observer data with SST information for CPUE standardization based on the measured SST.

The abundance indices estimated in 2013 covered all fished areas in the Southern Hemisphere, and increased significantly between 2007 and 2008, coinciding with the change to higher reporting rates. In the current study, indices were estimated for three separate areas, none of which changed in a comparable way. For this reason, along with the consistency with observer results, and the better accounting for vessel effects and spatial patterns at several scales; and despite concerns about potential violation of distributional assumptions; the indices developed here are preferred to those estimated in 2013. The

approaches used in this study are recommended for future application to developing CPUE indices. However, given the distributional problems with these indices, further work to improve and validate them is strongly recommended. The results suggest different trends by area, with increasing CPUE in the western Indian Ocean and declining CPUE in the Pacific. Such differences in trends suggest relatively low mixing of porbeagles between oceans, and across the Indian Ocean.

1. INTRODUCTION

Japan holds the longest-term and largest spatial extent of porbeagle shark (*Lamna nasus*) catch-effort data from longline fishing in the Southern Hemisphere, and also size and sex composition data collected by observers. Previously, the various sets of catch and effort data have been analysed to a point (i.e., standardised) (Semba *et al.* 2013), but opportunities have been identified for improvement. These include modelling spatial effects at a finer scale, investigating possible spatial variation in trends, accounting for the effects of targeting behaviour, and accounting for differences in catchability among vessels. Potential to examine reporting reliability was also identified. These changes could lead to substantially different indices, which might significantly affect the overall porbeagle assessment because of the crucial nature of the Japanese data. In a collaborative project, New Zealand and Japanese scientists worked together to reanalyse these data. We explored issues related to reporting reliability, analysed the spatial and temporal distribution patterns of different size and sex classes of porbeagles, and modelled catch rates in several different datasets.

Stock assessments require catch per unit effort (CPUE) series that index the abundance of a consistent component of the stock. When there is spatial or temporal subdivision in the population, it is important to identify this subdivision and develop separate indices. Stratification by sex and life history stage is a common feature of shark populations. In addition, sharks are bycatch of tuna fisheries, but the shark catch per set is often misreported as zero, and is affected by fishing strategy, so analyses of CPUE require specialised methods. In addition, the New Zealand fishery takes mainly young juvenile porbeagles (Francis 2015); mature sharks (particularly females) appear to occur in colder southern waters where their fishing mortality may be relatively low, but this needs to be confirmed.

Japan holds datasets that provide important information about shark species throughout the world's oceans, including Southern Hemisphere porbeagle sharks, with significant spatial coverage of the population (all oceans in the Southern Hemisphere), and a relatively long time series from the early 1980s to the present. Species-specific logbook data on shark catches is available since 1994. Japan routinely provides CPUE indices for Pacific stock assessments through the International Scientific Committee for Tuna and Tuna-like Species in the North Pacific Ocean (ISC) and the Western and Central Pacific Fisheries Commission (WCPFC). Improved methods developed by this project may be applied by Japanese and other distant water fishing nation (DWFN) scientists to other species.

The following Southern Hemisphere porbeagle shark data sources were available for the project (see detailed descriptions in Semba et al. (2013)):

1. Commercial southern bluefin tuna observer data: size, sex, maturity, 1992–2014.
2. Commercial operational catch (in number and weight) and effort data. 1994–2014.
3. Survey longline (butterfly tuna) data: number and weight of catch per set, 1987–94.
4. Survey driftnet (*Allothunnus*) data: number and weight of catch per set, 1982–90.
5. Survey driftnet (pomfret) data: number and weight of catch per set, 1984–86.

The objectives of the collaboration were as follows:

1. To use statistical methods to identify spatial and temporal patterns in porbeagle size, sex, and maturity distributions in the Southern Hemisphere, to permit the development of spatial definitions for fisheries that are suitable for stock assessment.

Our approach was to model size, sex, and maturity patterns in commercial longline observer data (and logbook data, if both length and weight are recorded with some reliability), and survey driftnet and longline data, to estimate patterns in sex ratio, life history stage, and size. We then standardised the data using generalized linear and generalized additive models to identify consistent spatio-temporal patterns, after taking potentially confounding factors into account (year, fishing method). We aimed to identify spatial and seasonal boundaries that defined 'fisheries' with distinct size/sex/life history stage patterns.

2. To use appropriate statistical methods to derive standardised CPUE indices for fisheries defined under the first objective.

We standardized the porbeagle shark catch rates in commercial southern bluefin tuna longline logbook data. This involved three main stages:

I. For fisheries in which more than one fishing strategy may have been applied (e.g. targeting southern bluefin tuna versus targeting bigeye tuna and swordfish), we applied cluster analysis to species composition data from fishing logbooks to separate the fishing strategies. Cluster analysis requires access to catch data for multiple species. For these fisheries the relevant species would include albacore, bigeye, yellowfin, and southern bluefin tuna, swordfish, and striped marlin. Data analyses also required access to data on catches of porbeagle sharks, and unidentified sharks.

II. We explored the relationships of size and sex with respect to covariates including space, time, and fishing characteristics, in order to identify potential separation into different fisheries.

III. For each fishery, we conducted a separate CPUE standardisation analysis and applied distributional assumptions according to the distribution of the data. We applied statistical weights according to the effort per stratum, in order to allow for changes in effort distribution through time.

Analyses were conducted over a two-week period at the National Research Institute of Far Seas Fisheries laboratory (NRIFSF) in Shimizu, Japan.

Results are presented in three sections. The first section describes the cluster analyses and the investigation of reporting rates. The second section describes the analyses of size and sex effects. The third section describes the analyses of CPUE.

2. IDENTIFYING LOGBOOK DATA THAT RELIABLY REPORT CATCHES OF BYCATCH SPECIES

2.1 Introduction

Catches of target and bycatch species are reported with varying reliability in the logbooks submitted to fishery managers. Reporting reliability varies among species, among vessels, and through time, and depends upon the choices and motivations of the people doing the reporting. This variation in reporting reliability affects the CPUE indices that are fundamentally important for stock assessments.

The Japanese longline fleet targets tuna and billfish species across all major oceans. Bycatch of sharks and other species is an increasing concern, with conservation measures being applied by many regional fishery management organizations (RFMOs). The Japanese longline fleet has two main components, targeting bigeye and yellowfin tuna in tropical and subtropical areas, and southern bluefin tuna further south in temperate waters (Okamoto *et al.* 1998). Observers have been deployed in the Japanese longline fleet since 1992, and have recorded data including operational factors, environmental parameters, and detailed catch information (CCSBT Secretariat 2015).

Sharks and other bycatch species are not always reliably reported. Reporting reliability may vary among bycatch species. For example, commercially valuable species may be reliably reported while low value species are not. Three broad reporting categories have been identified in the Japanese longline fishery (Nakano & Clarke 2006): (i) retention and use of all sharks; (ii) retention and utilization of high-value sharks only; and (iii) no retention of sharks.

In order to validate the reliability of shark reporting in logbooks, Nakano,Clarke (2006) developed filters for logbook data based on assumed ‘true’ shark reporting rates, with filters at different reporting rates recommended for different shark species, depending on their value. Kai,Yokawa (2015) used a more complex statistical approach to recommend reporting rate criteria for blue shark logbook catches. However, these methods assume a constant reporting rate for a species, which does not take into account the fact that shark bycatch rates vary with covariates such as fishing location, season, year, and the fishing methods being used. They may result in biased abundance estimates due to the inappropriate inclusion or omission of records of the shark’s catch.

Walsh,Kleiber (2001) modelled blue shark catch rates using observer data and identified significant effects on catch rates from spatial, temporal, environmental, and operational variables, and recommended that observer data could be used as a comparison standard against logbooks. Walsh *et al.* (2002) built on this work by using a generalized additive model (GAM) based on observer data to predict expected logbook catches, and investigated records with large differences between predicted and observed catches. They then modelled relationships between predicted catches and the observed values.

Our method extends those of Walsh *et al.* (2002) and Nakano,Clarke (2006), by modelling observer data and using it to predict logbook catch rates, and then using these expected catch rates to identify groups of logbooks that report shark catches in a way that is consistent with the reporting in the observer data. We assume that observer data are close to the truth, although not error-free.

2.2 Methods

Logbook data of Japanese longliners operating south of 30° S from 1994 to 2014 were compiled by the National Research Institute of Far Seas Fisheries (NRIFSF) (Table 2.1). The set-by-set data include information on catch numbers by species of tunas, billfish, swordfish and sharks, operation date, amount of effort (number of hooks), number of branch lines between floats (hooks between floats: HBF) as a proxy for gear configuration, vessel identity, and location (longitude and latitude) of set, with a resolution of 1° × 1° cell.

Observer data were collected from the national observer programme of the Commission for the Conservation of Southern Bluefin Tuna (CCSBT). The observer data cover longline operations in the areas south of latitude 30° S where southern bluefin tuna (*Thunnus maccoyii*) is targeted. The data include information on the body length and sex of the species caught, types of hooks (e.g. circle hook), materials of branch lines, etc. in addition to the information in the logbook data (Table 2.1). The extent of observer coverage (as a percentage of hooks observed) averaged 7.76% from 2002 to 2014.

In modelling the observer and logbook data, we use information on shark presence in the catch rather than modelling the numbers caught, because a) for confidentiality reasons we were provided only with presence-absence data for sharks other than porbeagles, and b) shark reporting rate per set has been previously shown to be informative about shark reporting quality (Nakano & Clarke 2006).

Nakano,Clarke (2006) defined the bycatch reporting rate *(RR*) per cruise, or vessel trip, as $RR = \frac{Number\ of\ sets\ with\ sharks\ recorded}{Total\ number\ of\ sets}$. The term 'reporting rate' is often used to refer to the accuracy of reporting, e.g. with tagging data, so to avoid potential confusion we rename this quantity reported incidence (RI). This ratio is affected by both reporting reliability and by the true catch rates of sharks, so we define two related terms: probability of shark presence in the catch, equal to $SP = \frac{Number\ of\ sets\ with\ sharks\ caught}{Total\ number\ of\ sets}$, and shark reporting reliability, equal to $SR = \frac{Number\ of\ sets\ with\ sharks\ recorded}{Number\ of\ sets\ with\ sharks\ caught}$. We note that the expected value of *RI* is equal to *SR* × *SP*.

In observer data where the reliability (*SR*) is assumed equal to 1, *SP* is assumed to be equal to *RI*. Our aim is to identify logbook data that reliably report sharks, and therefore have *SR* equal to 1. Our approach allows for the fact that *SP* will vary in time and space, and with the fishing methods used.

Initially we explored the logbook data and the observer data, and estimated the shark reported incidence *(RI)* by year-quarter.

Catch rates of all species vary according to the fishing method used, and we assigned each logbook set to a fishing method using cluster analysis of species composition data (He *et al.* 1997; Hoyle *et al.* 2015). Different fishing methods and habitats result in different mixtures of species being caught, including different levels of shark catch.

Fishing modes were determined in logbook data rather than observer data because the larger sample sizes improved the power of the analysis, and because the species used were generally reported reliably in logbook data. Clustering of fishing effort was carried out based on the species composition (proportions) per vessel-month of albacore, bigeye, yellowfin, striped marlin, swordfish, and southern bluefin tuna. A small number of sets did not catch any of these species, and were removed. Clustering was applied after aggregating by vessel-month, to allow for set-level variability in species composition. We applied Ward's hclust 'Ward.D' method and the kmeans method, both from the R 'stats' package (R Core Team 2015). The Ward.D method implemented in the hclust function is not the same as the standard Ward (1963) method (Murtagh & Legendre 2014), but we found it to discriminate fishing methods more effectively than the 'Ward.D2' method. For the kmeans method we plotted the relationship between number of clusters (between 2 and 15) and summed within-cluster sums of squares. For more detail on the methods see Hoyle *et al.* (2015).

The optimal number of clusters was determined by examining the kmeans plot and the hierarchical dendrogram produced by the hclust method, and by exploring the relationships between clusters and covariates such as fishing location, and between clusters and species compositions.

Once all remaining logbook sets had been allocated to clusters, the observer data were also allocated to clusters by linking observer sets to the equivalent logbook sets, based on vessel callsign and set date. The patterns of reported incidence (*RI*) were compared by cluster in the unstandardized observer and logbook data.

Next we modelled the patterns of shark reported incidence (RI_{obs}) by set in the observer data, assumed equivalent to presence (SP_{obs}), similar to the approach by Walsh,Kleiber (2001) and Walsh *et al.* (2002) but using incidence rather than CPUE as the response variable. We modelled shark reported incidence per individual set using a binomial GLM.

$$SP_{obs} = RI_{obs} \sim yrqtr + location + cluster + f(observed\ hooks) \qquad (1)$$

Time effects were modelled as year-quarter effects using categorical variables (*yrqtr*). Spatial patterns were modelled using 5° grid squares as categorical variables (*location*). Cluster was modelled as a categorical variable (*cluster*). Observed hooks were fitted with a cubic spline with 3 degrees of freedom (*f(observed hooks)*). Observers did not observe all hooks in every set. Vessel effects were not modelled because there were relatively few vessels in the observer data and little vessel overlap through time. We then plotted the relative changes across all observed values of each effect, while fixing the values of other effects at either the most common value or the median. Modal location was in the 5° square centred at latitude 37.5°S and longitude 102.5°, year-quarter was 2006 quarter 3, cluster 3, and median observed hooks was 2464.

The model of SP_{obs} developed with the observer data was then used to predict expected values of SP_{log} for each logbook set, using the predict.glm function in R. In logbook sets, shark presence applies to all fished hooks, but the observer may miss a shark capture that occurs in hooks not observed, resulting in a false negative. For prediction using logbook data, the observed hooks variable was replaced with the number of hooks set.

For an individual set the reported incidence RI_{log} is either 0 or 1, so shark reporting reliability (SR_{log}) was estimated by averaging RI_{log} / predicted SP_{log} by vessel trip. In addition to vessel trip we explored variability in SR_{log} by vessel and by vessel year, so as to identify criteria for selecting sets that were sufficiently reliable to use in CPUE standardization.

An alternative approach would be to model the observed shark reporting incidences with a second binomial GLM, this time fitting the vessel trip as a factor, and applying the expected SP_{log} as an offset. This approach would permit exploration of the effects of covariates (such as the presence of an observer) on reporting reliability, and allow statistical comparison of vessel trip, vessel year, and vessel parameters, i.e.:

$$RI_{log} \sim vessel\ trip + covariates + offset(SP_{log}) \qquad (2)$$

However due to computational constraints it was not feasible to apply this approach to over 300 000 logbook sets in the time available.

2.3 Results

Hierarchical clustering using the Ward hclust method identified two clear groups and a further split at a lower level (Figure 2.1). Comparison of within-groups sums of squares using the kmeans clustering method similarly indicated a large reduction in variability with a single split, moderate with a second split, but relatively little further reduction with additional groups (Figure 2.2). We grouped sets into 2 and 3 clusters and examined species compositions and covariates. The 3 cluster grouping identified groups that corresponded to fisheries catching 1) a mixed-temperate combination of albacore and southern bluefin tuna, 2) albacore, bigeye, and yellowfin tunas, and 3) almost exclusively southern bluefin tuna (Figure 2.3).

Operational characteristics were not strongly differentiated between clusters in the available data (Figure 2.4), with slightly fewer hooks and somewhat higher hooks between floats (HBF) in the tropical tuna cluster, but considerable overlap between clusters. However, there was significant spatial separation, with the tropical tuna cluster occurring further north, mostly north of latitude 35° S but extending to 40° S near South Africa (Figure 2.5). The southern bluefin tuna cluster occurred mostly south of latitude 35° S, and the mixed-temperate cluster occurred to some degree from 30° S to 45° S. There was some change in cluster distribution through time, with the mixed-temperate albacore and southern bluefin cluster becoming more prevalent in recent years relative to the southern bluefin cluster (Figure 2.4 and Figure 2.6). Albacore targeting is understood to have increased during this period (T. Matsumoto, personal communication). There was also considerable seasonal variability (Figure 2.7), with the tropical tuna cluster dominating the January-March period, when there is in any case little fishing effort; the mixed-temperate and southern bluefin clusters becoming significant from April, and the southern bluefin cluster dominating the period from September to December.

The incidence of shark catch being reported in logbook sets showed a distinctive pattern with a 2008 step change in all three clusters (Figure 2.8). From 1992 to 2007, reported incidence was generally low and averaged 0.2 for cluster 3, and 0.4 for clusters 1 and 2. In 2008 the averages of all three clusters increased to about 0.8, remained high for 4 years, and then declined somewhat to a level in 2014 of between 0.6 and 0.7. In contrast, the incidence rate in the observer data maintained an average of about 0.9 for the whole period.

Standardizing the observer data on reported incidence RI_{obs}, assumed equivalent to SP_{obs}, showed significant variation in incidence associated with location, year-quarter, observed hooks, and cluster (Table 2.2). The proportions of observed sets with sharks were relatively stable through time (Figure 2.9). Areas with fewer sharks generally occurred in the southern latitudes 40–45° S, particularly to the southwest of Australia and southwest of South Africa (Figure 2.10). Shark catch rates were slightly higher in the mixed temperate cluster than in the other two clusters (Figure 2.11), and as expected there was a generally increasing trend of reported incidence with observed hooks (Figure 2.12).

The observer data models were then used to produce predictions of shark presence in the logbook data, SP_{log}, which were used to estimate logbook reliability SR_{log}. Estimates of SR_{log} (the ratio of predicted to reported shark incidences) showed different patterns before and after 2007. Until 2007 the frequency distribution was dominated by zeroes, with low but stable proportions for reporting reliability between 0.4 and 1.1, and then declined to zero by about 1.3 (Figure 2.13). After 2008 there were relatively few zeroes, and reliability estimates were dominated by estimates between 0.75 and 1.

Boxplots of mean reporting reliability estimates per vessel per year (SR_{log}) also showed a distinct change in 2008 (Figure 2.14). From 1994–2007 the reliability was estimated to be zero for a number of vessels, with a small number in each year close to 1. The proportion close to 1 declined through time to reach the lowest level in 2002–04. 2008 saw a complete change in the distribution of reliability estimates with very few vessels close to zero and the majority close to 1. The 2006 and 2007 distributions were similar to one another, as were the 2008 and 2009 distributions, suggesting that most of the change occurred with the change of calendar year. The proportion at or close to zero increased again in 2012–14.

2.4 Discussion

This method effectively identifies groups of sets that reliably report sharks, given that their reporting rates are similar to those seen in the observer data. It has advantages over the method of Nakano & Clarke (2006) since it adjusts for variation in the expected catch rates of sharks, which occurs spatially and temporally. The reliability estimates close to 1 are equivalent to category 1 of Nakano & Clarke (2006), with retention and use of all sharks. Vessel months with reliability estimates above 0 but below 1 may correspond to category 2, in which only high value sharks are retained, and this could be checked by estimating reliability based on high value species only.

The estimated reliability of shark reporting in logbooks appeared to increase sharply in 2008, with the proportions of nonzero shark catches almost reaching the levels in the observer data. Subsequently, there was a small decline in reporting rates, though there is also a (small) decline in incidence rates in the observer data. The estimates of reporting reliability for 2008–2014 were quite different from 1994–2007, with the majority of reliability estimates above 0.5 and with a large peak at 1.

The reasons for the 2008 change are unclear, but it will be important to identify them. Increased reporting rates are likely to affect CPUE indices derived from the logbook data, and a large increase in CPUE in 2008 is apparent in previously estimated porbeagle shark CPUE indices (Semba *et al.* 2013). Identifying causes will help to determine whether other indices may be affected. In the 2000s and later, many countries, areas, territories, and RFMOs adopted management measures related to shark finning, for example requiring the retention of sharks from which fins are removed by imposing a 5% fin-to-body weight ratio for finned sharks on board vessels (Fischer *et al.* 2013).

Reporting reliability before 2008 appeared to be low, and removing the less reliable data may make it difficult to estimate logbook indices during this period. Since porbeagle sharks are a high value species in Japanese fisheries, it is possible that some of the logbooks with reliability estimates in category 2 could be retained in the dataset. This should be explored in future analyses. However, some of the vessels reporting in this category may have changed their behaviour in 2008, which will need to be addressed when modelling.

Our method is similar to the methods of Walsh *et al.* (2002) in that it models observer data and uses the covariates to predict catch rates for commercial logbook data. It extends this method by using the predictions to estimate reliability scores for groups of data, which analysts can use to identify which logbook data to use in further analyses. This approach has advantages over the methods proposed by Nakano,Clarke (2006) and Kai,Yokawa (2015) because it provides the *RI* by covariate. Its main disadvantage is that it requires observer data to reliably predict for the fishery of interest.

Data preparation included cluster analysis which appeared to effectively separate the data based on species composition into different targeting strategies. Species compositions were very distinct between the fishing strategies, with effort targeted at southern bluefin tuna reporting very low catch rates of other tuna and billfish species. Fishing strategies were also spatially and seasonally separated, but the separation was sufficiently complex and variable that categorization based on covariates would have resulted in different allocation of sets. There may be covariates that would reliably differentiate fishing strategies, but if so, these have not been recorded, or were not available to the analysts. The strategies that Japanese longline vessels use to target different species have in some cases changed through time (Hoyle & Okamoto 2011; Hoyle & Okamoto 2013), suggesting that species composition may be more useful than, or complementary to, operational covariates as an indicator of the intentions of individual vessels.

We aggregated data by vessel-month before clustering. There can be considerable randomness in the species composition of individual sets, leading to misclassification into the wrong fishing strategy. Aggregating the data reduces the randomness by identifying the average species composition across multiple sets. On the other hand, an individual boat may change fishing behaviour during a month, either temporarily or longer term. For example, since the mid-2000s, regulation of the SBT fishery has tightened with declining TACs. Once the quota has been taken, vessels change target to other species, such as tropical tunas. Therefore, some of the data aggregated across a vessel-month will include more than one targeting strategy, resulting in misclassification. We recommend further work to explore aggregation at alternative scales, to identify strategies that minimise misclassification. Other approaches may use a shorter time scale (vessel-week), include other variables (vessel-month-cell), or explicitly consider the quota situation during each year.

Standardization of the observer data indicated that shark incidence rates in cluster 1, the fishery catching albacore and southern bluefin tuna, were slightly higher than in the bigeye-yellowfin-albacore fishery and the fishery dominated by southern bluefin tuna. There was considerable spatial variability in incidence rates, even between adjacent 5° squares, and also between adjacent year-quarters. This variability may reflect low sample sizes in the observer data, and suggests that higher levels of spatial and temporal smoothing should be explored in future analyses.

2.5 Tables

Table 2.1: Table of all data sources used in the report.

Data source	Years	Fields
Commercial logbooks	1992–2014	set date, lat, lon, callsign, tonnage, license, nominal target species, mainline material, branchline material, bait, hooks between floats, number of hooks, southern bluefin tuna number, albacore number, bigeye number, yellowfin number, swordfish number, striped marlin number, porbeagle number, shark incidence (T/F), trip start date
Observer data	1992–2014	cruise ID, operation ID, call sign, set date, lat_noon, lon_noon, SST_noon, hooks between floats, hooks set, hooks observed, shallowest depth, deepest depth, use of wire leader, bait type1, bait type2, bait type3, bait type4, bait type5, target species, type of hook1, ratio of hook1, type of hook 2, ratio of hook2, mainline material, mainline code, branch-line material, branch-line code, no of branches, species, body length, body length code, total weight, total weight code, processed weight, process code, sex, notes, error, start time of set, start time of hauling
JAMARC driftnet data	1982–1989	Date, latitude, longitude, no of nets, effective no of nets, SST, porbeagle catch number, porbeagle catch weight
JAMARC longline data	1987–1996	cruise name, no of operations, date, latitude, longitude, number of baskets, number of hooks, hooks per basket, catch number porbeagle, catch weight porbeagle, processed weight porbeagle

Table 2.2: Analysis of deviance for a GLM of the probability of nonzero shark catch in observer data. The full model included all four predictor variables, and the Δ values represent change in AIC and residual variance due to dropping each variable.

Predictor variable	ΔAIC	Δ Residual variance	df
Location	682.1	786.1	52
Year-quarter	299.6	423.6	62
Observed hooks	83.9	89.9	3
Cluster	7.6	11.6	2

2.6 Figures

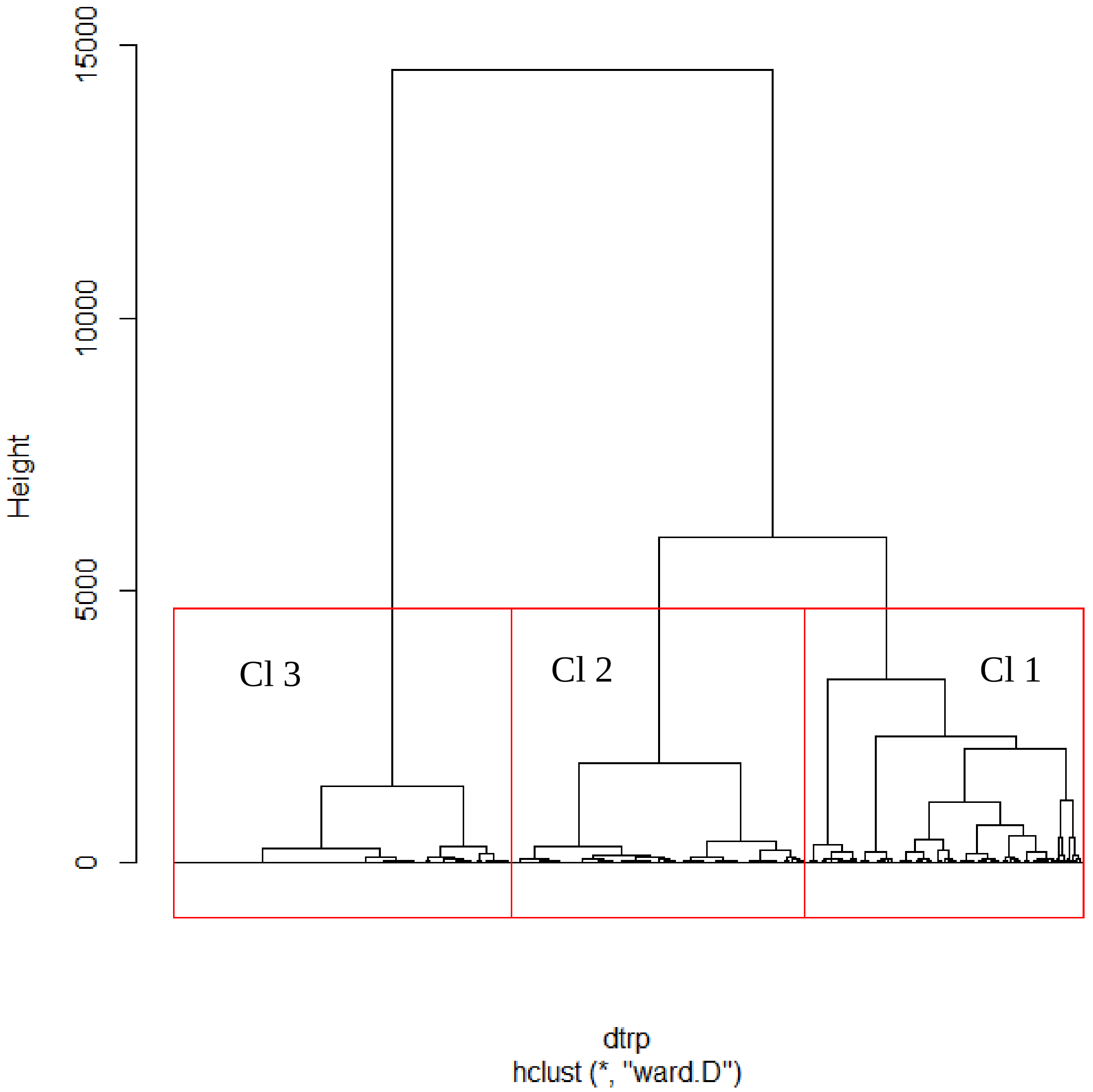

Figure 2.1: Dendrogram from cluster analysis of aggregated logbook species compositions using the Ward minimum variance method, as implemented in the R stat package with the 'Ward.D' option. The three clusters discussed later are here identified as Cl. 1, 2, and 3.

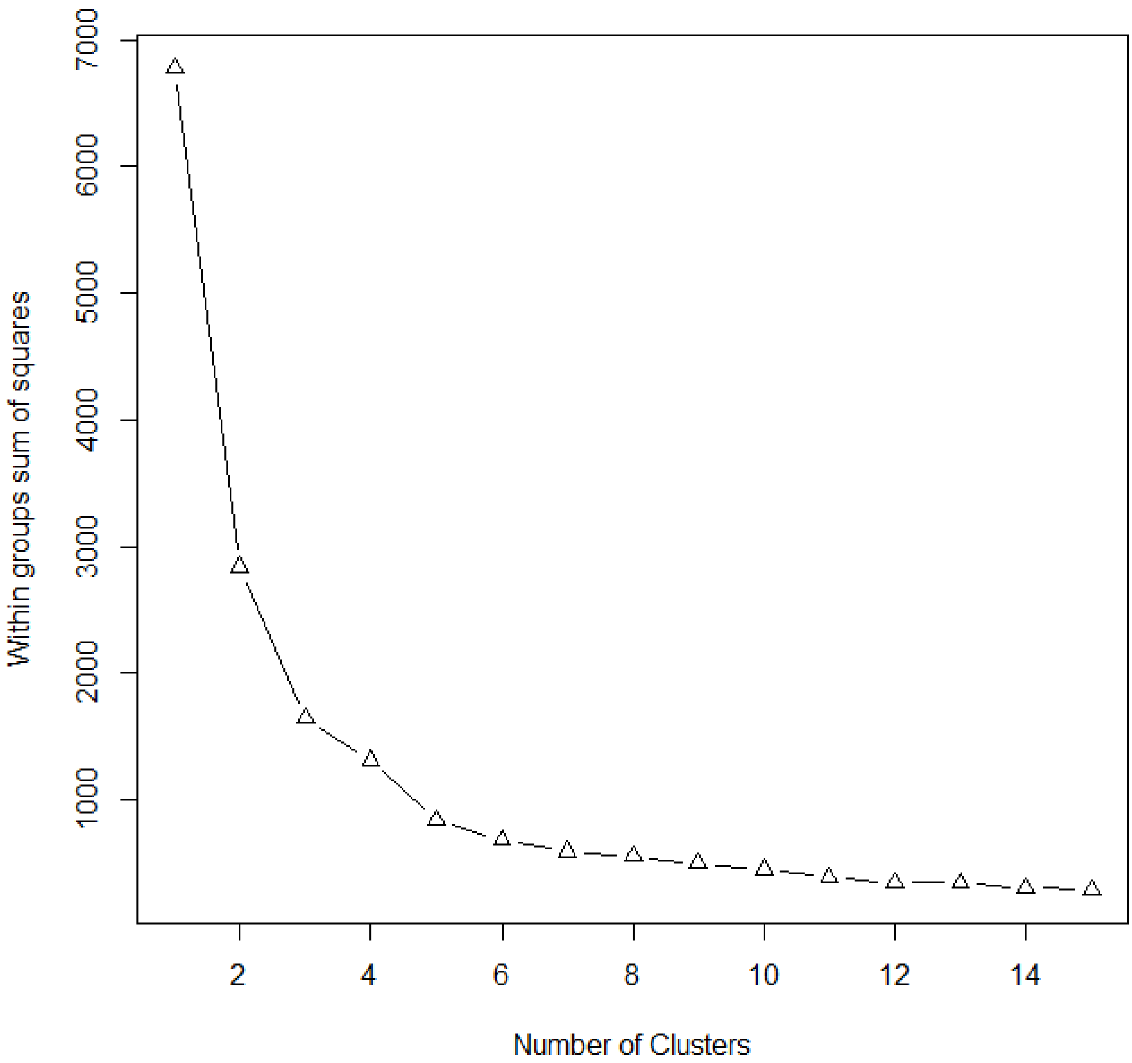

Figure 2.2: Plot of number of groups versus within-group sums of squares, after clustering the aggregated logbook species compositions using the kmeans method.

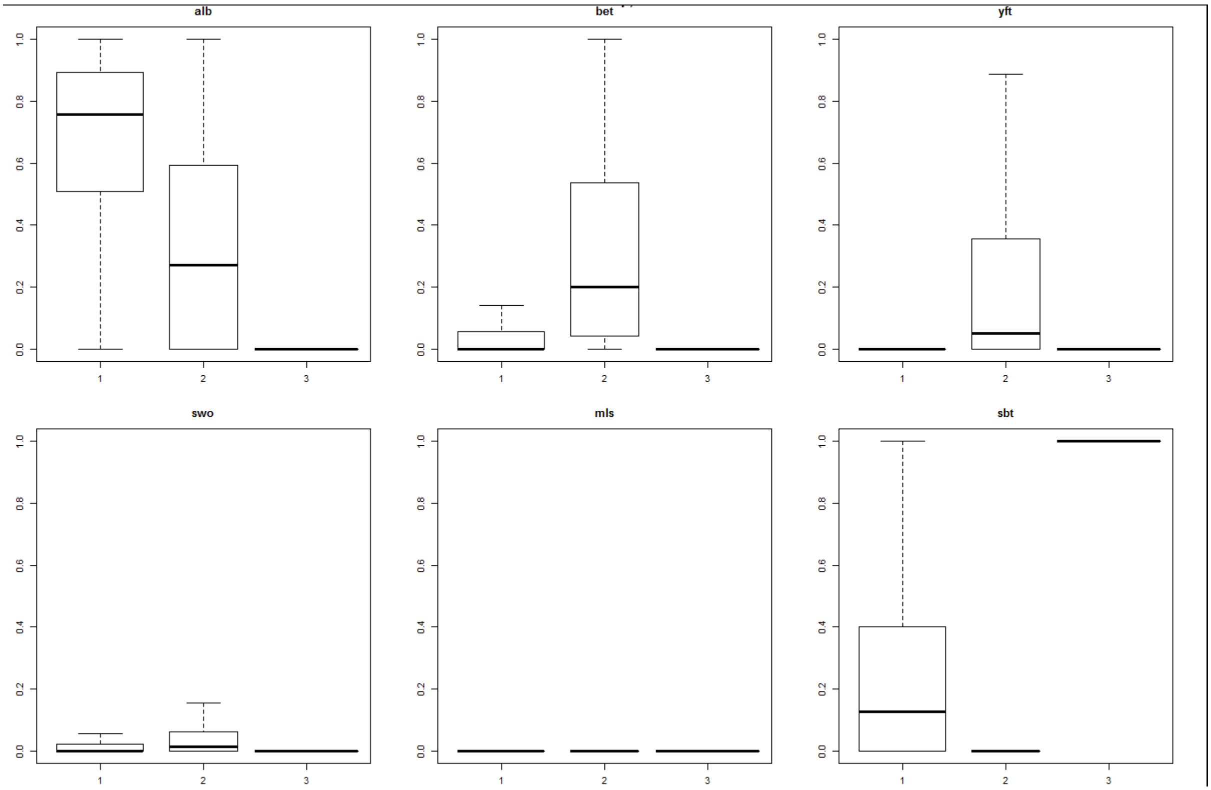

Figure 2.3: Boxplots of species proportions per set by species, with cluster (1–3) on the x axis, after clustering by species composition at the vessel-month level using the Ward hclust method with logbook data. The horizontal line is at the median, the boxes represent the quartiles, and whiskers extend to the extremes. Box widths are proportional to the number of sets per group. Species are alb = albacore, bet = bigeye, yft = yellowfin, swo = swordfish, mls = striped marlin, and sbt = southern bluefin tuna.

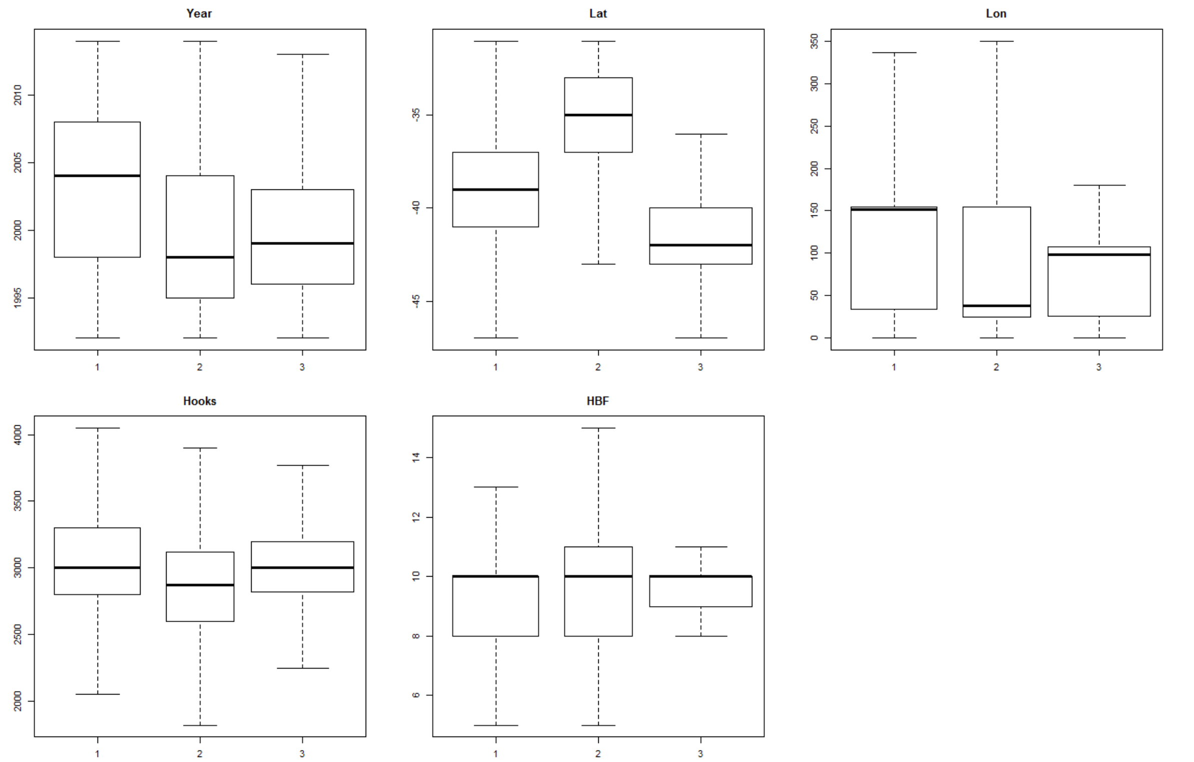

Figure 2.4: Boxplots of covariate distributions by cluster (1–3), after clustering by species composition at the vessel-month level using the Ward hclust method with logbook data. The horizontal line is at the median, the boxes represent the quartiles, and whiskers extend to the extremes. Box widths are proportional to the number of sets per group.

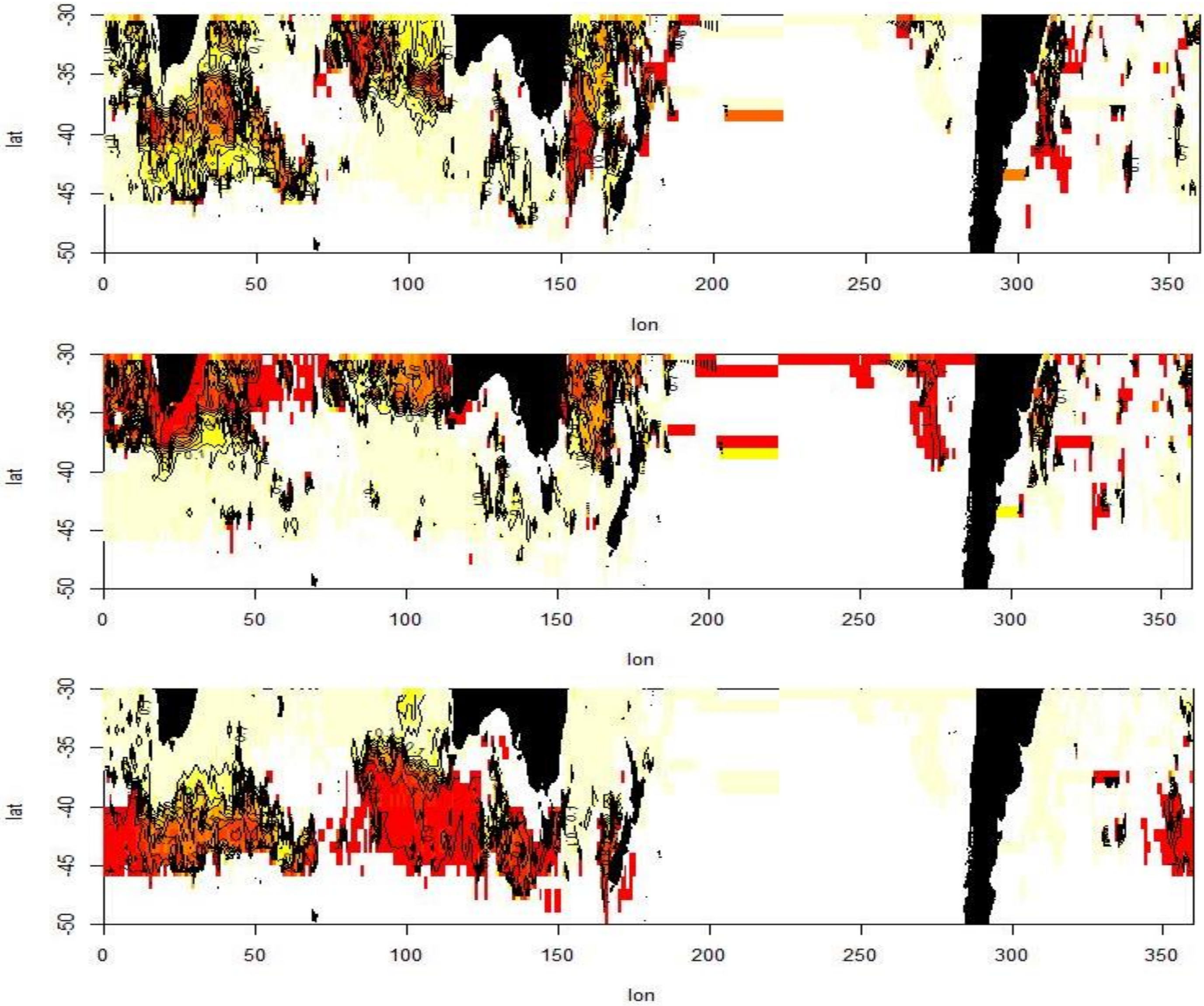

Figure 2.5: Maps showing the proportion of sets in each cluster by 1° square, based on logbook data. Red colour indicates a high proportion of sets in the cluster, and pale yellow (cream) indicates a very low or zero proportion. White background indicates no data. Several isolated patches of colour, particularly in the central Pacific, are plotting errors.

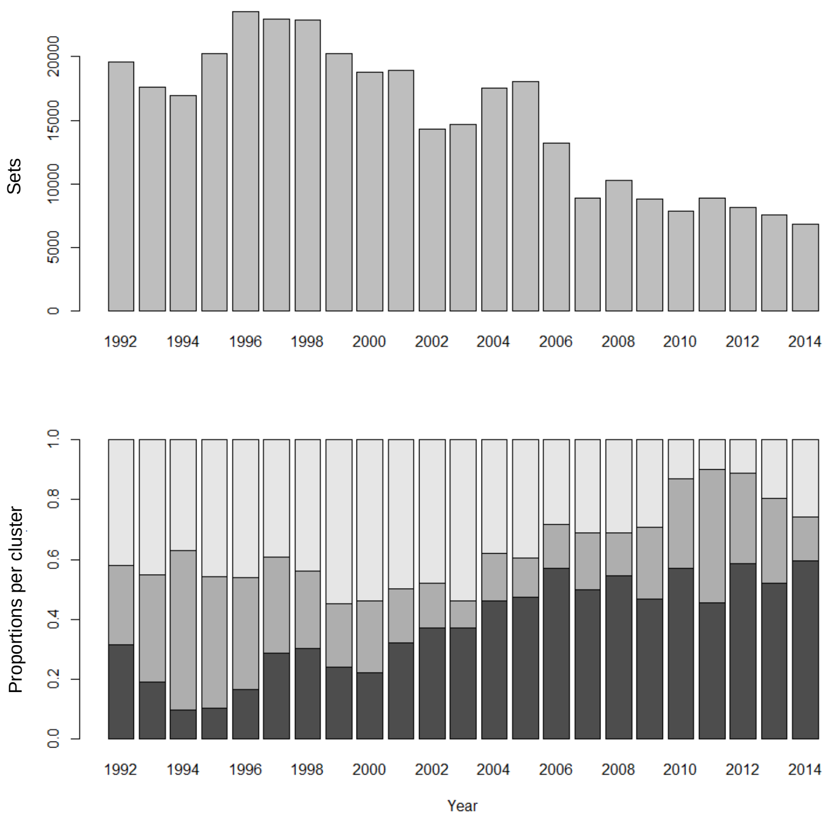

Figure 2.6: Number of sets per year (above) and proportions of sets per cluster by year, with clusters 1–3 shaded dark–light (below), based on logbook data.

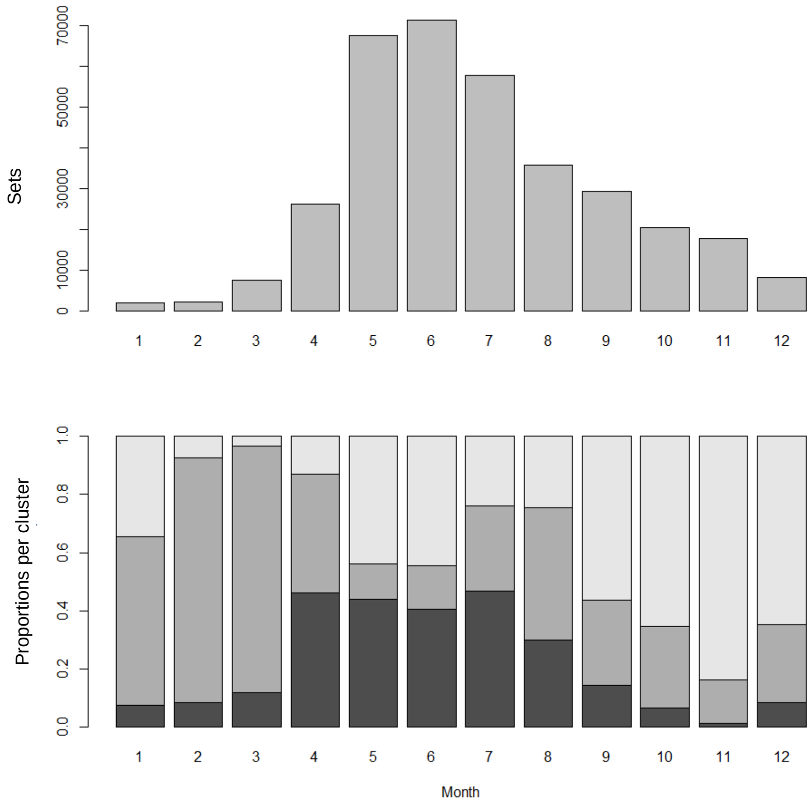

Figure 2.7: Number of sets per month (above) and proportions of sets per cluster by month (month 1 = January), with clusters 1–3 shaded dark–light (below), based on logbook data.

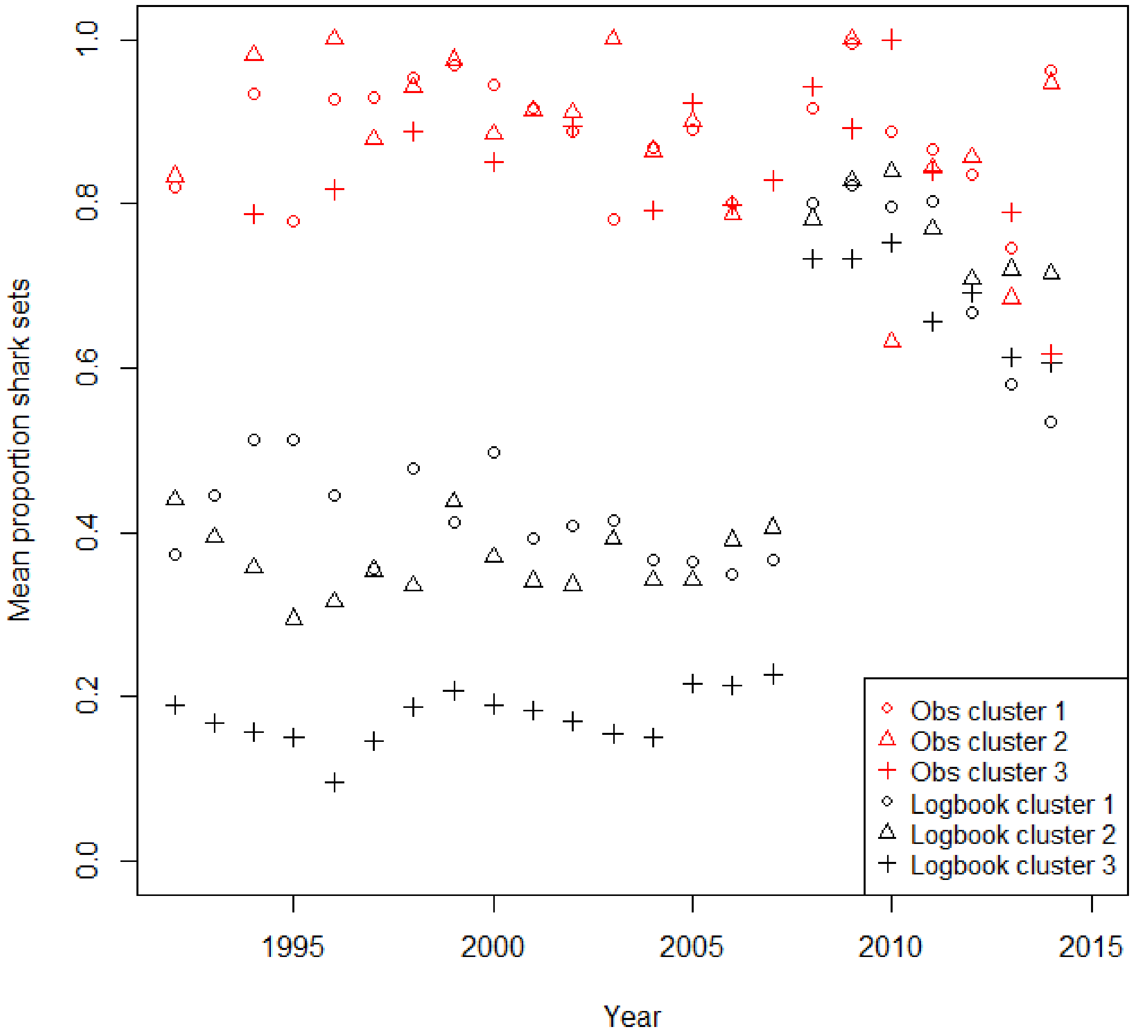

Figure 2.8: Mean proportions of logbook (black) and observed (red) sets reporting nonzero shark catch, by year and cluster.

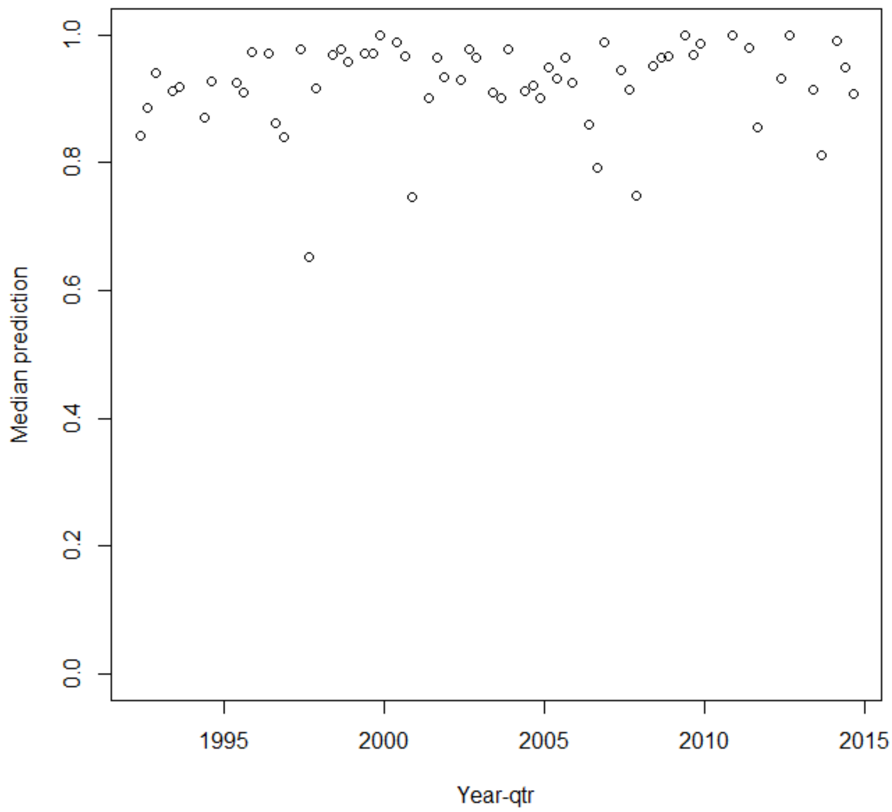

Figure 2.9: Predicted time effects from model of shark reported incidence in observer data.

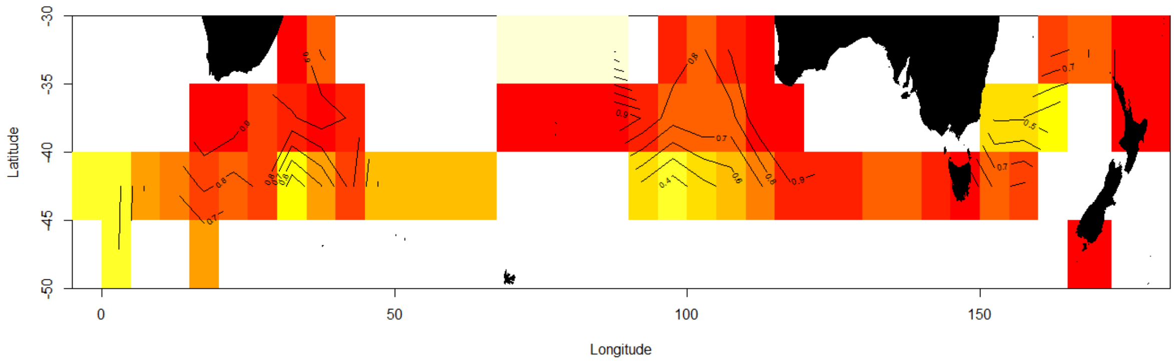

Figure 2.10: Predicted spatial effects from model of shark reported incidence in observer data. Red colour indicates a high incidence, and pale yellow (cream) indicates a low incidence. Isobars occur at 0.1 intervals.

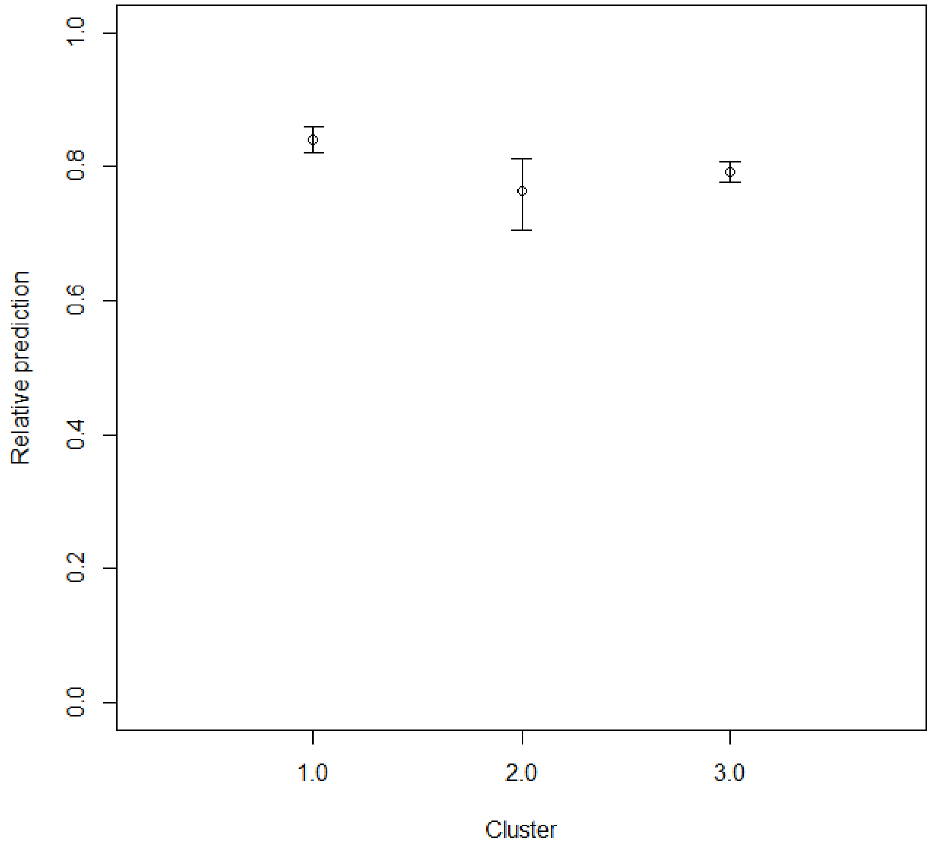

Figure 2.11: Predicted cluster effects from model of shark reported incidence in observer data.

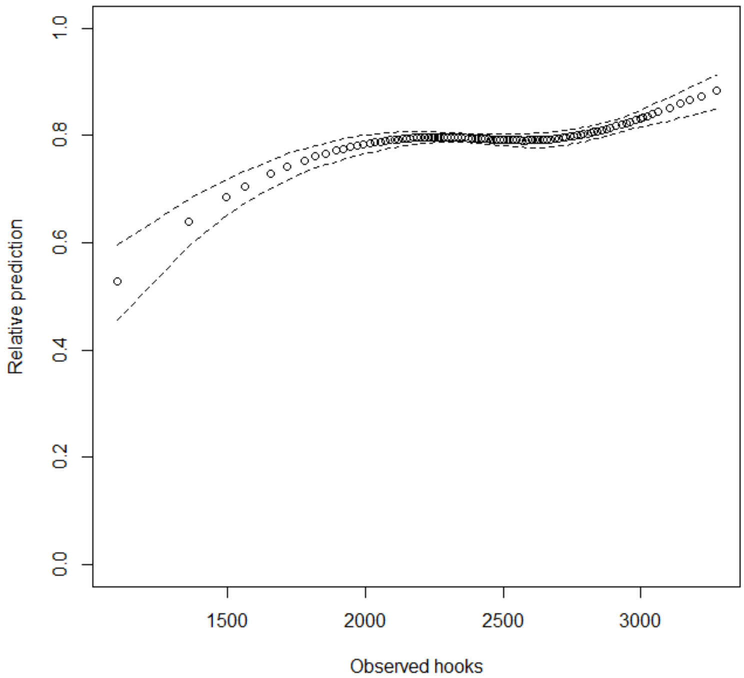

Figure 2.12: Predicted hook effects (circles, with 95% confidence interval shown by dashed lines) from the model of shark reported incidence in observer data.

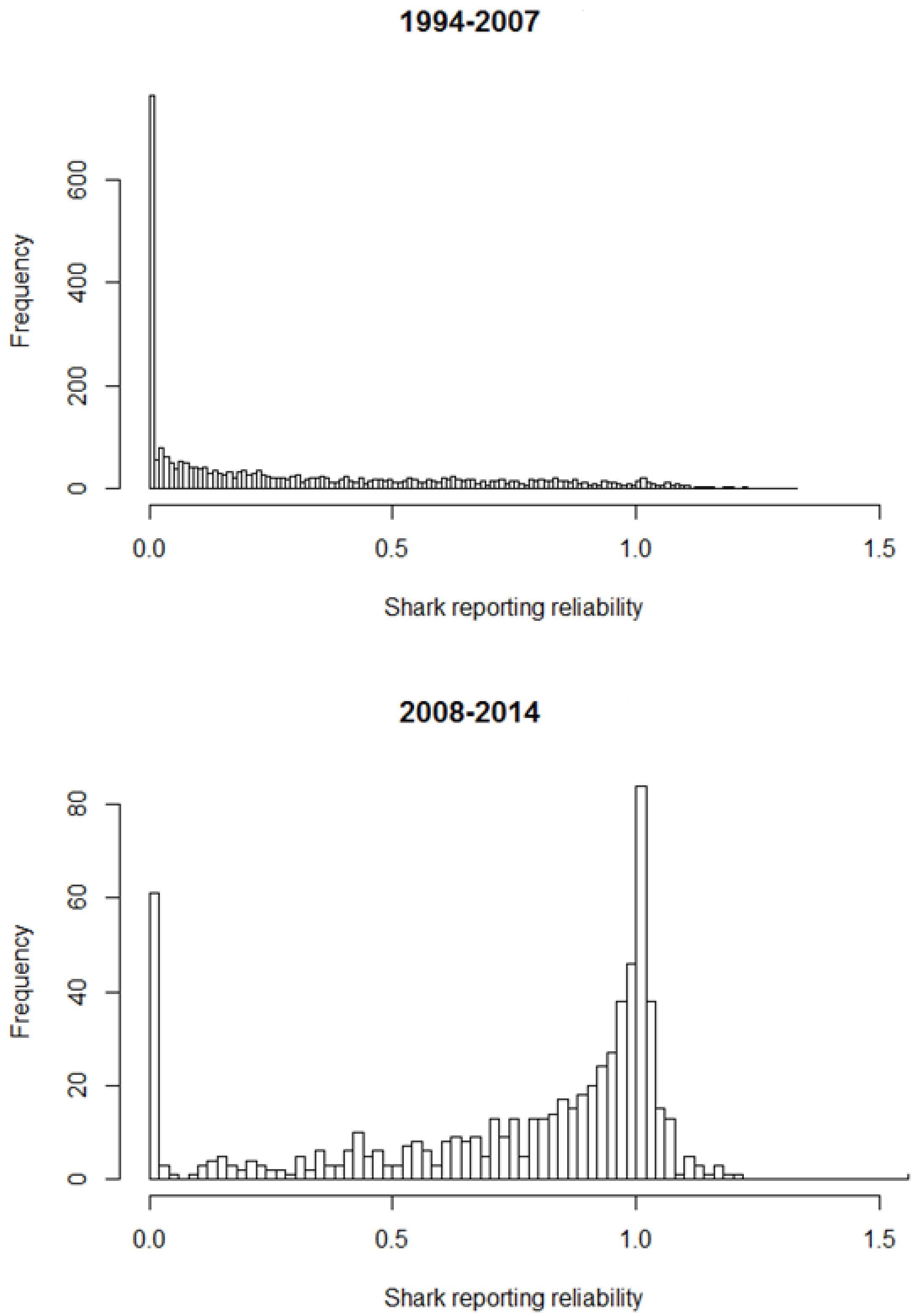

Figure 2.13: Histogram of estimates of mean shark reporting reliability (SR), by vessel trip, for 1994–2007 (above) and 2008–2014 (below).

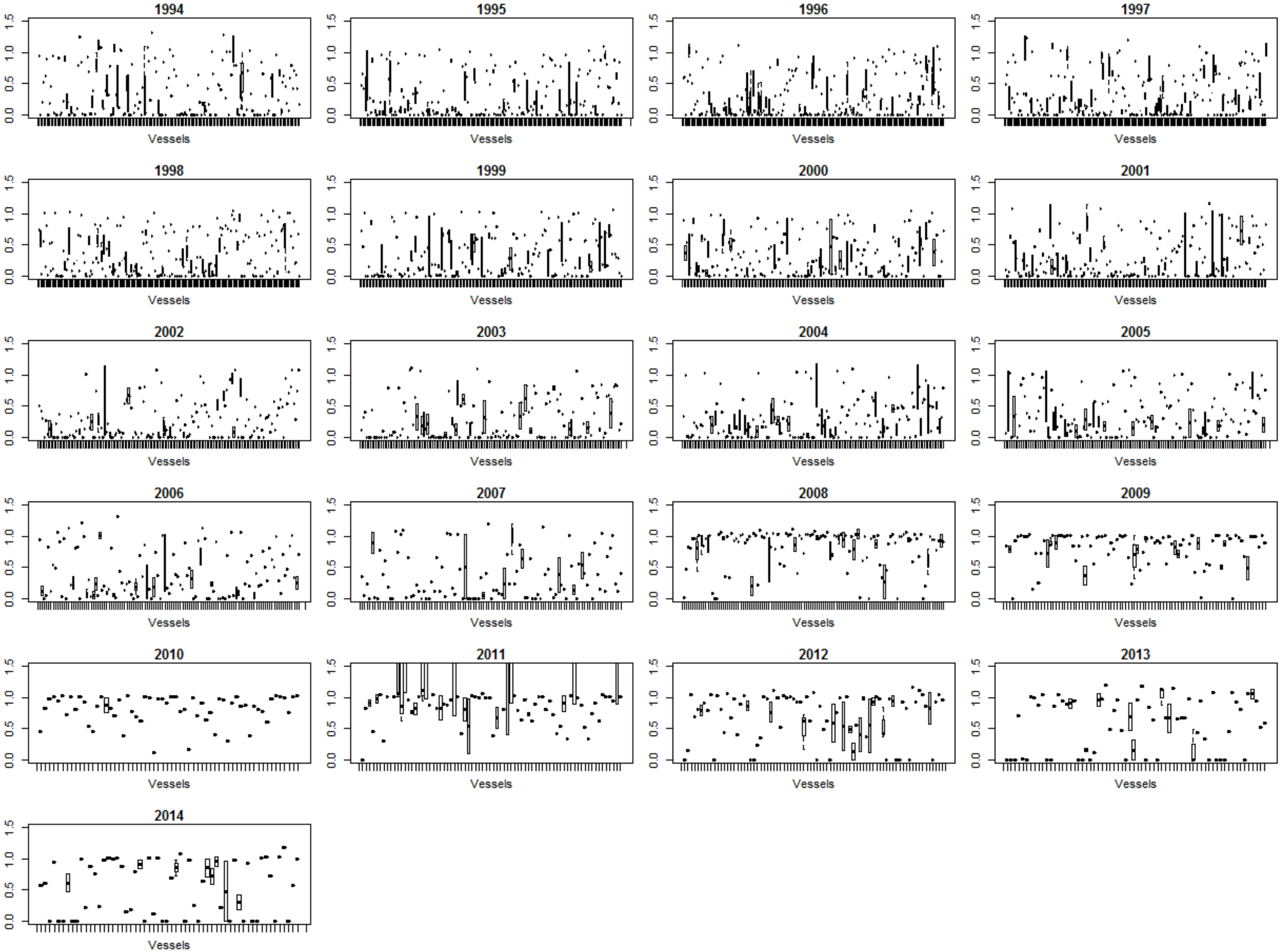

Figure 2.14: Boxplots of mean reporting reliability estimates by vessel, per year.

3. SPATIAL AND TEMPORAL SIZE AND SEX DISTRIBUTIONS OF PORBEAGLE SHARKS

3.1 Introduction

Spatial segregation within a population has implications for stock assessments, which need to allow for separation of population components and their associated movement patterns, and to incorporate appropriate fishery definitions and selectivity. Fishing pressure may differ by life history stage (Mucientes *et al.* 2009).

Sharks often separate spatially by sex (Wearmouth & Sims 2008) and life history stage (Grubbs 2010). In particular, segregation by sex and life history stage have been identified for porbeagle sharks (Semba *et al.* 2013), with seasonal patterns in the sex ratios. Adult porbeagles have been found to move north and south seasonally (Francis *et al.* 2015). Better understanding of spatial segregation and movement patterns would allow them to be taken into account when defining fisheries in stock assessments.

Indices of relative abundance for use in most stock assessments need to have consistent selectivity through time, due to the 'separability assumption'. We therefore needed to identify factors affecting the size and sex of porbeagles caught, including the spatial distribution.

When investigating spatial and temporal patterns in size and sex data, as with similar analyses of catch and effort data, there is a need to use modelling approaches known as standardization methods. The data identify different types of fishing effort which may select different sizes or sexes of fish from the same population, due to features of the effort such as the location, season, depth, or bait used. Fishing effort and its spatial distribution tends to change through time, which introduces its own patterns and biases into the observed data. Standardizing for factors such as location and season allows the true patterns to be identified by adjusting for operational covariates.

Sex distributions can be modelled straightforwardly using generalized linear models with binomial errors. Size distributions are more difficult to model because size patterns can be complicated, with distributions affected by size cohorts. These factors combine with the skewness of size distributions and the fact that distributions can vary among groups, such as by area, to make it difficult to achieve appropriate error distributions even after data transformation. It is possible to simplify the modelling and avoid the need for data transformation by using binomial error distributions, and modelling the probability that sharks are larger than a chosen size threshold value.

We analysed spatial distributions by size and sex for porbeagle sharks caught in the southern bluefin tuna fishery, the Japan Marine Fisheries Resources Research Center (JAMARC) longline survey, and the JAMARC gillnet survey.

3.2 Methods

Logbook data from Japanese longliners operating south of 20° S from 1994 to 2014 were compiled by the National Research Institute of Far Seas Fisheries (NRIFSF). The set-by-set data include information on catch numbers by species of tunas, billfish, swordfish and sharks, operation date, amount of effort (number of hooks), number of branch lines between floats (hooks between floats: HBF) as a proxy for gear configuration, vessel identity, and location (longitude and latitude) of set with a resolution of 1° × 1° square. Effort that captured porbeagle sharks was concentrated in the Indian Ocean to the south of South Africa and the southwest of Australia, and in the Pacific to the east of Tasmania (Figures 3.1 and 3.2).

Observer data were collected from the Japanese national observer programme of the Commission for the Conservation of Southern Bluefin Tuna (CCSBT). The observer data were cleaned to remove longline operations north of latitude 20° S where southern bluefin tuna (*Thunnus maccoyii*) is not targeted. The data include information on the body length and sex of the species caught, bait type, materials of branch lines, set time, haul time, estimated shallowest and deepest hook depth, and bait type, in addition to the information in the vessel logbook (Table 2.1). The observer coverage (as a percentage of hooks set) averaged 7.76% from 2002 to 2014. After cleaning, the observer dataset included 9847 sets (Figures 3.3 and 3.4).

Size data were mostly measured and recorded by observers as snout to precaudal pit length (PCL), with a minority recorded as total length or caudal fork length, with a code to indicate the measurement type. Since 2005 the code has not been recorded and all measurements were assumed to be PCL. Other length types were converted to PCL using the conversion factors described by Francis (2013).

The observer data were linked to the logbook data based on the vessel callsign and the set date. Data were allocated to 5° squares. Moon phases were calculated from the date as a continuous variable from 0 to 1 using the function lunar.illumination in the R package 'lunar' (Lazaridis 2014).

Two datasets derive from Japanese longline research and driftnet research conducted by JAMARC conducted longline surveys for butterfly kingfish *Gasterochisma melampus* from 1987–1994 (Figure 3.5). They also conducted a large-mesh driftnet survey targeting slender tuna *Allothunnus fallai* between 1982 and 1990 and targeting pomfret (Family Bramidae) between 1984 and 1986 (Figure 3.6). JAMARC data were cleaned by removing isolated sets from 5° squares with only one set.

Sea surface temperature data from observers on vessels were mapped by season, to show the SST patterns associated with fishing effort (Figure 3.7).

Regression trees are useful for exploring patterns in data and generating hypotheses, but sensitivity to starting values and small changes in the input data means that other approaches are more reliable for inference. In order to explore the dataset and identify potentially important variables, factors affecting catch rates were explored with regression trees, using the R package 'rpart' (Therneau *et al.* 2015). Length was modelled as a function of year, month, longitude, latitude, moon phase, set time, haul time, cluster, HBF, hooks set, shallowest and deepest depth, use of a wire leader, and bait type. Trees were pruned using the 1-standard error rule (Breiman *et al.* 1984) and plotted.

Generalized additive modelling was applied to size data using the R package mgcv (Wood 2006). Length was assumed to be lognormally distributed, and was modelled as a function of year, month, location, cluster, sea surface temperature, hooks between floats, sex, and hooks per set. All factors were fitted with smoothers except for cluster and sex. Location (1 by 1) was fitted with a two dimensional tensor spline. The model took the following form, where *k* sets the upper limit to the degrees of freedom for an mgcv smooth:

$$\log(len) \sim s(year, k=22) + s(month, k=8) + te(lon, lat, k=10) + cluster + s(SST, k=20) + s(hbf, k=8) + sex + s(hooks) \quad (1)$$

The commercial fishery data could be spatially subdivided into three areas: western Indian Ocean, eastern Indian Ocean, and western Pacific, with longitudinal splits at 70° E and 140° E. We tested for spatial effects by fitting either one or two models to the Indian Ocean, divided at 70° E. We also tested two further approaches: omitting sea surface temperature; and modelling spatial effects using categorical 5° squares rather than a smoother.

Model selection was based on minimization of both the Generalized Cross-Validation statistic (GCV) and the Akaike Information Criterion (AIC). Within a model the significance of each model term was assessed using Wald-like tests, conditional on the smoothing parameter estimates, using the function anova.gam() from the mgcv package in R. Effects were plotted by predicting lengths across the range of observed values of the parameter of interest, while fixing all other parameters. Numeric variables were fixed at their medians except *year* and *month* which were fixed at 2000 and July respectively. The categorical variables *cluster* and *sex* were set to *cluster*=1 (catching a mixture of albacore and SBT) and *sex*=male. Confidence intervals were predicted at the 95% confidence level for the parameter of interest.

Similar approaches were applied to analysing the distribution of porbeagle sex ratio in relation to observed variables. We initially used random forests via the R package randomForest (Liaw & Wiener

2002) to explore the data and identify significant variables. Subsequently, we used generalized additive models, as above. We tested for spatial effects by fitting either one or three models, divided at 70° E and 140° E. We also tested omitting sea surface temperature (Equation (2)) and modelling spatial effects using categorical 5° squares rather than a smoother (Equation (3)).

$$\log(len) \sim s(year, k=22) + s(month, k=8) + te(lon, lat, k=10) + cluster + s(SST, k=20) + s(hbf, k=8) + sex + s(hooks) + s(SST) \quad (2)$$

$$\log(len) \sim s(year, k=22) + s(month, k=8) + 5°cell + cluster + s(SST, k=20) + s(hbf, k=8) + sex + s(hooks) \quad (3)$$

Size distributions were also explored in the JAMARC datasets. For these datasets total weights per set and numbers caught were available, and mean weight per set was calculated by dividing catch weight by catch number. Size distributions were modelled with generalized additive models using the R package mgcv (Wood 2006). Mean weights were modelled as a function of year, month, location, and (for the gillnet data) sea surface temperature. The following model was applied to the gillnet data. The same model without the SST term was applied to the JAMARC longline data.

$$mean\ wt \sim s(year, k=9) + s(month, k=9) + te(lon, lat, k=13) + s(SST, k=10)$$

Mean weights were log transformed for the gillnet data in order to normalise the residuals. Residuals for the JAMARC longline data were normally distributed without transformation.

3.3 Results

Regression tree modelling of lengths in the observer data showed significant variation associated with sea surface temperature, with the most significant split at 12 °C, with larger sharks observed at lower temperatures. Two other splits were observed at about 10.5 °C and 16 °C, again with larger sharks at lower temperatures (Figure 3.8).

Generalized additive modelling supported separate models to the east and west of 70° E, with AIC for the pooled dataset of -7317 versus -7497 for separate models. Models with two-dimensional smoothed latitude and longitude fitted better than models using categorical 5° squares (ΔAIC = 118.1 in the western IO and 121.8 in the eastern IO). Including SST in the models was supported in all areas (ΔAIC = 103.2 in the western IO, 2.3 in the eastern IO, and 2.9 in the Pacific). Tests of parameters in the selected models (Tables 3.1 and 3.2) supported the inclusion of location and hooks between floats in all areas; year, month, targeting cluster, and hooks in the Indian Ocean but not in the Pacific; and SST was strongly supported in the western Indian Ocean but less so in the eastern IO, and marginal in the Pacific.

Results generally indicated that larger sharks were caught at lower temperatures, further south, and in cluster 2 (catching albacore, bigeye and yellowfin tunas) (Figures 3.9 to 3.14). In the western Indian Ocean (Figure 3.9) and the Pacific (Figure 3.13), higher HBF was associated with larger size, but the opposite was true in the eastern IO (Figure 3.11). The effect of hooks varied between areas. In the eastern Indian Ocean, shark sizes tended to decrease through time until 2011, followed by fluctuations.

For sex ratio, random forest analyses showed variation associated with (in decreasing importance) moon phase, longitude, latitude, set time, and sea surface temperature (Figure 3.15). Generalized additive models fitted better when data were separated at 70° E and 140° E, compared to the pooled dataset (ΔAIC = 11.1). There was further spatial variation within the western area (Table 3.3), with more females in the northeast (Figure 3.17). Spatial variation was not statistically significant in the eastern Indian ocean or the Pacific (Tables 3.4 and 3.5). Slightly higher proportions of females were captured at the new moon. There was significant inter-annual variation in sex ratio in the western and eastern Indian Ocean. Higher HBF was associated with capture of more males in the western Indian Ocean (Figure 3.16), no clear trend in the eastern Indian Ocean (Figure 3.18), and more females in the Pacific (Figure 3.19). Sex ratios of observed sharks were female-biased in the Pacific, but not in the Indian Ocean.

Analyses of JAMARC data suggested some spatial patterning. The longline data showed widely distributed porbeagle sharks, with larger mean sizes further south and in the east, closer to South America (Figure 3.20). The gillnet data showed widely distributed porbeagle captures, and a similar spatial size pattern when temperature data were excluded. Including temperature data in the analysis explained most of the spatial variation and indicated that larger sharks tended to be caught at lower temperatures (Figure 3.21).

3.4 Discussion

Modelling of the length data suggested that length is strongly associated with SST. Smaller sharks appeared to prefer waters warmer than about 12 °C, and this pattern was apparent in a number of datasets. Surprisingly, the more northerly mixed tuna fishery was associated with positive effects on shark size (i.e., sharks were relatively large). However, the relative size of these sharks was deduced after taking the warmer temperature and northern location into account, so this conclusion may reflect the effects of unmeasured covariates associated with the fishing strategy. It may also reflect the northward winter movement of mature females (Francis *et al.* 2015).

Given the spatial size variation associated with water temperature, grouping the data into separate fisheries at 40° S for CPUE standardization is considered appropriate. It may also be appropriate to use oceanographic information to group logbook data based on whether the water temperature is estimated to be above or below 12 °C. The sex ratio in the Pacific was significantly biased towards females, but similar proportions of both sexes were caught in the Indian Ocean. Sex ratios appeared to vary most strongly with hooks between floats. In the western Indian Ocean, more males were caught at higher HBF, while in the Pacific more males were caught at lower HBF. HBF is an indicator of both fishing strategy and fishing depth. These results suggest that there may be some sex partitioning by depth, but the spatial variation is interesting and may reflect seasonal or spatial variation in fishing strategy and population composition. Further analyses of this dataset are recommended. The differing sex ratio in the Pacific suggests some spatial partitioning, which supports analysing this area separately.

Given the spatial size variation associated with water temperature, grouping the data into separate fisheries at 40° S for CPUE standardization may be appropriate. This latitude approximates a 12 °C water temperature, on average across seasons. It may also be appropriate to use oceanographic information to group logbook data based on whether the water temperature is estimated to be above or below 12 °C. Observer data with SST information may be grouped for CPUE standardization based on the measured SST.

The mean sizes of the sharks in this analysis suggests that the majority of the catch comprises neonates and 1-year old sharks, particularly in the areas north of 40° S and above 12 °C. It is theoretically possible to catch mostly young fish in two ways (or a combination): 1) the population contains many age classes, but the fishery selects the young fish, or 2) the population contains mostly young fish, and the fishery catches all age classes. Natural mortality rates of porbeagle sharks are generally assumed to be low (Clarke *et al.* 2015). For option 2 to be true would require very high total mortality, with few sharks surviving past age 2. Such high levels of total mortality are not plausible, because with such high total mortality and porbeagles' low reproductive output the population would decline and the CPUE would reduce, whereas in fact the CPUE appears stable in the Indian Ocean. Therefore, it is likely that the fishery is selecting young/small sharks, probably because it is fishing in areas occupied mostly by small sharks. This selectivity is something that stock assessment needs to take into account.

3.5 Tables

Table 3.1: Significance tests for categorical variables in models of porbeagle length in the western Indian Ocean (west IO), eastern Indian Ocean (east IO), and Pacific Ocean.

Parameter	Area	df	F	p-value
Cluster	west IO	2	12.80	<0.00001
	east IO	2	2.74	0.06490
	Pacific	2	0.44	0.64500
Sex	west IO	1	1.96	0.16200
	east IO	1	2.10	0.14750
	Pacific	1	0.26	0.61200

Table 3.2: Significance tests for smoother parameters in models of porbeagle length in the western Indian Ocean (west IO), eastern Indian Ocean (east IO), and Pacific Ocean.

Parameter	Area	edf	F	p-value
s(hbf)	west IO	3.57	4.72	0.00086
	east IO	3.84	7.05	<0.00001
	Pacific	1.10	5.85	0.01450
s(hook)	west IO	5.67	2.26	0.02224
	east IO	7.64	3.12	0.00118
	Pacific	5.36	0.97	0.34910
s(month)	west IO	2.83	7.95	0.00002
	east IO	5.60	7.38	<0.00001
	Pacific	1.88	0.45	0.60500
s(SST)	west IO	15.41	9.67	<0.00001
	east IO	2.04	2.59	0.05106
	Pacific	10.77	1.46	0.13120
s(year)	west IO	20.61	10.51	<0.00001
	east IO	19.03	5.53	<0.00001
	Pacific	3.11	0.56	0.56860
te(lon,lat)	west IO	45.56	4.80	<0.00001
	east IO	41.74	5.43	<0.00001
	Pacific	33.25	2.60	<0.00001

Table 3.3: Western Indian Ocean models of sex ratio.

Variable	df	χ^2	p-value
Year	17	89.56	<0.001
	edf	χ^2	p-value
te(lon,lat)	14.703	37.319	0.010
s(moon)	8.136	22.442	0.007
s(HBF)	2.787	8.572	0.062
s(hook)	7.429	18.285	0.019

Table 3.4: Eastern Indian Ocean models of sex ratio.

Variable	df	χ^2	p-value
Year	17	33.941	0.0085
HBF	3	8.164	0.0427
	edf	χ^2	p-value
te(lon,lat)	3.001	5.364	0.147
s(SST)	12.132	25.589	0.035

Table 3.5: Pacific Ocean models of sex ratio.

Variable	df	χ^2	p-value
Year	9	10.67	0.299
HBF	4	11.65	0.020
	edf	χ^2	p-value
te(lon,lat)	16.233	16.984	0.727
s(moon)	1	2.295	0.130
s(hook)	2.247	5.325	0.109

3.6 Figures

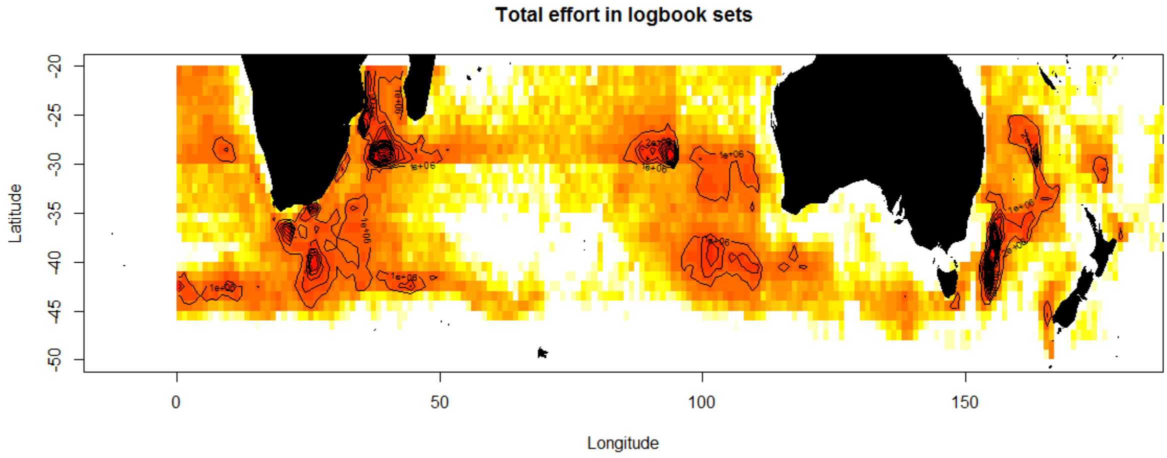

Figure 3.1: Spatial distribution of effort in longline fishery logbook data. Darker colour indicates more effort.

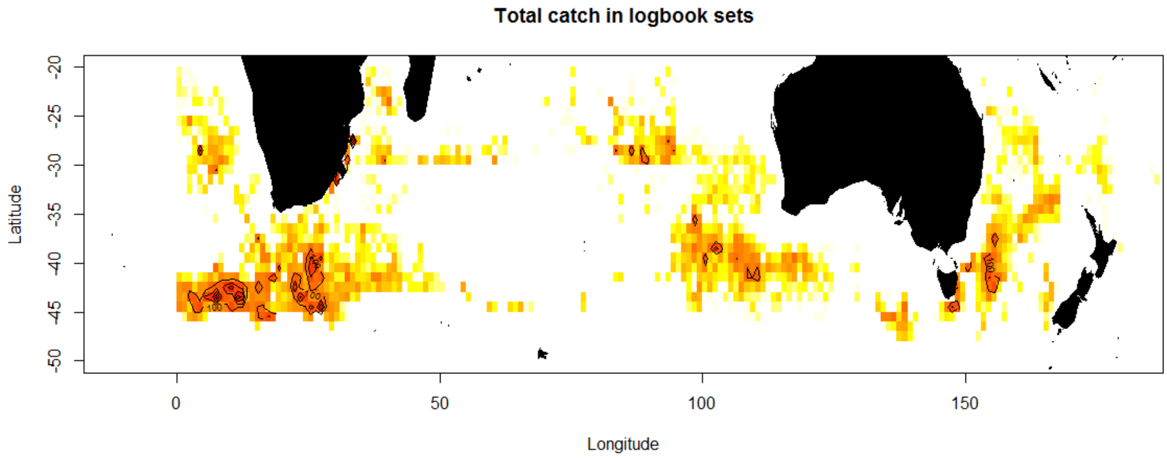

Figure 3.2: Spatial distribution of reported porbeagle catch in longline fishery logbook data. Darker colour indicates more catch.

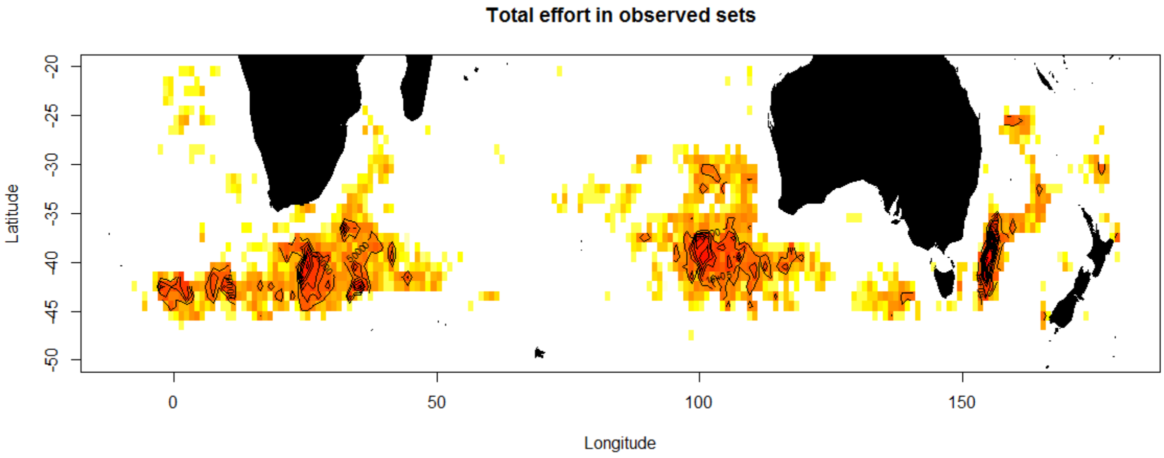

Figure 3.3: Spatial distribution of observed effort in longline fishery, by 1° square. Darker colour indicates more effort.

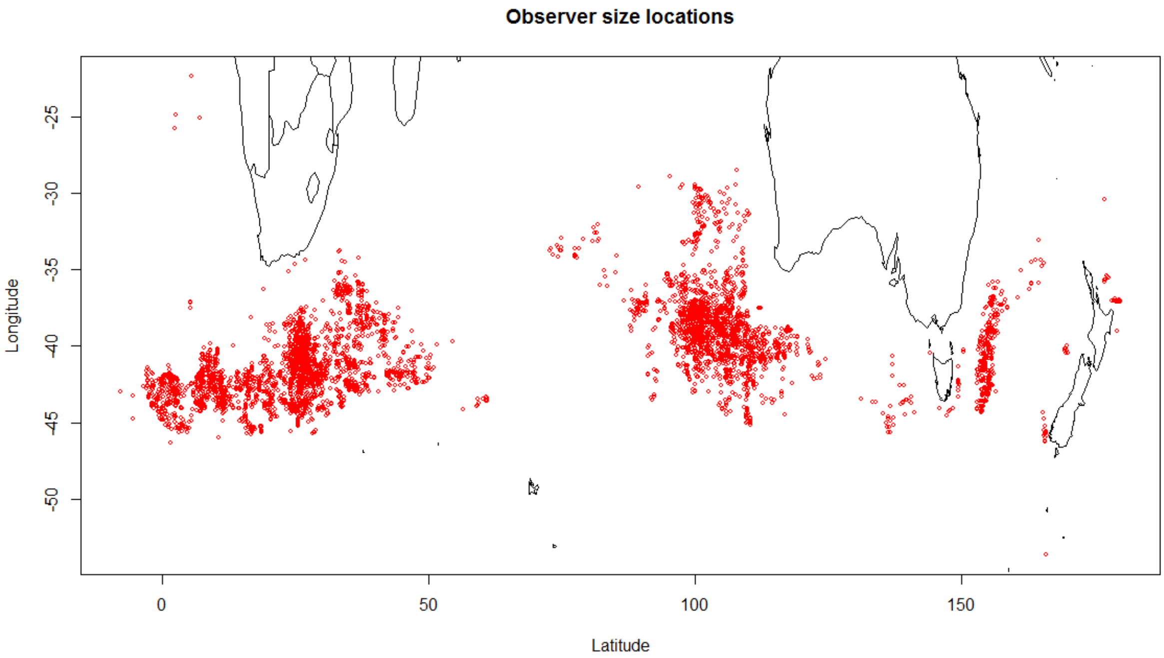

Figure 3.4: Locations of observer sets that reported porbeagle sizes.

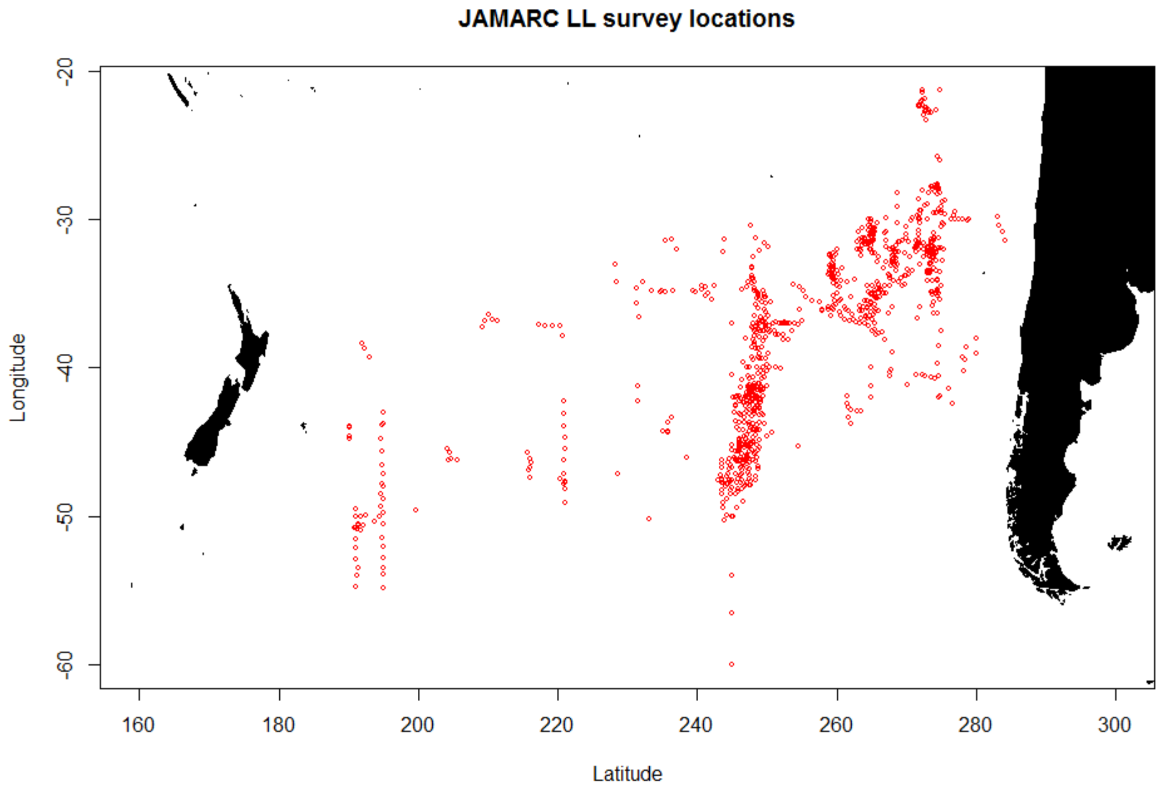

Figure 3.5: Locations of JAMARC longline survey sets.

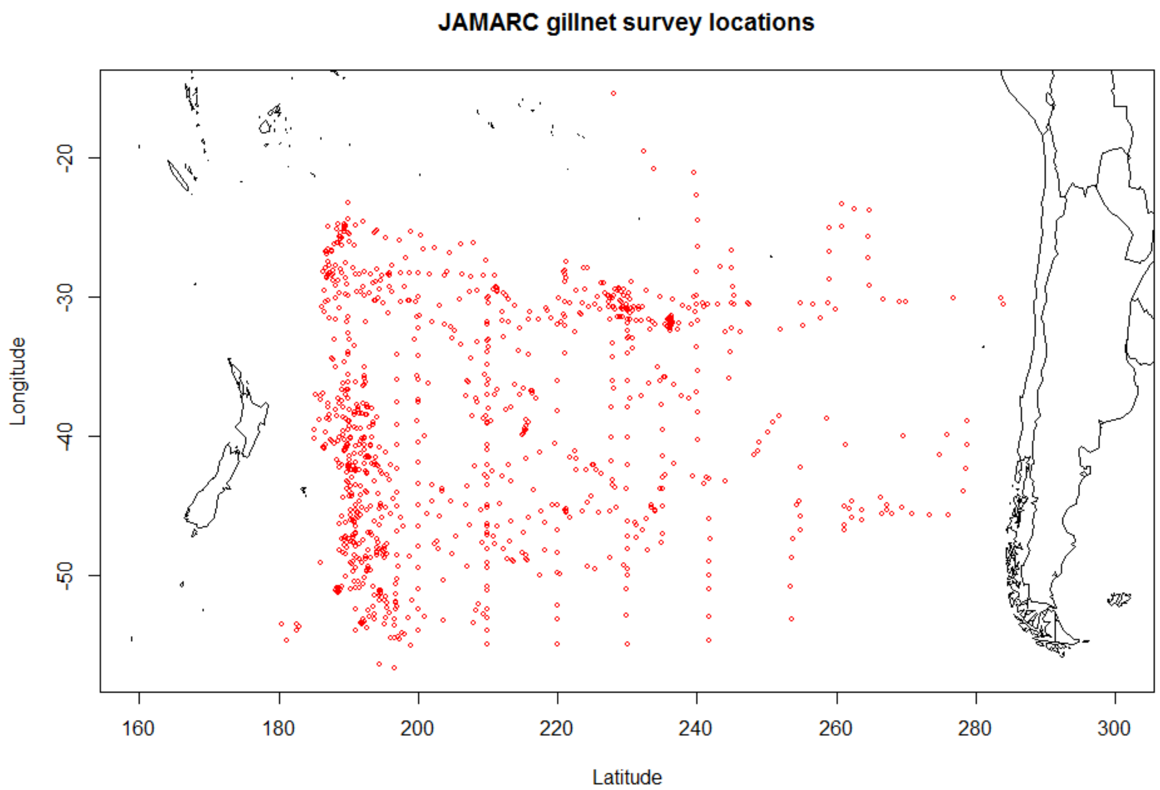

Figure 3.6: Locations of JAMARC gillnet survey sets.

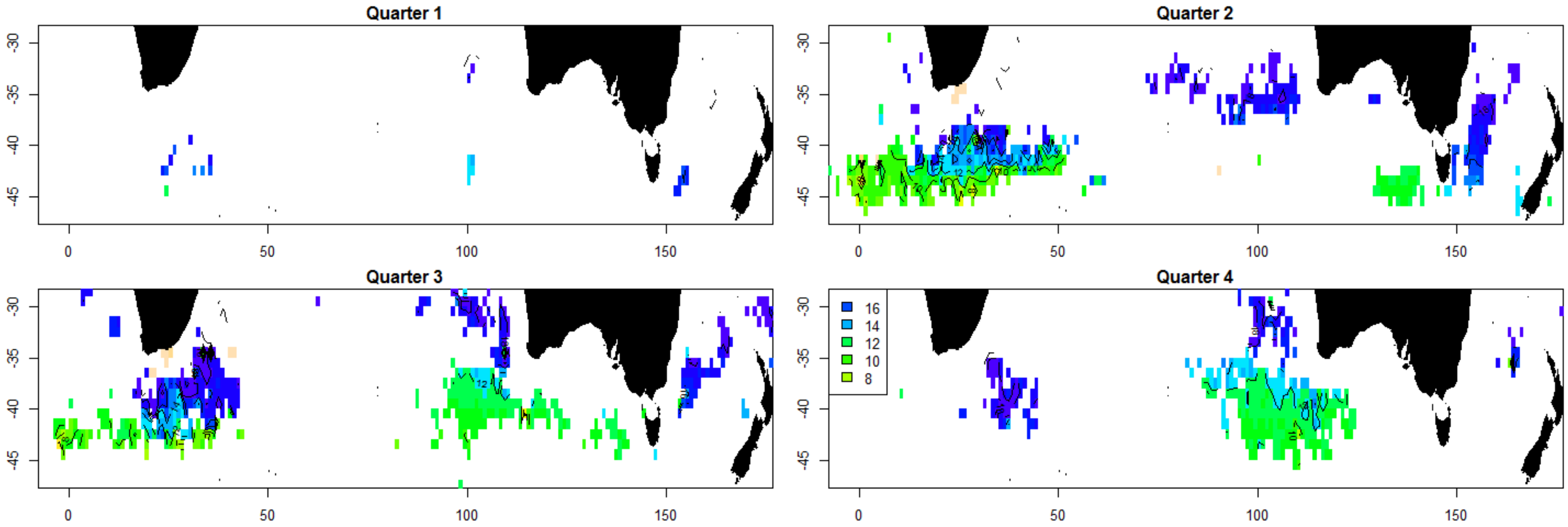

Figure 3.7: Vessel-based estimates of sea surface temperature, averaged by 1° square and quarter. Isotherms are at 2° intervals. Quarters 1-4 represent January–March, April–June, July–September, and October–December respectively.

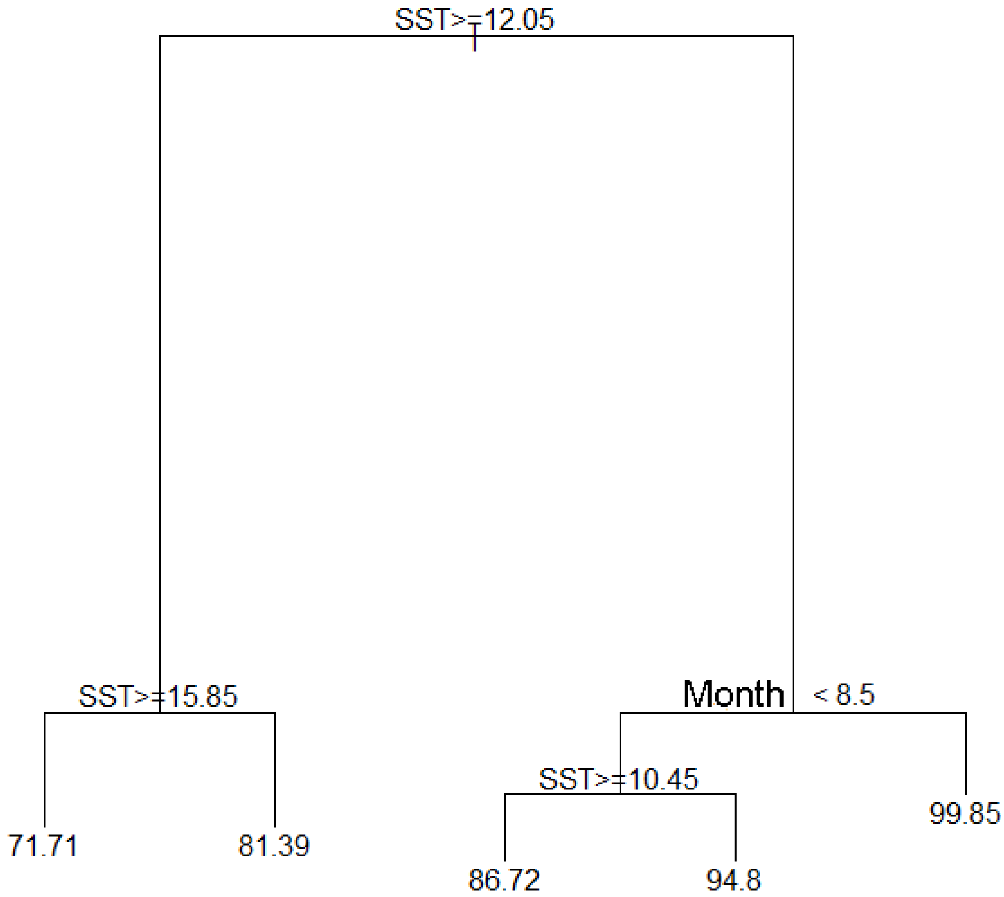

Figure 3.8: Regression tree of factors affecting the lengths of porbeagle sharks reported in longline observer data. The values at the ends of the five branches show mean shark length (snout to precaudal pit length, cm). SST is sea surface temperature. At each branch, the 'true' branches are on the left.

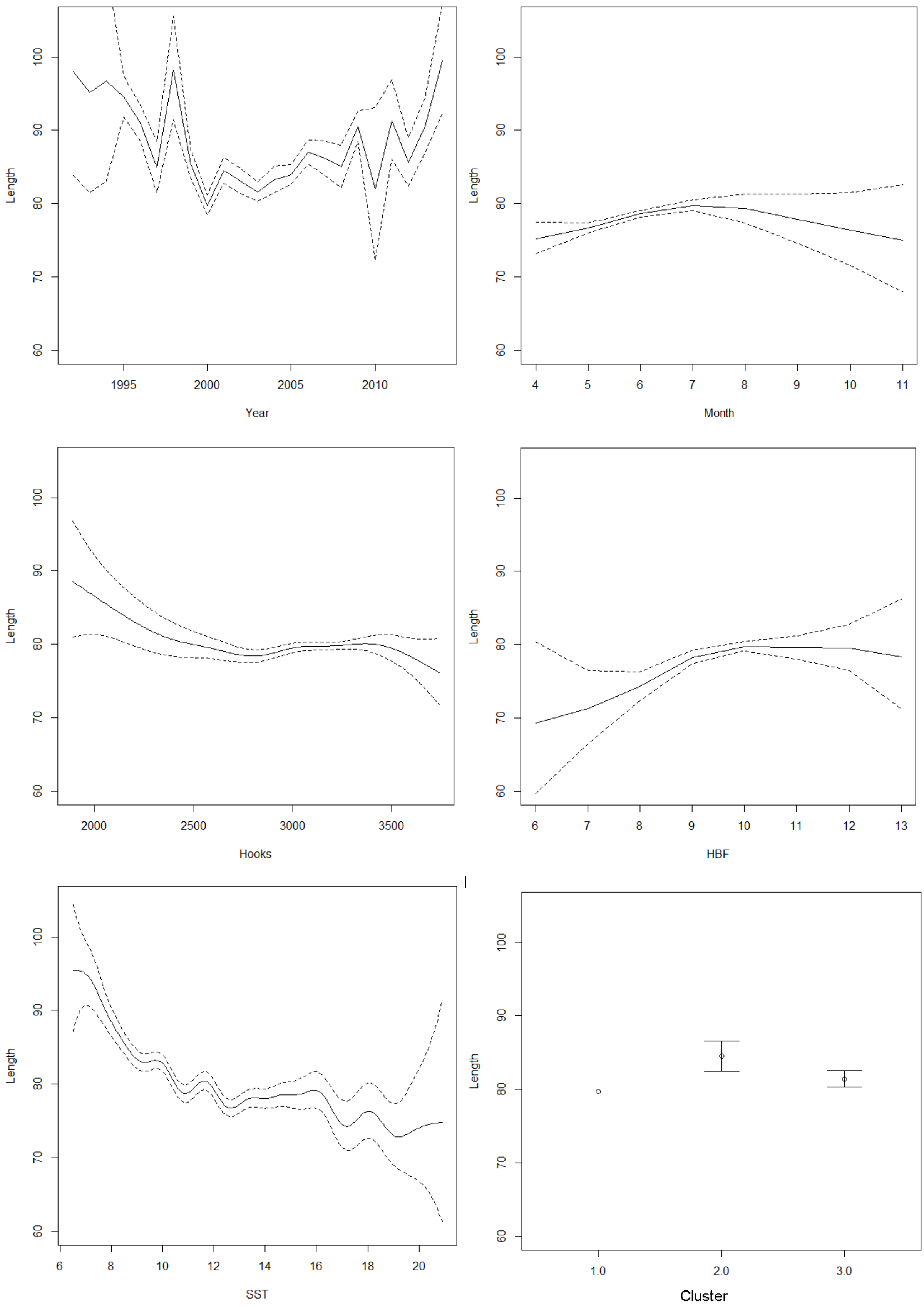

Figure 3.9: Predicted porbeagle shark lengths (snout to caudal pit length, cm) versus modelled variables for the western Indian Ocean, with 95% confidence intervals. Model variables are year, month, hooks, HBF, SST, and cluster.

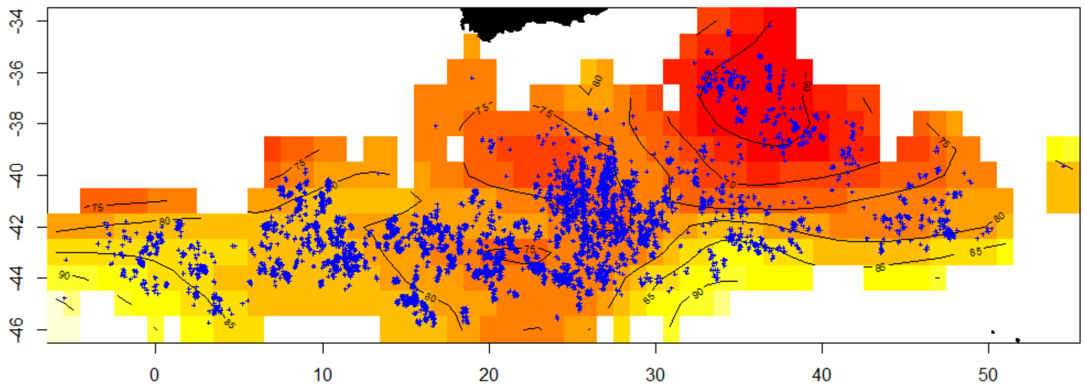

Figure 3.10: Predicted porbeagle shark lengths versus location for the western Indian Ocean. Yellow colour indicates greater length. Blue crosses indicate sampled locations.

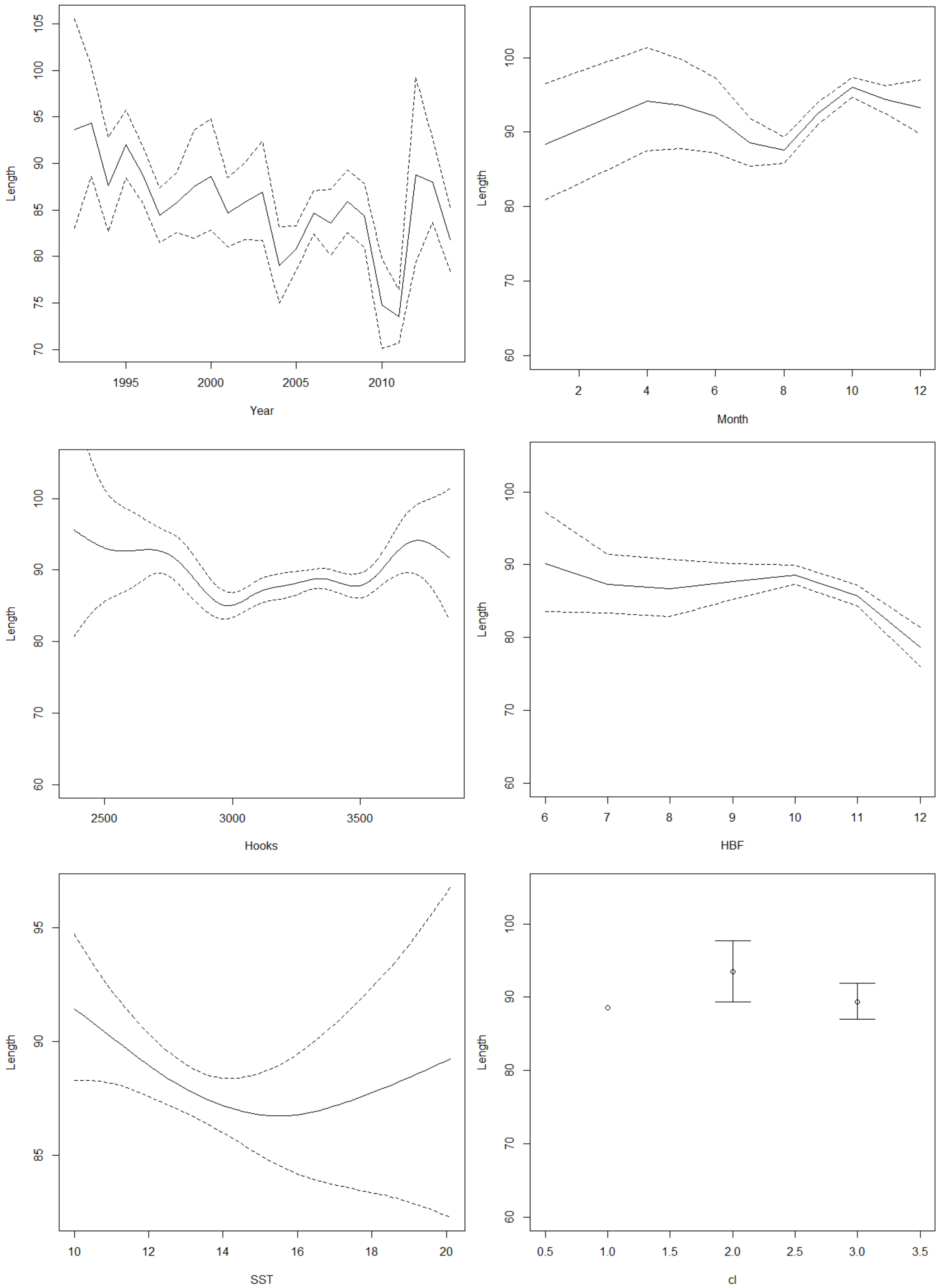

Figure 3.11: Predicted porbeagle shark lengths versus modelled variables for the eastern Indian Ocean, with 95% confidence intervals. Model variables are year, month, hooks, HBF, SST, and cluster.

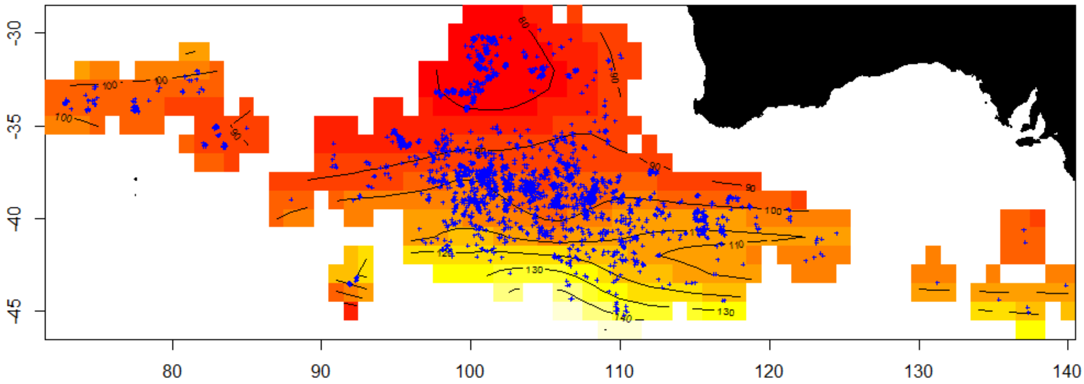

Figure 3.12: Predicted porbeagle shark lengths versus location for the eastern Indian Ocean. Yellow colour indicates greater length. Blue crosses indicate sampled locations.

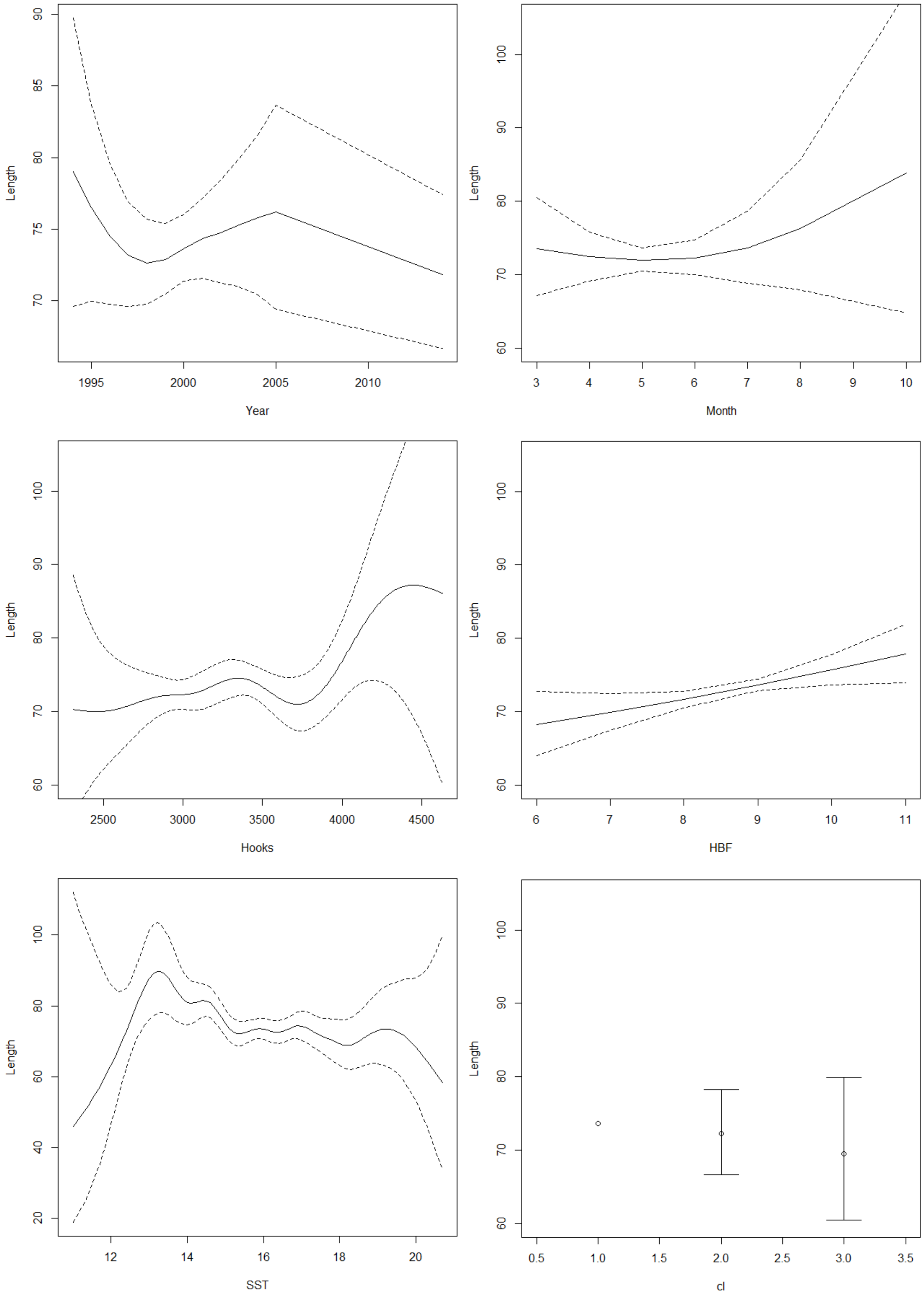

Figure 3.13: Predicted porbeagle shark lengths versus modelled variables for the Pacific, with 95% confidence intervals. Model variables are year, month, hooks, HBF, SST, and cluster.

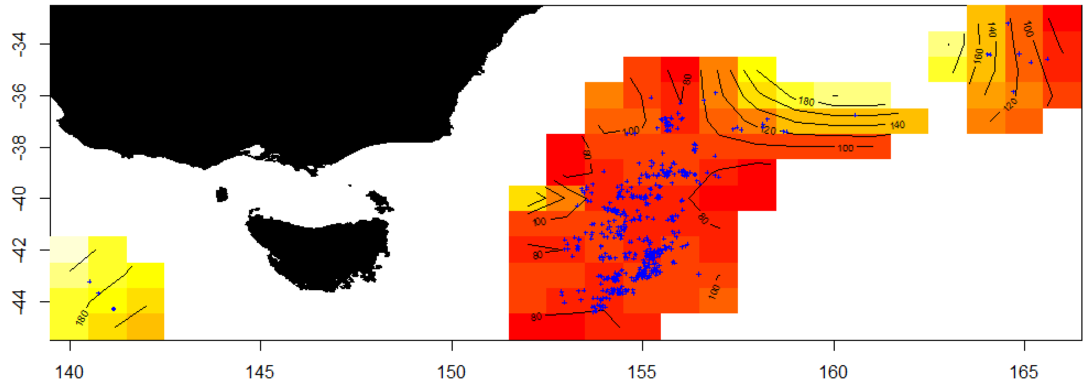

Figure 3.14: Predicted porbeagle shark lengths versus location for the Pacific Ocean. Yellow colour indicates greater length. Blue crosses indicate sampled locations.

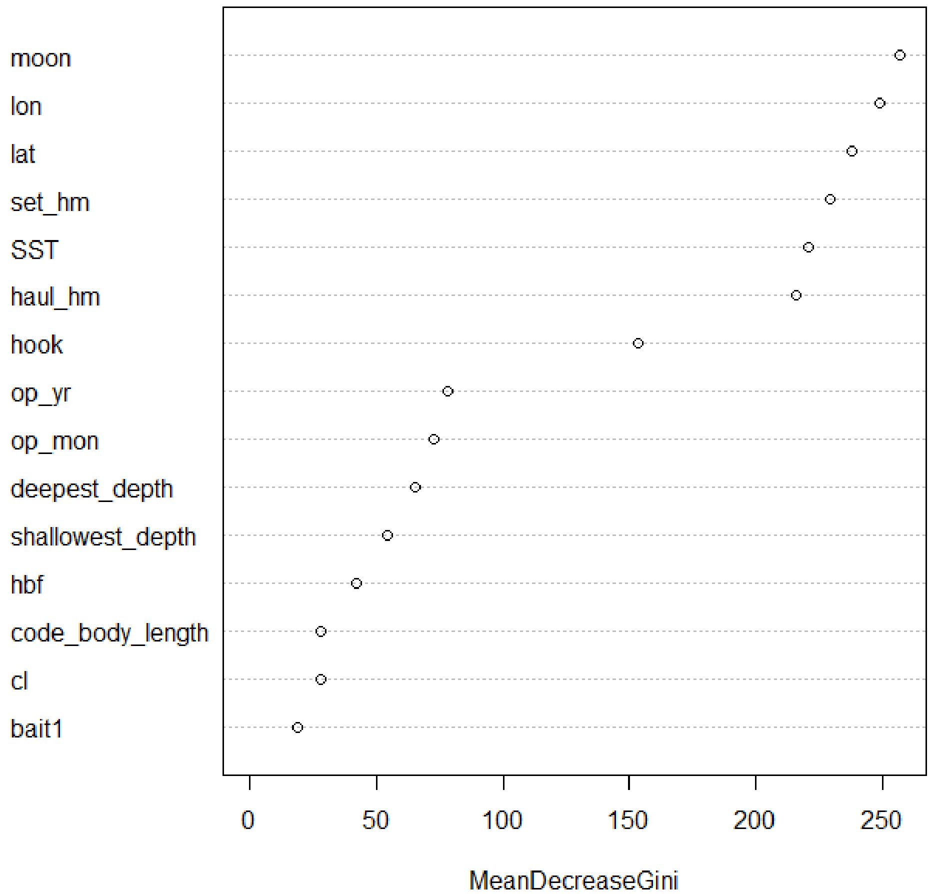

Figure 3.15: Random Forest Importance plot for parameters associated with the sex ratio of porbeagles in longline sets.

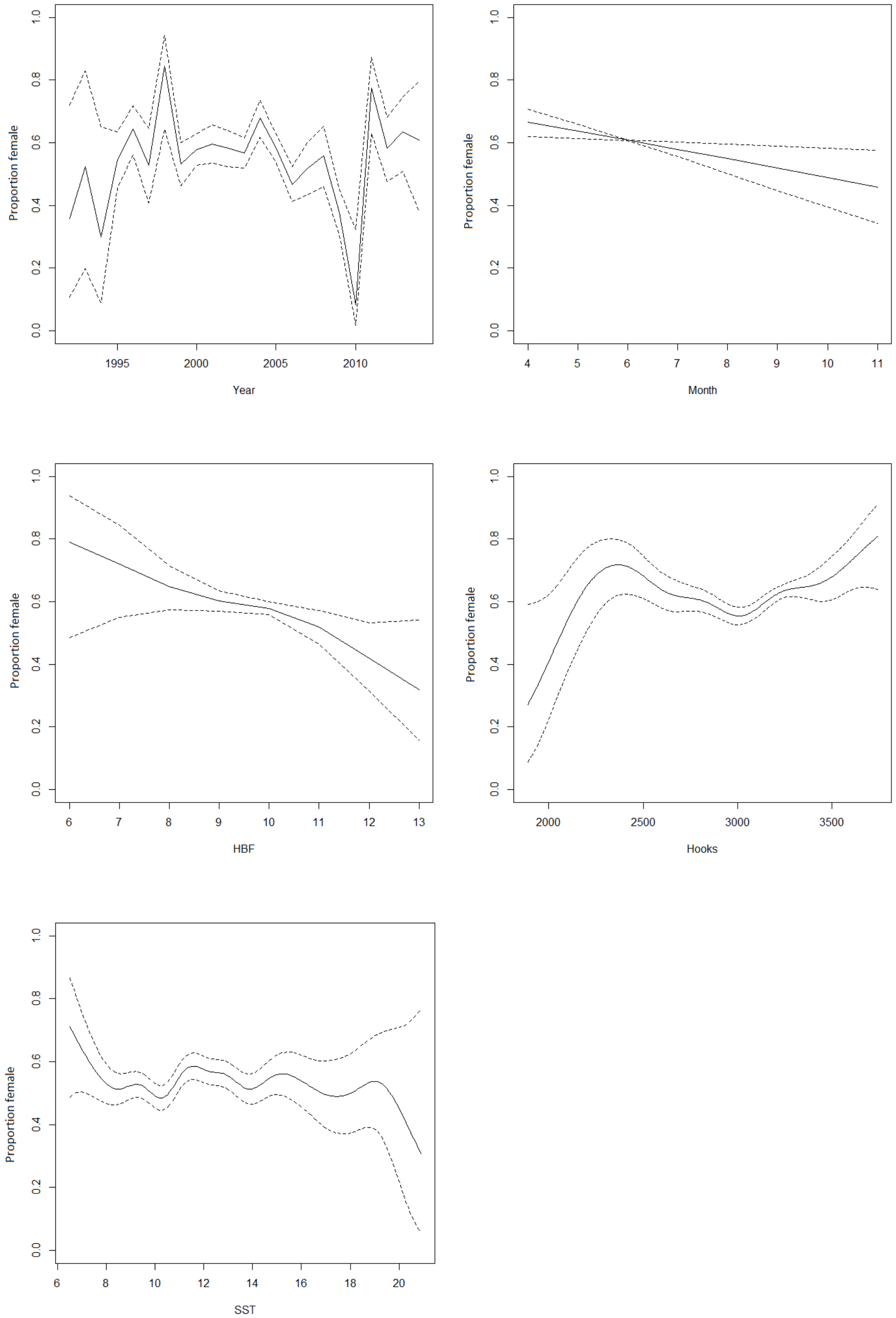

Figure 3.16: Plots of mean sex ratio (proportion female) versus variable values for the western Indian Ocean.

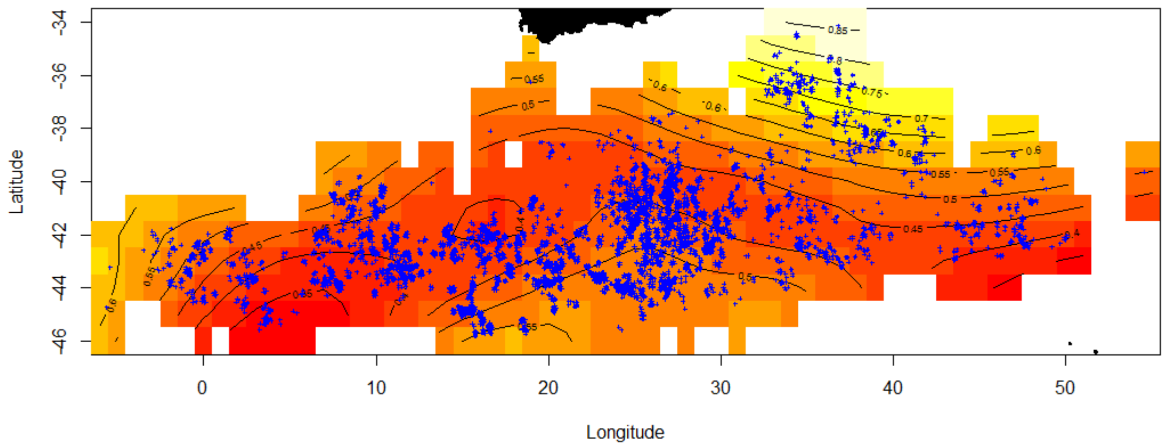

Figure 3.17: Plots of mean sex ratio (proportion female) versus location for the western Indian Ocean. Yellow colour indicates a higher proportion of females. Blue crosses indicate sampled locations.

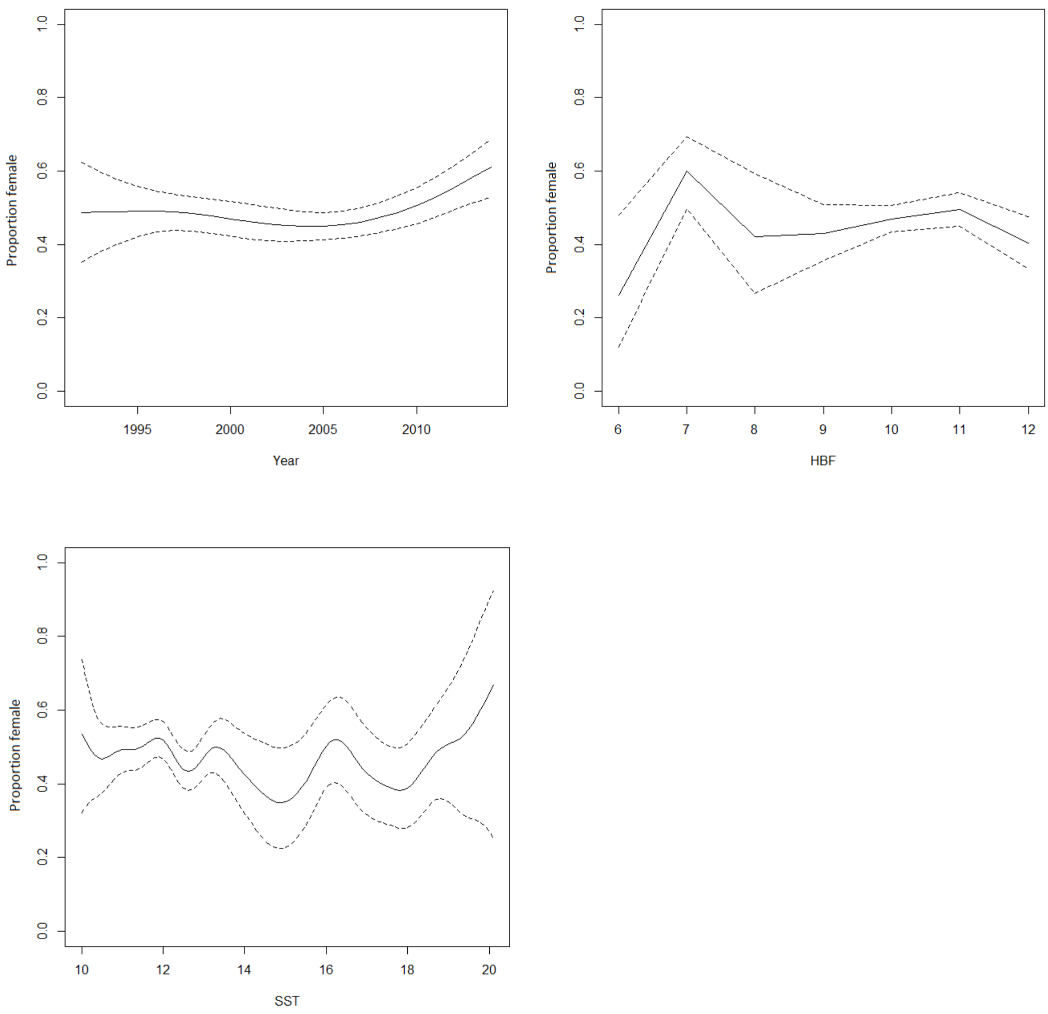

Figure 3.18: Plots of mean sex ratio (proportion female) versus variable values for the eastern Indian Ocean.

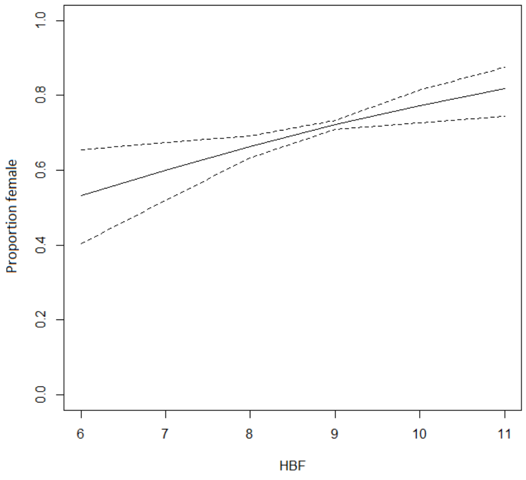

Figure 3.19: Plots of mean sex ratio (proportion female) versus variable values for the Pacific Ocean.

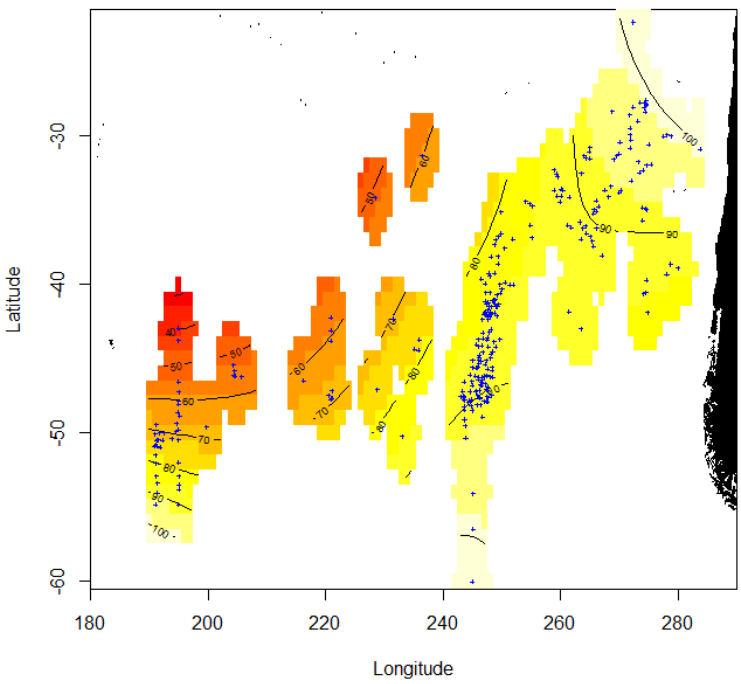

Figure 3.20: Map showing mean size (weight in kg) versus location for JAMARC longline samples in the Pacific Ocean. Yellow colour indicates larger average size. Blue crosses indicate shark capture locations.

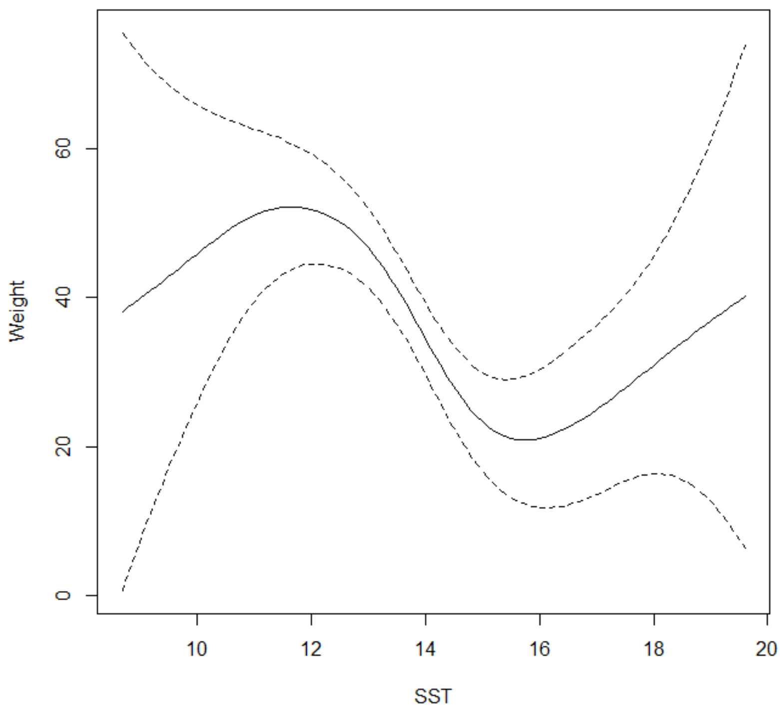

Figure 3.21: Plot showing mean size (weight in kg) versus sea surface temperature (SST) for JAMARC gillnet samples in the eastern Pacific. Dotted lines indicate ± 2 standard errors.

4. ANALYSES OF PORBEAGLE SHARK CPUE.

4.1 Introduction

These analyses were carried out to develop indices of abundance for porbeagle shark, for use in a planned Southern Hemisphere stock assessment.

Indices of relative abundance for use in most stock assessments need to have consistent selectivity through time, due to the 'separability assumption'. If different population components, such as different age classes or sexes, occur in different areas, the areas may have different abundance trends and therefore need to be standardized separately. For example, under constant fishing pressure the relative abundance will decline more severely for older than for younger age classes, because the older age classes experience more cumulative fishing mortality.

Standardization is always required when deriving indices of abundance from catch and effort data. The data include different types of fishing effort, and the nature of the effort varies seasonally and spatially. In addition, there is seasonal variation in shark distribution, with porbeagle sharks moving south in summer to remain in cooler waters (Francis *et al.* 2015). Neonates are found further north and in warmer waters than adult sharks. The analyses of sex and size distribution demonstrated that smaller sharks tend to be found at temperatures above 12 °C. It may be reasonable, therefore, to define fisheries based on water temperature as an alternative to location.

Bycatch data are often characterized by large numbers of zeros, which require appropriate methods when modelling at the set level, because the log of zero is undefined. Potential approaches include adding a constant to the catch rate, fitting a two-part model such as hurdle (e.g. delta lognormal) or zero-inflated model, or a distribution that permits zero values such as the Poisson, negative binomial, or Tweedie.

4.2 Methods

The models used logbook and observer data from Japanese longliners, as described in Section 2.2 (Figures 4.1 and 4.2). The observer data were linked to the logbook data so that observer data could be allocated to clusters. Data were linked by vessel callsign and set date, and clustered as described in Section 2. The logbook data were cleaned by using only the vessel-months in which the shark reporting reliability SP_{log} exceeded 0.9.

Data were clustered as described in Section 1 of this report.

Data were cleaned using the approaches described in Section 1, so that only sets in which reporting was considered reliable were included in the logbook dataset.

Fishing effort was grouped into regions according to several different definitions, in order to examine different aspects of catch rate trends. The first option split the data into three regions at longitudes 70° E and 145° E. (An unintentional difference from the eastern boundary for size and sex analyses at 140 °E which made, given the sample locations, no effective difference to results). The second option further split the Indian Ocean into four regions, with a split between north and south at 40° S to reflect the prevalence of neonates in the north and adults in the south. The third option was similar to the second, but split the Indian Ocean north-south using a sea surface temperature of 12 °C rather than latitude, to reflect the importance of temperature in determining porbeagle distribution, and distribution by size.

The operational set-by-set data were standardized using generalized linear models in R (R Core Team 2015). Analyses were conducted separately for the logbook and observer data, and for each region. Each model was run on a computer with 20 GB of memory. The following 'lognormal constant' model was used for data exploration, since it runs quickly and provides results similar to those of alternative models:

$$\log(CPUE_s + k) \sim year + quarter + vessid + latlong5 + cluster + f(HBF) + \varepsilon,$$

where log was the natural logarithm, *year* was the effect of year, *vessid* was the effect of the individual vessel, *latllong5* was a 5° square spatial effect, *cluster* was the effect of cluster, and *f(HBF)* was a cubic spline with 3 degrees of freedom on the effect of hooks between floats. The constant *k*, added to allow for modelling sets with zero catches of the species of interest, was 10% of the mean CPUE for all sets. Errors ε were assumed to be normally distributed.

In addition, the delta lognormal approach to standardization (Lo *et al.* 1992; Maunder & Punt 2004) was used.

$$\Pr(Y = y) = \begin{cases} w, & y = 0 \\ (1 - w)h(y) & otherwise \end{cases}$$

This approach uses a binomial distribution for the probability *w* of catch being zero and a probability distribution *h(y)*, where y was log(catch/hooks set), for non-zero catches. The probability of a zero set w was modelled as $g(w) = z = year + quarter + vessid + latlong5 + f(HBF) + j(hooks) + \varepsilon$, where g was the logit function, and *j(hooks)* was a cubic spline with 10 degrees of freedom on the number of hooks in the set. The distribution of catch rates in nonzero sets was modelled as $h(y) = u = year + quarter + vessid + latlong5 + f(HBF) + \varepsilon$, where errors ε were assumed to be normally distributed. An index was estimated for each year-quarter, which was the product of the year effects for the two model components, $(1 - w).E(y|y \neq 0)$.

The vessel identifier (*vessid*) was included as a categorical variable in the analyses of logbook data, but it was not included in the observer data analyses because the vessels with observers changed through time, and there was insufficient overlap through time in vessel identifiers to use them in the analysis.

For both the lognormal constant and lognormal positive GLMs, model fits were examined by plotting the residual densities and Q-Q plots. Catch data (numbers of porbeagles) in both types of GLM were 'area-weighted', with the statistical weights of the sets adjusted so that the total weight per year-quarter in each 5° square would sum to 1. This method was based on the approach identified using simulation by Punsly (1987) and Campbell (2004), that for set *j* in area *i* and year-qtr *t*, the weighting function that gave the least average bias was: $w_{ijt} = \frac{log(h_{ijt}+1)}{\sum_{j=1}^{n} \log(h_{ijt}+1)}$. Given the relatively low variation in number of hooks between sets in a stratum, we simplified this to $w_{ijt} = \frac{h_{ijt}}{\sum_{j=1}^{n} h_{ijt}}$.

Indices of abundance for the delta lognormal GLM model were obtained by taking the year effects from the GLM, and setting their mean to the proportion of positive sets across the whole dataset. Alternatively, the mean could be set to the mean of the average annual proportions of positive sets. However, the main aim with this approach is to obtain a CPUE index that varies appropriately, since variability for a binomial is greater when the mean is at 0.5 than at 0.02 or 0.98, but the multiplicative effect of the variability is greatest when the mean is low. Lognormal positive time effects were obtained by exponentiating the time effects from the GLM. This approach does not provide an uncertainty estimate for the base temporal effect, but comprehensive estimates of observation error were not of interest to us in this study. The outcomes were reported as relative CPUE with mean of 1.

4.3 Results

In the logbook data the positive sets were relatively sparse after the data cleaning process (Table 4.1). In a number of years and areas, no porbeagles were reported in the part of the dataset that had been identified as more reliable. The observer data had more consistent rates of positive sets.

Standardization models for logbook data generally showed vessel effects to explain the most variability in the rates of positive catches (Table 4.2). The next most important variable was the year effect, followed by spatial effects. Seasonal (qtr), gear (hbf) and cluster effects explained similar amounts of variability. In analyses of the positive catches, vessel effects were far less dominant and similar to year effects and spatial effects, while seasonal, hbf, and cluster effects were also weaker and explained little or no variability in some cases.

In models for the observer data, year and spatial effects explained most variability in both the binomial and lognormal positive components. Other model components had less influence and were statistically significant in some but not all models.

Indices from the lognormal constant models were very variable, but showed relatively consistent results for both logbook and observer data, in northern and southern regions (Table 4.3, Figure 4.3). Indices for the western Indian Ocean suggested increasing catch rates. Eastern Indian Ocean indices were uncertain and variable, with little indication of trend. Indices for the Pacific suggested a decline in catch rates. Residuals from lognormal constant models for the logbook data indicated substantial non-normality and large outliers (Figure 4.4). Residuals from lognormal constant models for the observer data also showed patterns but were more normal and with far fewer outliers (Figure 4.5).

Delta lognormal indices were more variable than the lognormal constant indices with missing values or very large confidence intervals associated with the binomial components in a number of cases, particularly for the logbook data (Table 4.4, Figure 4.6). Due to these problems with the binomial components, indices were also estimated based on the lognormal positive component (Table 4.5, Figure 4.7). Residual plots for the lognormal positive indices appeared normally distributed (Figure 4.8).

4.4 Discussion

Of the indices estimated here, we base our inferences on the lognormal constant indices, which show relatively consistent results within regions, given the variability and uncertainty of the indices. There are some large fluctuations associated with low sample size (e.g., peaks in 2000 and 2009 in the NW observer indices). The CPUE indices estimated here differ from those estimated by Semba *et al.* (2013) using logbook data. Their 2013 indices showed an increase between 2007 and 2008 that is not apparent in the present results. This increase coincided with the period of higher reporting rates starting in 2008 (see Section 1), which is likely to have elevated the catch rates during this period. The importance of the 5° square spatial effects supported the use of a finer spatial scale than used in the 2013 analyses. For similar reasons, the use of vessel effects in logbook analyses is supported. The differing trends and population structures identified here between areas also supported the current approach of estimating separate indices by spatial region. For these reasons, and despite the concerns about potential violation of distributional assumptions expressed below, we prefer the indices developed here to those estimated in 2013.

Nevertheless, the reason for the striking change in reporting pattern needs to be understood, because it may have implications for the abundance trend. If some vessels are under-reporting porbeagles but others are reporting accurately, then our data cleaning methods will be effective at identifying the more reliable data. However, if there is a more complex and systematic pattern to the under-reporting, then our method may be less effective at reducing biases associated with misreporting.

Model fits were poor for the estimators using logbook data, with large outliers and non-normal residual distributions apparent. Although estimates of CPUE can be robust to non-normality, we strongly recommend further work to resolve these issues. In the delta lognormal analyses, the positive sets' residuals appeared to be normally distributed. Delta lognormal models, or the related zero-inflated approaches are generally useful for bycatch data give the large numbers of zeroes. However, the delta model estimates were not successful because of the many spatial strata in which no porbeagles were observed, resulting in spatial effects with inestimable parameters. These problems can be resolved with further work to remove the problematic spatial strata. There were also some temporal strata with no porbeagles caught, and no indices could be estimated for these periods. The indices based on positive data are presented for interest.

With two weeks available for analysis, and the need identified to address concerns about reporting rates, there was insufficient time to explore the data distributions and try alternative standardization approaches to improve the fits to the data. Such exploration may substantially improve the models and should be considered a high priority. Issues to consider include exploring the data to identify factors associated with outliers, and applying alternative distributions such as negative binomial and Tweedie models. Data cleaning methods and their effects on outcomes should also be explicitly considered.

Logbook data and observer data both have benefits and drawbacks for CPUE standardization. Observer data are usually reliable but coverage may be low, resulting in uncertainty. With low coverage vessel effects cannot be included, because each vessel only occurs in a small part of the time series. Logbook data have larger sample sizes but there are concerns about reliability and changes in reliability through time. Filtering the logbook data by excluding vessel-months with shark reporting reliability less than 0.9 increased reliability but reduced sample sizes, though there are still generally many more logbook than observer sets (Table 4.1). Reducing the reliability benchmark to 0.8 or 0.7 would increase the quantity of available data, which may result in better indices despite the lower quality. A simulation study may be needed to explore these options.

The overall sample sizes of sets per year affect the variability of the trends. In most datasets and periods there are more logbook sets than observed sets. There are also fewer vessels and a much smaller fished area for the observer data (Figures 4.1 and 4.2). We therefore expect the observer indices to be more variable, due to observation error, and this is apparent in most sets of indices. There are also periods (northeast and southeast areas before 2006) when there are fewer retained logbook sets than observed sets, and the early logbook trend is very variable in the southeast.

The results suggest different trends by area, with increasing CPUE estimated in the western Indian Ocean and declining CPUE estimated in the Pacific. If confirmed, such differences in trends suggest relatively low mixing between the areas. This may be reasonable given the large distances involved, although porbeagles have been observed to move east-west (Francis *et al.* 2015).

In the Pacific, the declining trend is apparent in both the logbook and the observer lognormal constant indices, but is less obvious in the observer indices which are considerably more variable. Much of the decline is associated with lower proportions of positive sets. In fact, no positive sets are reported in retained logbooks for 2003–2008, 2010 and 2013, and so delta lognormal and lognormal positive indices are unavailable for these years. There are, proportionally, considerably fewer positive sets in the logbook than in the observer data after 2000, and in many years fewer in absolute numbers as well. Further data analysis is needed to determine if this difference is due to underreporting in the logbooks, or if the relative spatial distributions and/or targeting practices of logbook and observer data are contributing.

The lognormal positive indices for logbook data indicate fewer porbeagles reported per positive set after 2000. In the observer data there is no temporal trend in the numbers of porbeagles reported per positive set, indicating that the trend in the lognormal constant observer indices is driven by declining proportions of positive sets. The low numbers of positive sets after 2001 in both the logbook and observer datasets increases the uncertainty of the estimates.

Although the Pacific lognormal constant indices show a decline, the interpretations of the declines are unclear. Possibilities include a decline in the regional porbeagle population, changes in fishing or reporting (for the logbook indices) practices that were not detected by our earlier analyses, and an effect of breaches of the modelling assumptions previously discussed. Given the trends identified, we recommend further work to explore the indices in more detail.

The data used in these analyses cover most of the Japanese fleet, but appear to omit data for the charter vessels fishing close to New Zealand. It would be useful for future analyses to include this dataset as well, to increase the sample sizes in the Pacific region.

In comparison with the indices presented here, analyses of longline data from the New Zealand region showed inconclusive results (Francis *et al*. 2014), with wide confidence intervals and/or no apparent trend. Indices based on observer data dropped sharply between 1999 and 2002, but this may have been an artefact of low and unrepresentative observer coverage in the earlier period. The New Zealand observer data indices were stable after 2002, during a period with higher sample sizes. The Japanese observer data indices were also relatively stable over this period.

The peaked distributions of residuals from the lognormal constant models of logbook data and the importance of vessel effects in the logbook standardization models both reflect large differences between vessels in rates of positive catches reported in logbooks. This is likely to reflect differences in both catch rates and reporting rates between vessels. In the observer data, vessel effects were still important (results not presented) but explained less variability and caused estimation problems due to the limited time period available for each vessel; they were not included in the final models using observer data.

4.5 Tables

Table 4.1: Numbers of sets per year used in the generalized linear modelling, for logbook (upper) and observer data (lower), in lognormal constant and binomial models (left) and in lognormal positive models (right), and by region (NW, SW, NE, and SE are Indian Ocean, P is Pacific Ocean).

	Logbook					Logbook positive				
	NW	SW	NE	SE	P	NW	SW	NE	SE	P
1994	593	73	-	-	635	79	21	-	-	1
1995	148	101	247	70	676	6	58	75	46	47
1996	136	24	82	-	1160	-	-	33	-	127
1997	328	167	27	105	463	28	-	3	74	40
1998	279	181	-	-	1009	23	38	-	-	90
1999	59	166	142	56	901	-	-	5	6	219
2000	171	283	-	-	777	35	50	-	-	31
2001	138	332	162	162	334	4	101	81	22	8
2002	-	149	225	168	257	-	7	15	37	1
2003	28	313	70	20	-	-	69	-	-	-
2004	388	363	-	-	222	13	20	-	-	-
2005	470	497	-	-	190	20	132	-	-	-
2006	615	394	82	62	188	25	109	-	-	-
2007	361	219	73	76	190	23	38	-	-	-
2008	1402	1139	1254	598	618	101	274	138	109	-
2009	870	363	1230	344	456	30	102	104	107	17
2010	1273	717	334	81	264	16	111	2	33	-
2011	1158	752	689	137	441	7	203	19	-	14
2012	854	512	1034	31	229	97	115	30	1	1
2013	730	267	786	12	173	2	30	22	-	-
2014	141	70	1040	-	326	-	25	2	-	64

	Observer					Observer positive				
	NW	SW	NE	SE	P	NW	SW	NE	SE	P
1992	97	161	167	147	125	23	54	78	24	76
1993	40	191	99	87	-	18	74	52	27	-
1994	-	189	133	162	30	-	72	73	39	6
1995	23	213	341	72	43	21	133	237	17	8
1996	28	186	198	53	47	14	104	88	11	1
1997	96	119	69	231	129	4	56	41	89	42
1998	27	80	167	21	67	11	30	97	12	20
1999	32	130	72	21	163	11	84	24	4	46
2000	51	177	-	40	215	10	147	-	10	109
2001	97	290	28	116	85	29	170	14	37	21
2002	40	195	57	20	164	26	147	24	5	26
2003	-	242	132	37	231	-	194	88	26	12
2004	53	342	21	101	77	9	153	14	25	7
2005	324	211	122	86	87	89	168	78	41	3
2006	187	449	184	28	28	34	246	99	13	-
2007	190	73	56	61	-	95	56	16	8	-
2008	-	64	77	39	70	-	52	43	21	9
2009	77	30	65	35	51	47	30	21	17	6
2010	1	-	37	25	-	-	-	27	10	-
2011	42	150	172	-	48	2	66	47	-	1
2012	43	35	134	-	70	19	35	38	-	-
2013	-	97	143	-	30	-	51	41	-	-
2014	59	107	200	-	210	15	18	105	-	50

Table 4.2: ΔAIC values for individual models. NW, SW, NE, and SE are four sections of the Indian Ocean.

Dataset	Model	Variables	NW	SW	NE	SE	Pacific
Logbooks	logn const	Full model	0	0	0	0	0
Logbooks	logn const	op_yr	665.9	954.5	259	274.9	532.1
Logbooks	logn const	qtr	33.2	57.9	26.8	13	68.8
Logbooks	logn const	latlong	280.5	106.9	79.4	30.3	268.2
Logbooks	logn const	ns(hbf, 3)	18.1	54.2	-1.1	-3.3	71.9
Logbooks	logn const	vessid	3490.6	3566.4	5034	1157.7	3388.3
Logbooks	logn const	cl	128.4	56.1	7.6	-0.6	131
Logbooks	binomial	Full model	0	0	0	NA	0
Logbooks	binomial	op_yr	271.3	592.8	141.5	NA	209.4
Logbooks	binomial	qtr	50.3	62.5	19.5	NA	15.1
Logbooks	binomial	latlong	8.7	123.2	8.2	NA	45.6
Logbooks	binomial	ns(hbf, 3)	4.6	100.5	14.9	NA	19.7
Logbooks	binomial	ns(hooks, 10)	24.8	7.5	-3.1	NA	16
Logbooks	binomial	vessid	1400.8	3072.6	1210.3	NA	733
Logbooks	binomial	cl	23.3	43.8	7.5	NA	73.2
Logbooks	logn positive	Full model	0	0	0	0	0
Logbooks	logn positive	op_yr	129.9	143.8	149.7	19.3	59.9
Logbooks	logn positive	qtr	-1	23.5	3.9	8.8	25.9
Logbooks	logn positive	latlong	42.1	185.2	143.4	33.3	84.6
Logbooks	logn positive	ns(hbf, 3)	26	4.7	68.2	-4.8	-3.1
Logbooks	logn positive	vessid	43.8	226.7	121.1	27.7	54.7
Logbooks	logn positive	cl	-3	13.5	-0.9	-3.3	0.7
Observer	binomial	Full model	0	0	0	0	0
Observer	binomial	op_yr	164.6	145.8	133.1	62	196.7
Observer	binomial	qtr	14.9	46	11.7	14.5	55
Observer	binomial	latlong	146.3	151.4	91.8	19.6	144.5
Observer	binomial	ns(hbf, 3)	2.9	6.7	8.6	-2.5	-5.2
Observer	binomial	ns(hooks, 10)	8.3	51.8	39.3	17.9	18
Observer	binomial	cl	-2.5	16.9	-1.9	-3.6	-0.3
Observer	logn positive	Full model	0	0	0	0	0
Observer	logn positive	op_yr	109.8	308.6	119.7	53.4	30
Observer	logn positive	qtr	14.6	42.7	-4.4	-3.7	12.4
Observer	logn positive	latlong	54.9	237.6	130.2	26.4	102.9
Observer	logn positive	ns(hbf, 3)	-3.4	-3	-2.9	6.9	-4.6
Observer	logn positive	cl	5.1	5.9	2.8	-3.2	-0.1

Table 4.3: Indices from lognormal constant models. NW, SW, NE, and SE are Indian Ocean, P is Pacific Ocean.

Logbook	NW	SW	NE	SE	P
1994	1.822	0.880	-	-	1.324
1995	0.712	1.743	0.755	-	1.355
1996	1.315	0.563	1.413	6.373	2.669
1997	0.691	0.466	0.411	0.048	1.247
1998	0.611	0.920	-	-	0.985
1999	0.431	0.054	0.895	0.673	2.160
2000	0.416	0.559	-	-	1.243
2001	0.850	0.666	1.082	1.241	1.058
2002	-	0.322	1.008	1.215	1.547
2003	0.711	0.308	0.466	0.689	-
2004	0.687	0.230	-	-	0.631
2005	0.697	0.223	-	-	0.683
2006	1.069	0.987	0.956	0.715	0.956
2007	0.671	0.510	1.039	0.460	0.694
2008	1.167	1.552	1.226	0.577	0.562
2009	1.286	1.039	1.034	0.446	0.725
2010	1.502	1.359	1.360	0.493	0.473
2011	0.933	1.749	1.203	0.482	0.558
2012	1.170	1.493	1.150	0.316	0.316
2013	1.875	2.180	1.114	0.272	0.310
2014	1.385	3.196	0.889	-	0.504
Observer	NW	SW	NE	SE	P
1992	0.039	0.235	0.892	0.245	-
1993	0.070	0.898	0.898	0.949	4.721
1994	-	0.452	0.752	0.499	1.437
1995	1.197	0.645	1.204	0.473	0.425
1996	1.415	0.473	0.447	0.699	0.734
1997	0.153	0.531	0.787	0.527	3.138
1998	0.517	0.500	0.587	0.630	0.897
1999	0.711	0.361	0.429	0.715	0.704
2000	2.545	0.843	-	1.531	1.680
2001	0.547	0.418	0.550	0.828	0.431
2002	0.555	0.714	0.847	0.435	0.557
2003	-	1.007	2.164	1.714	0.422
2004	0.948	0.530	2.518	0.390	0.848
2005	1.210	1.133	2.765	0.964	0.713
2006	0.767	0.760	0.803	1.133	0.419
2007	1.809	0.663	1.513	0.893	-
2008	-	1.625	0.815	4.223	0.539
2009	3.230	6.241	0.360	0.984	0.878
2010	0.371	-	0.564	1.167	-
2011	0.612	0.281	0.362	-	0.585
2012	1.170	3.083	0.679	-	0.349
2013	-	0.417	0.827	-	0.092
2014	1.135	0.191	1.238	-	0.429

Table 4.4: Indices from delta lognormal models. NW, SW, NE, and SE are Indian Ocean, P is Pacific Ocean.

Logbook	NW	SW	NE	SE	P
1994	4.520	0.612	-	-	0.801
1995	1.047	1.109	0.044	-	2.893
1996	-	-	0.066	1.930	1.872
1997	0.083	-	0.027	0.000	0.868
1998	0.121	0.674	-	-	1.156
1999	-	-	0.023	0.359	0.833
2000	0.065	0.000	-	-	1.572
2001	0.643	0.161	0.286	0.947	0.258
2002	-	0.000	0.080	0.747	0.058
2003	-	0.391	-	-	-
2004	0.005	0.124	-	-	-
2005	0.035	0.183	-	-	-
2006	0.284	0.449	-	-	-
2007	0.114	0.780	-	-	-
2008	0.355	1.433	0.601	0.000	-
2009	0.454	1.398	0.959	0.000	0.746
2010	0.213	0.988	1.697	0.000	-
2011	0.093	1.511	2.017	-	0.563
2012	0.422	1.239	2.507	0.000	0.000
2013	1.339	0.524	0.261	-	-
2014	-	1.478	0.000	-	0.427
Observer	NW	SW	NE	SE	P
1992	0.062	0.125	0.508	0.072	-
1993	0.151	0.327	0.486	0.450	1.060
1994	-	0.184	0.614	0.470	0.724
1995	1.555	0.174	0.595	0.090	0.863
1996	0.729	0.107	0.269	0.447	0.343
1997	0.012	0.186	0.768	0.229	1.338
1998	0.514	0.113	0.419	0.220	0.669
1999	0.839	0.133	0.241	0.257	0.903
2000	1.640	0.380	-	0.253	1.127
2001	0.321	0.065	0.254	0.250	0.608
2002	0.614	0.280	0.362	0.212	0.630
2003	-	0.337	0.812	0.594	0.346
2004	0.191	0.124	0.752	0.317	0.809
2005	0.640	0.348	1.346	0.316	0.558
2006	0.355	0.194	0.485	0.542	-
2007	0.576	0.403	1.001	0.163	-
2008	-	0.482	0.515	0.963	0.717
2009	1.423	3.252	0.143	0.415	0.728
2010	-	-	0.086	0.195	-
2011	0.138	0.121	0.237	-	0.456
2012	0.848	1.837	0.344	-	-
2013	-	0.234	0.445	-	-
2014	0.222	0.059	0.717	-	0.740

Table 4.5: Indices from lognormal positive models. NW, SW, NE, and SE are Indian Ocean, P is Pacific Ocean.

Logbook	NW	SW	NE	SE	P
1994	5.056	0.626	-	-	0.803
1995	2.757	1.160	0.047	-	2.893
1996	-	-	0.067	1.930	1.872
1997	0.236	-	0.028	0.312	0.870
1998	0.263	1.151	-	-	1.156
1999	-	-	0.024	0.359	0.833
2000	0.263	0.040	-	-	1.572
2001	1.723	0.614	0.288	0.947	0.258
2002	-	0.260	0.082	0.747	0.436
2003	-	0.705	-	-	-
2004	0.166	0.393	-	-	-
2005	0.398	0.605	-	-	-
2006	0.730	1.142	-	-	-
2007	0.463	2.119	-	-	-
2008	0.794	1.554	3.049	2.159	-
2009	0.610	1.608	1.373	1.142	0.768
2010	0.393	1.153	1.864	0.770	-
2011	0.373	1.588	2.776	-	0.573
2012	0.436	1.273	2.582	0.633	0.526
2013	1.339	0.532	0.296	-	-
2014	-	1.478	0.523	-	0.440
Observer	NW	SW	NE	SE	P
1992	0.414	0.749	0.894	0.922	-
1993	0.442	1.027	0.802	0.953	1.101
1994	-	0.701	1.037	1.077	0.779
1995	1.688	0.721	0.894	1.028	1.040
1996	1.032	0.663	0.813	0.966	0.608
1997	0.484	0.707	1.213	0.806	1.385
1998	0.816	0.946	0.841	0.565	0.718
1999	1.494	0.776	0.716	1.040	1.018
2000	2.166	0.789	-	1.087	1.212
2001	0.724	0.500	0.769	0.780	0.871
2002	1.211	0.881	0.942	1.030	1.013
2003	-	0.978	1.115	0.794	0.897
2004	1.023	0.719	0.842	1.123	1.357
2005	0.997	1.027	1.545	0.938	0.873
2006	0.806	0.820	0.824	1.058	-
2007	0.796	0.843	2.278	0.949	-
2008	-	1.844	1.121	1.414	1.066
2009	1.529	3.252	0.794	1.559	0.871
2010	-	-	0.418	0.911	-
2011	0.739	0.804	0.864	-	0.771
2012	1.141	1.837	0.955	-	-
2013	-	0.835	1.102	-	-
2014	0.498	0.582	1.223	-	1.420

4.6 Figures

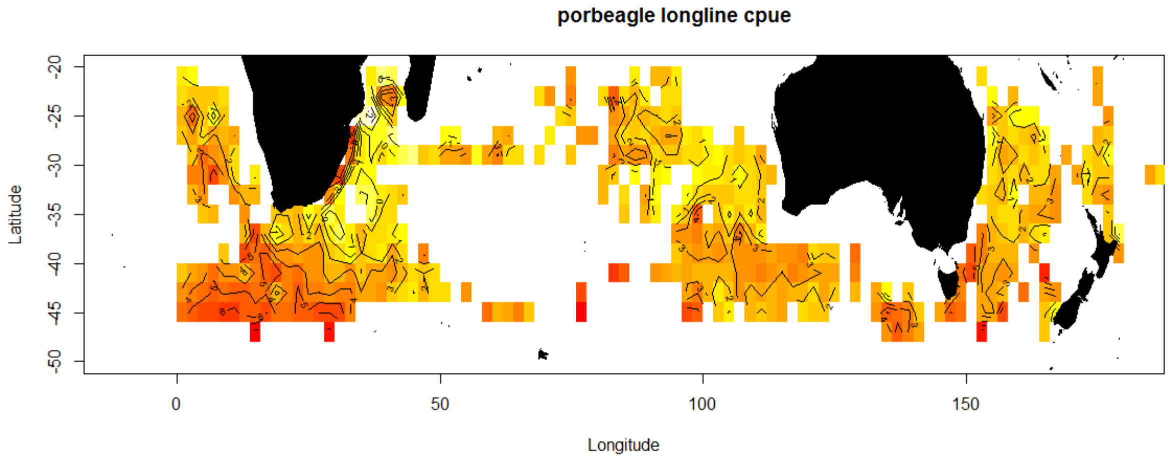

Figure 4.1: Spatial distributions of CPUE in the logbook data used in these analyses. Darker colours indicate higher levels of CPUE.

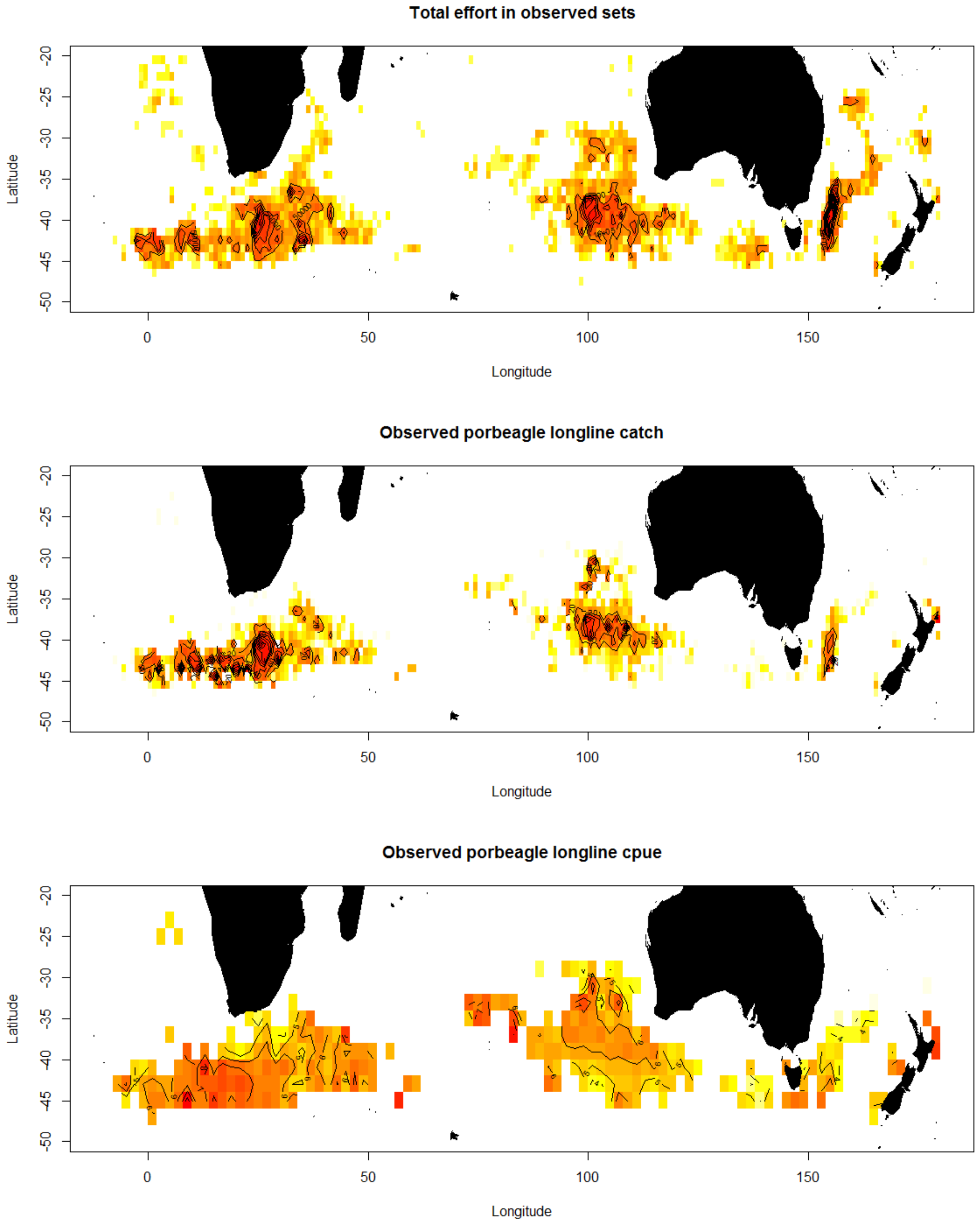

Figure 4.2: Spatial distributions of effort, catch, and nominal CPUE in observed longline sets. Darker colours indicate higher levels of CPUE.

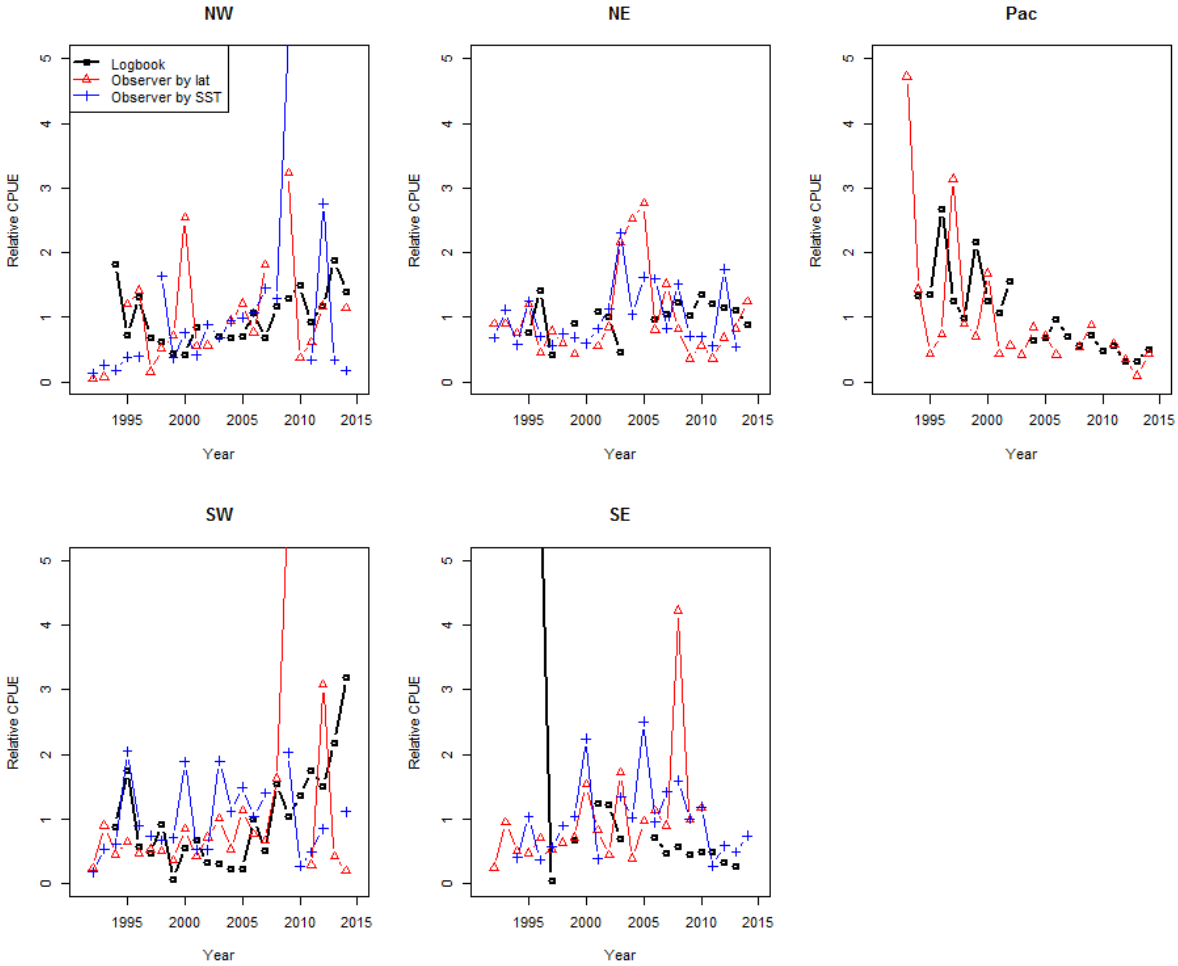

Figure 4.3: Porbeagle shark CPUE indices based on lognormal constant models, estimated from logbook (black circles) and observer data. The observer dataset for the Indian Ocean is split north-south either at 40° S (red triangles), or by SST at 12 °C (blue crosses). NW, SW, NE, and SE are Indian Ocean, Pac is Pacific Ocean.

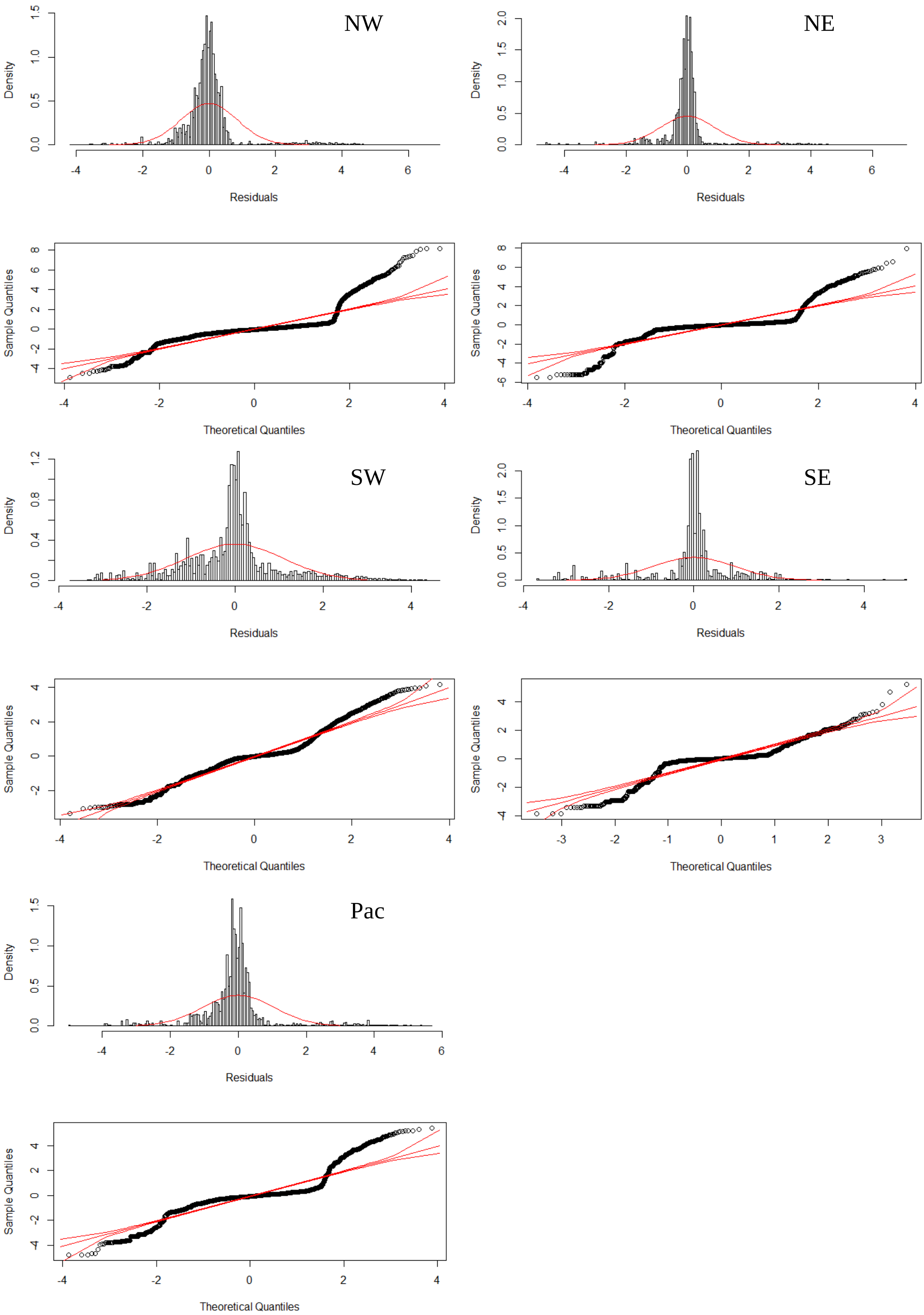

Figure 4.4: Residual distribution plots for lognormal constant logbook analyses. NW, SW, NE, and SE are Indian Ocean, Pac is Pacific Ocean.

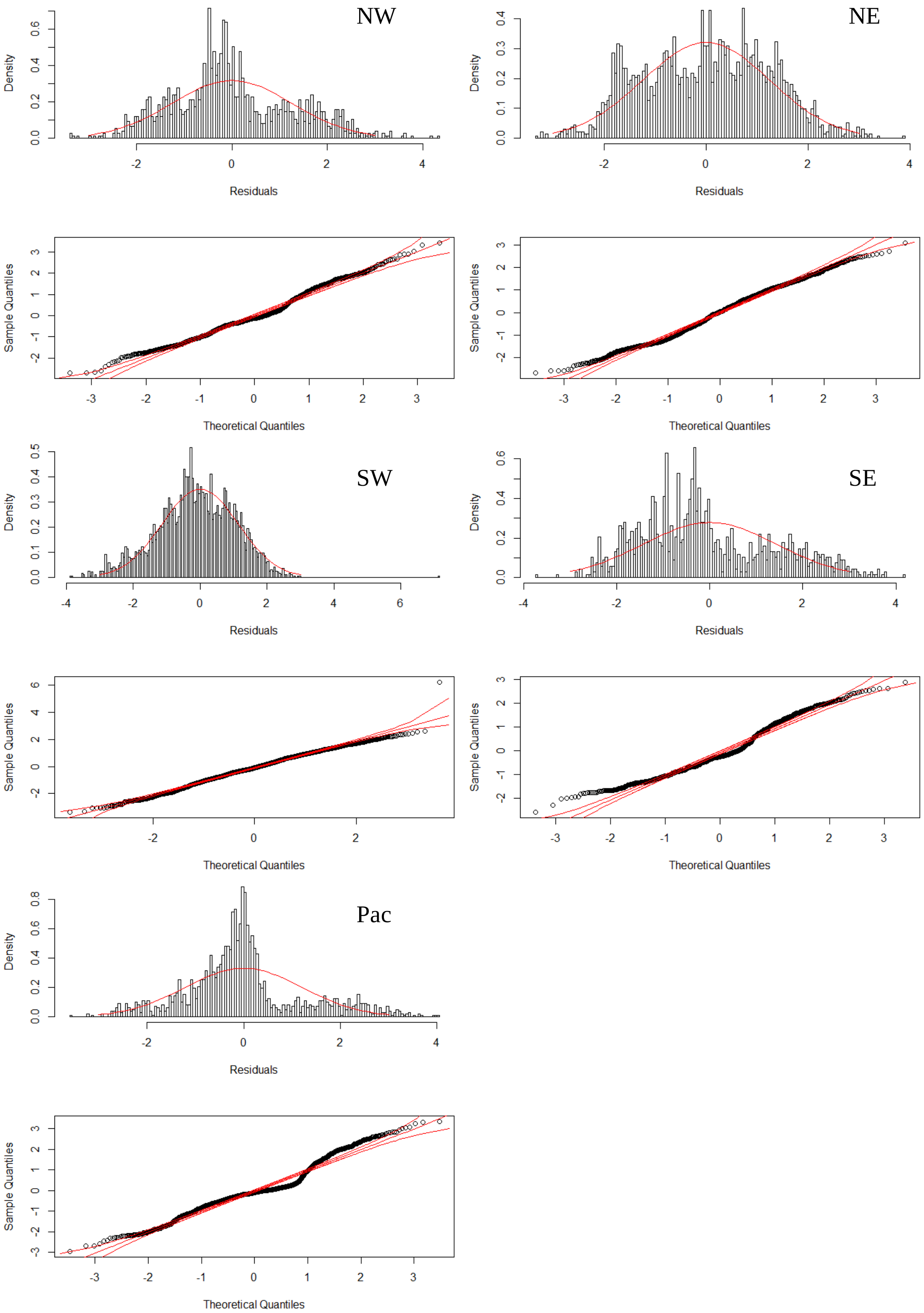

Figure 4.5: Residual distribution plots for lognormal constant observer data analyses. NW, SW, NE, and SE are Indian Ocean, Pac is Pacific Ocean.

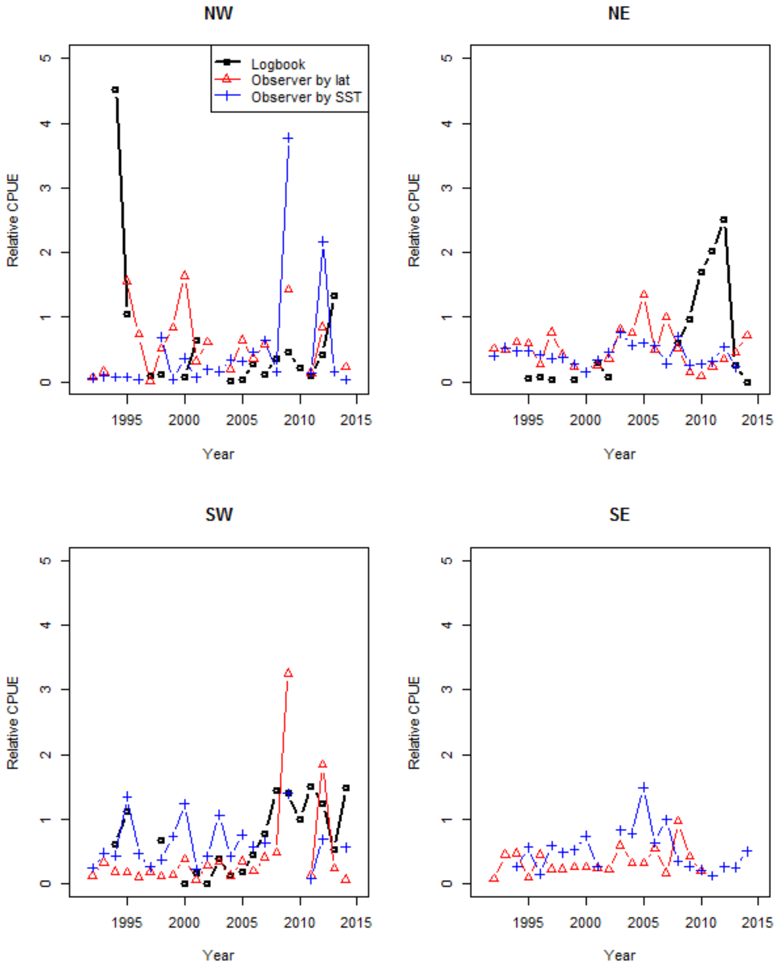

Figure 4.6: Porbeagle shark CPUE indices based on delta lognormal analyses, estimated from logbook (black circles) and observer data. The observer dataset for the Indian Ocean is split north-south either at 40 S (red triangles), or by SST at 12 °C (blue crosses). NW, SW, NE, and SE are Indian Ocean, Pac is Pacific Ocean. Estimate not available for logbook data in SE region since the binomial model did not converge.

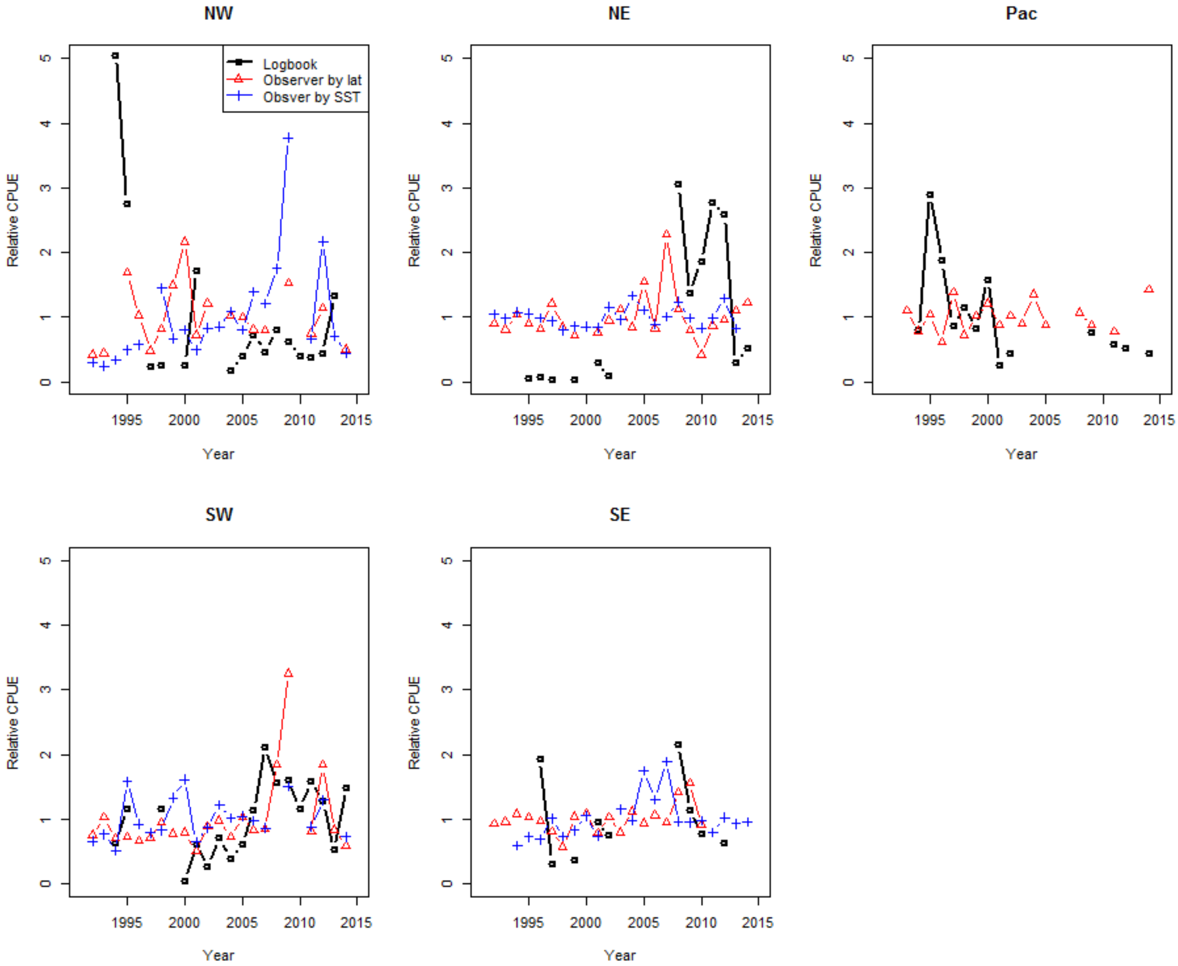

Figure 4.7: Porbeagle shark CPUE indices based on lognormal analyses of nonzero catches, estimated from logbook (black circles) and observer data. The observer dataset for the Indian Ocean is split north-south either at 40 S (red triangles), or by SST at 12 °C (blue crosses). NW, SW, NE, and SE are Indian Ocean, Pac is Pacific Ocean.

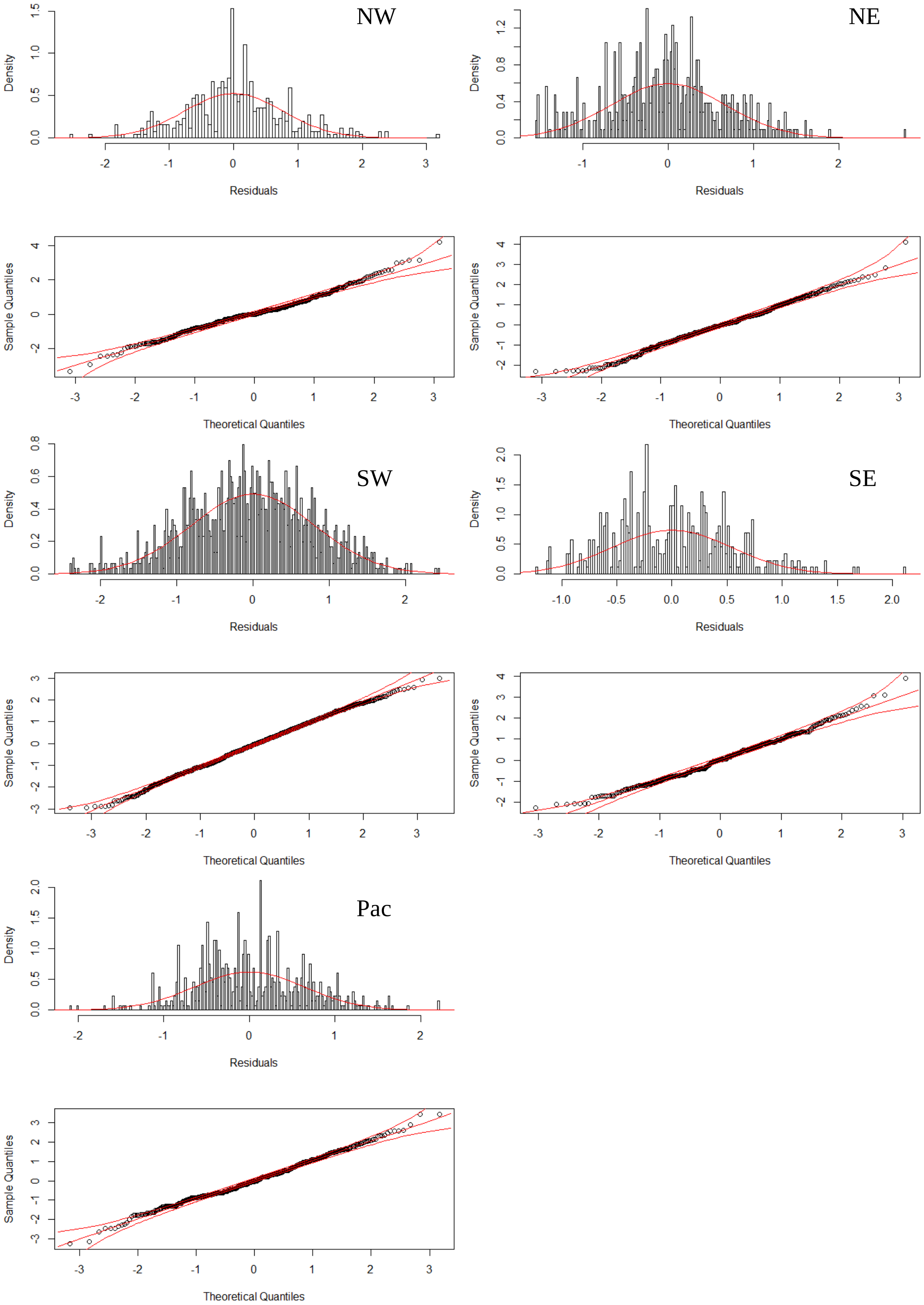

Figure 4.8: Residual distribution plots for lognormal positive logbook data analyses. NW, SW, NE, and SE are Indian Ocean, Pac is Pacific Ocean.

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