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Analysis of stock status and related indicators for key shark species of the Western Central Pacific Fisheries Commission

WCPFC-SC11-2015/SA-IP-05

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Executive Summary

1 Introduction

The status of the many shark species, espically those designated as (*key shark species*) in the western and central Pacific Ocean was is under review and instead of doing a southern blue shark stock assessment you all asked for this. An indicator analysis of blue, mako, thresher, silky and oceanic white tip sharks in the waters of the WCPO. We didn't do any fancy assessment work or models, but rather make colorul plots and tabulate laregly useless statistics (the geometric mean of the sandardized counts of other sharks has decreased relative to the base year but is comparable to the initial year). All in all this paper should give you a good understanding of the uncertainty regarding any species population viability, and even more confusioin regarding what we can, have or would do about it. Becauses sharks are often caught as bycatch in the Pacific tuna fisheries (though some directed mixed species fisheries, sharks and tunas/billfish, do exist) sharks are doomed.

While we cannot specify a percent reduction in fishing mortality of approximately needed for any specific species to reach MSY levels in the western central Pacific Ocean, we do know that- based on modeling of the factors influenciing the catch rate - the most effective way to improve population outlook would be the banning of shark lines.

2 General Methods

2.1 Description of Data Sources

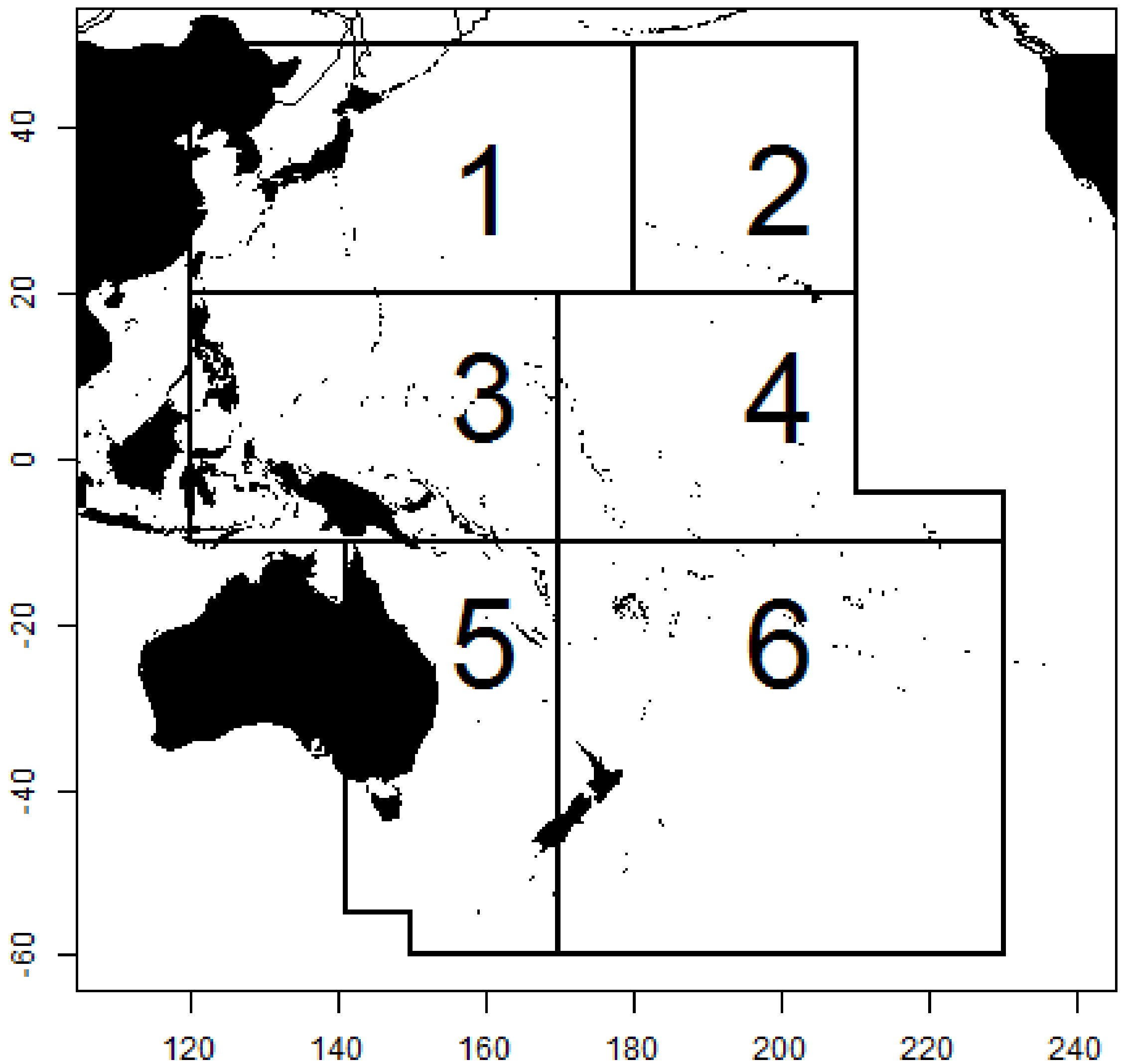

Figure 1: Map of WCPO and regions used for the analysis.

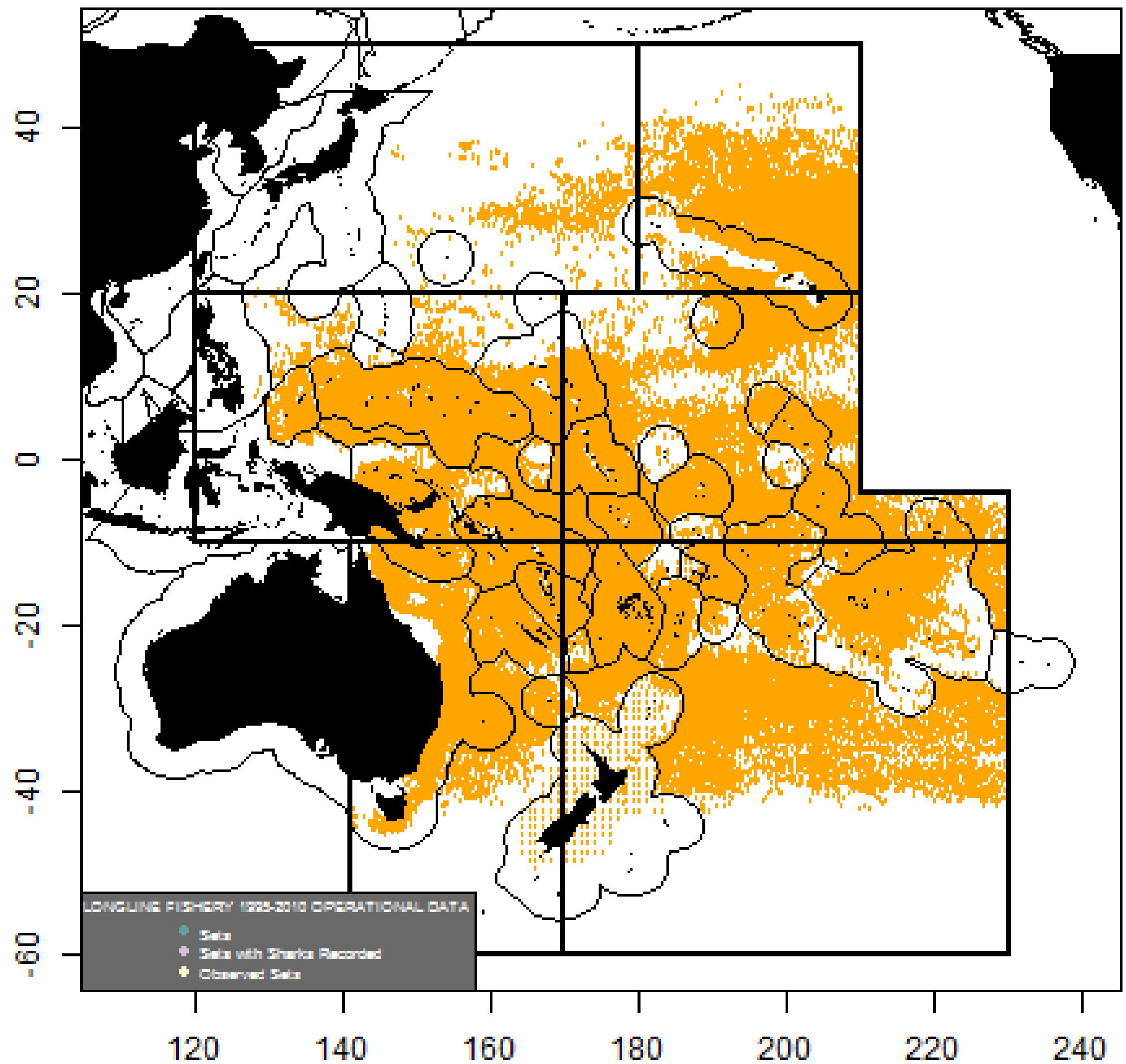

Figure 2: Map of WCPO and observed effort and observed shark catch.

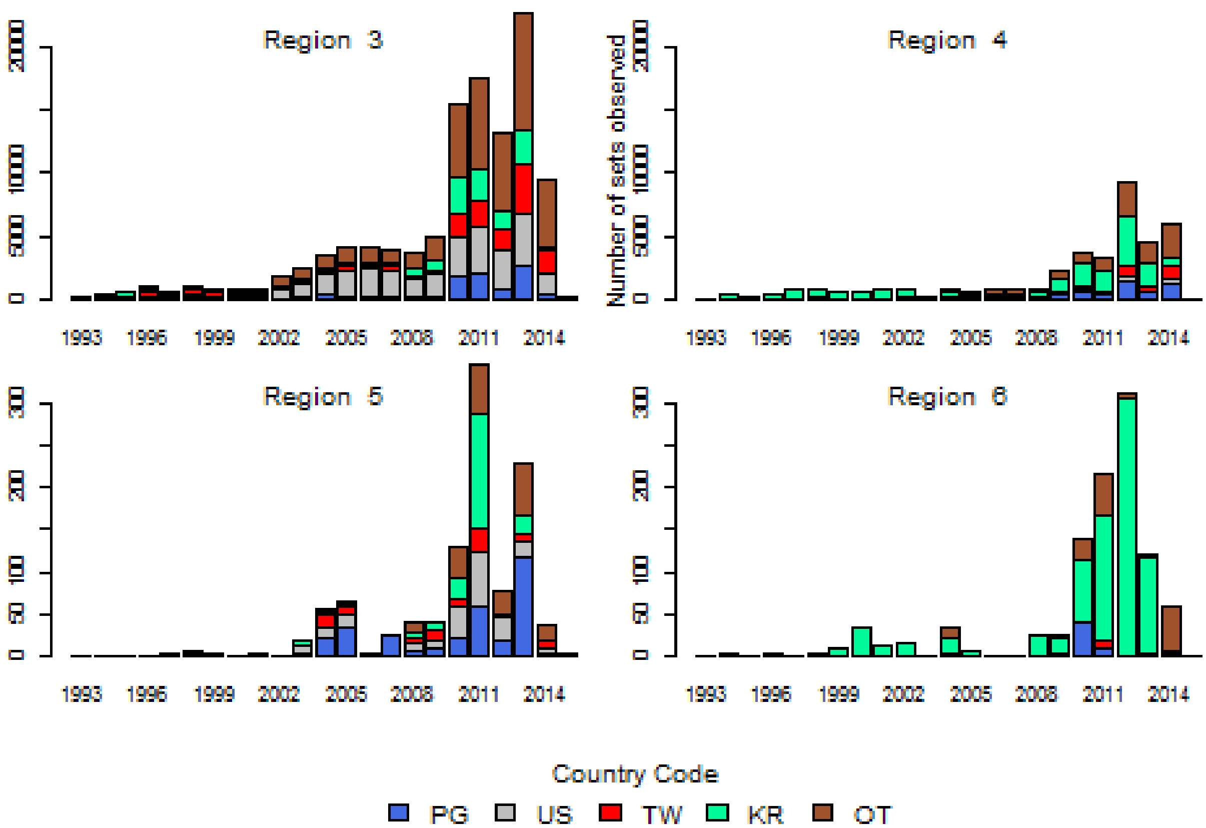

Figure 3: Observed purse seine in the WCPO showing the top four fishing nations and all others combined.

2.2 Data formatting

2.3 Limitations - Caveats

3 Distribution Indicator Analyses

3.1 Introduction

3.2 Methods

3.3 Results

3.3.1 Fishing Effort

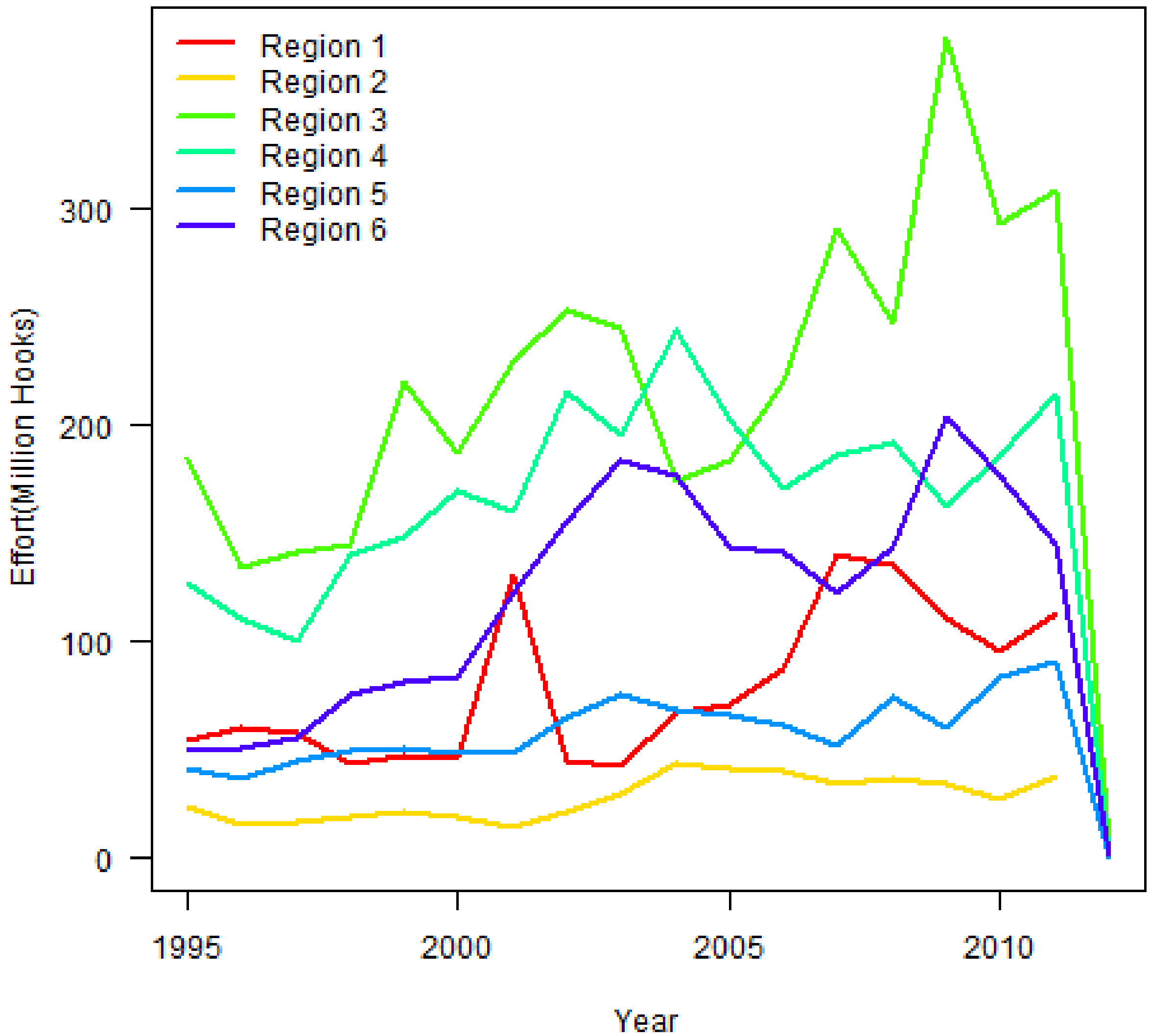

Figure 4: Aggregate effort by region. needs updating

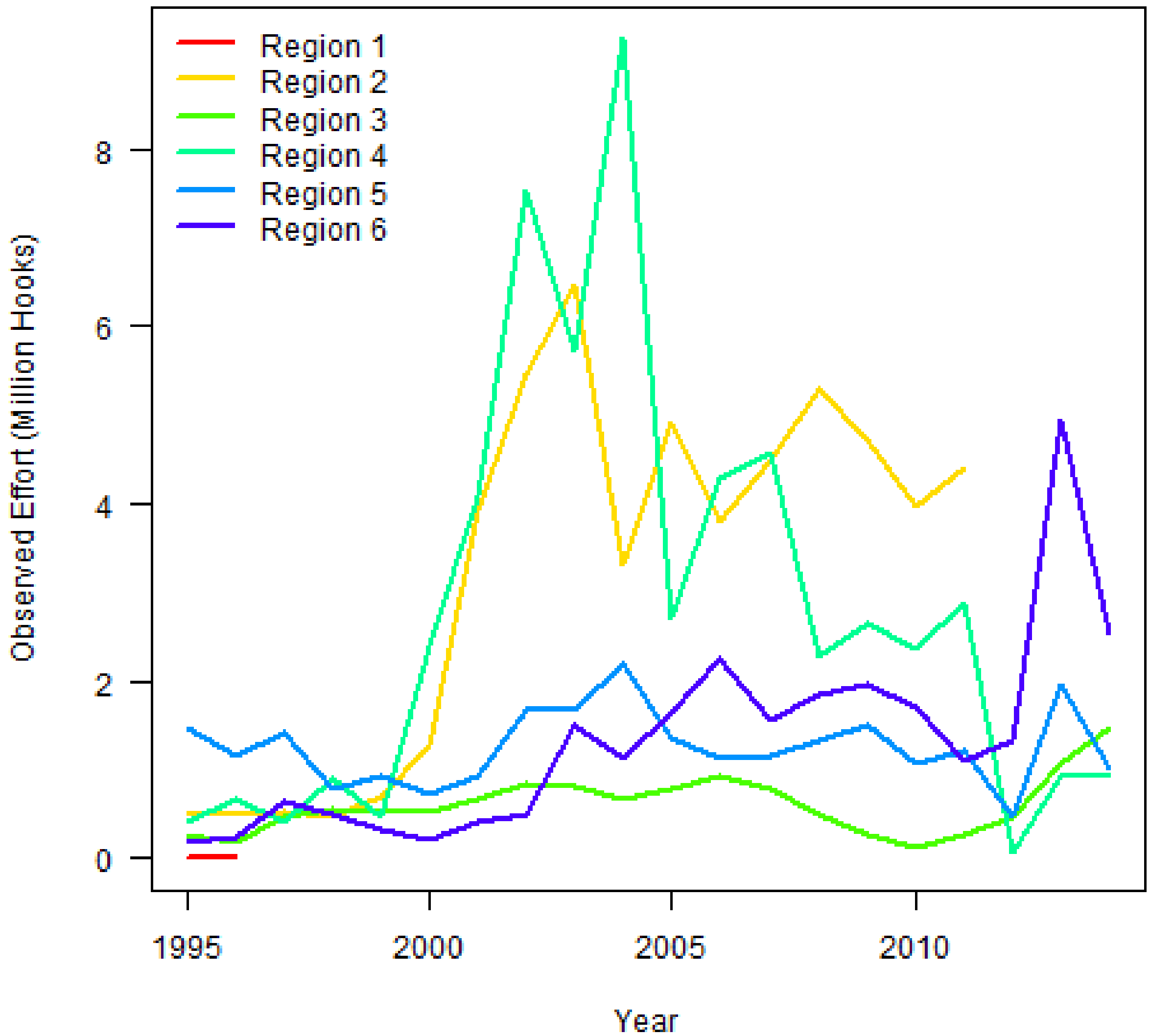

Figure 5: Observed effort by region.

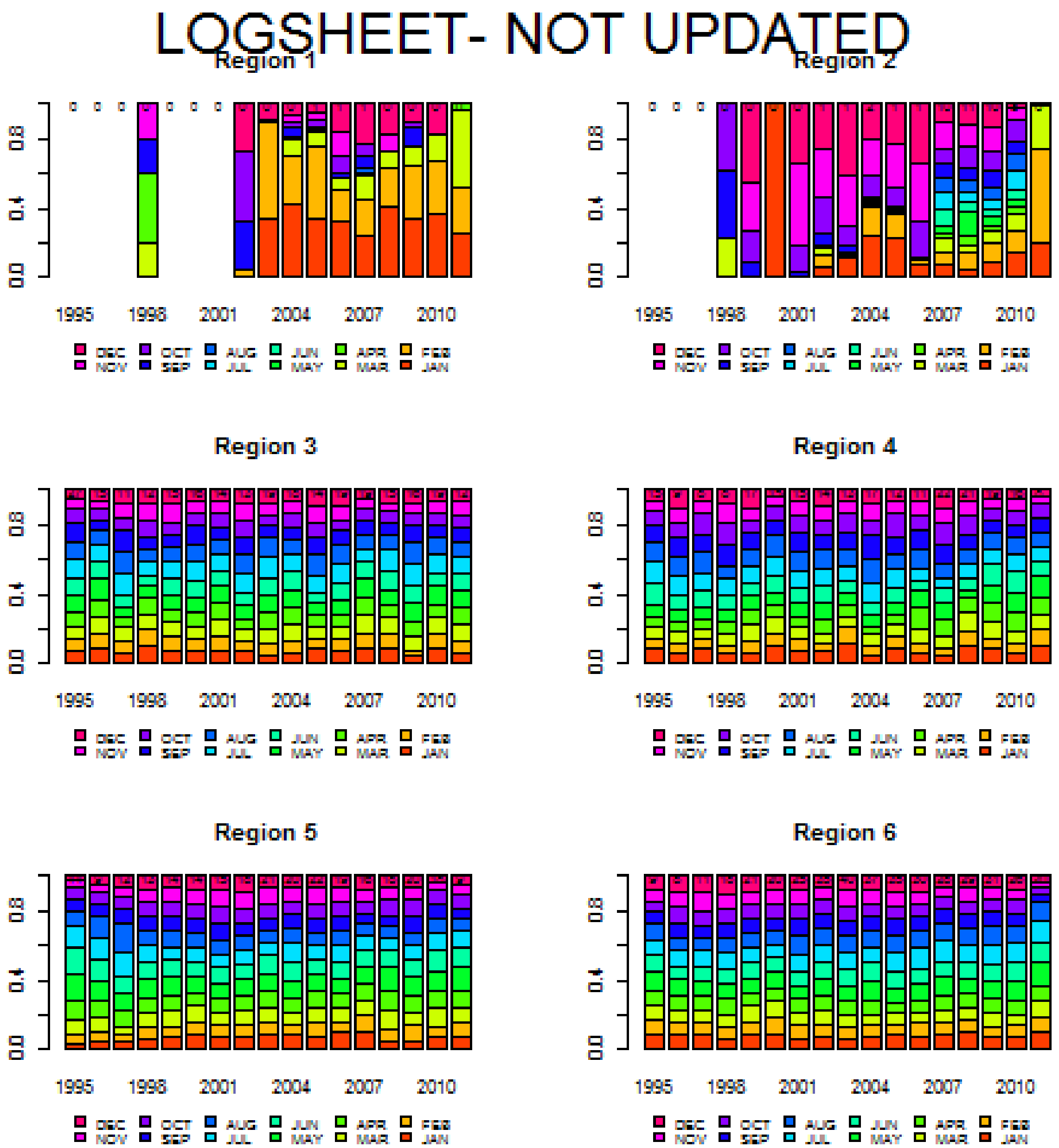

Figure 6: Logsheet effort by month.

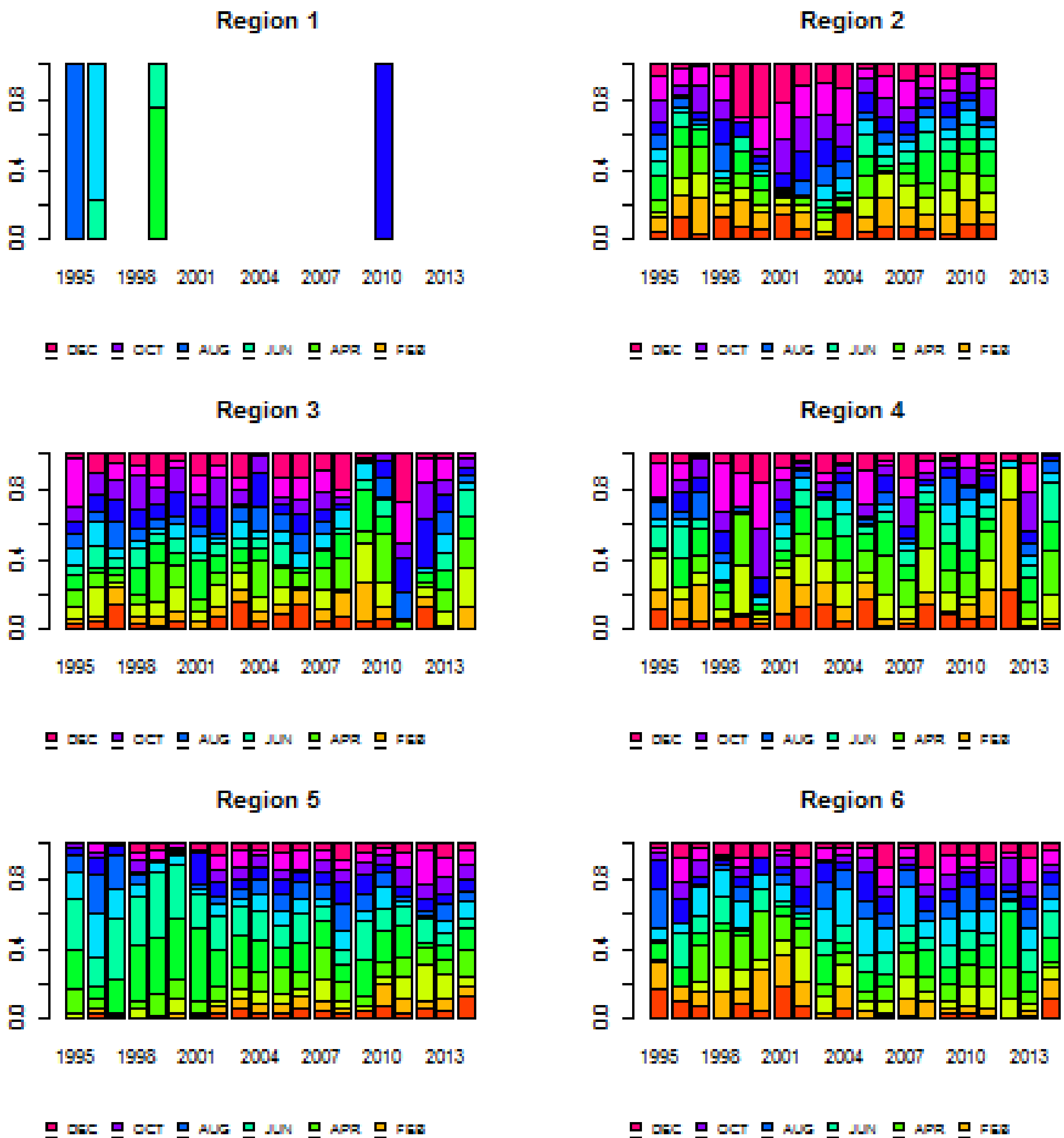

Figure 7: Observed effort by month.

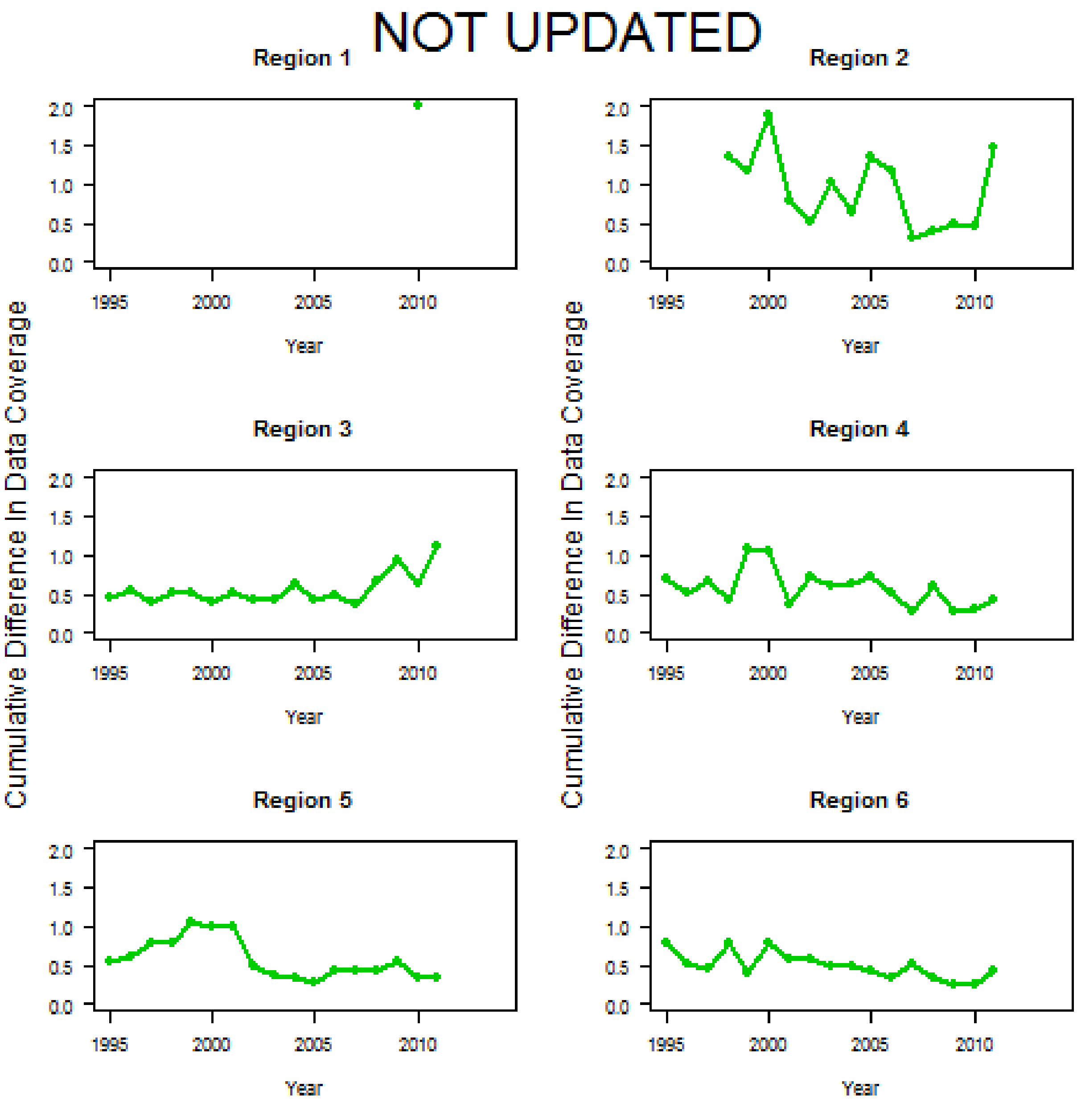

Figure 8: Absolute percent difference in effort between reported (logsheet) effort and observed effort.

3.3.2 Blue Shark

Figure 9: Blue shark distribution indicators. Proportion of positive sets, observer data.

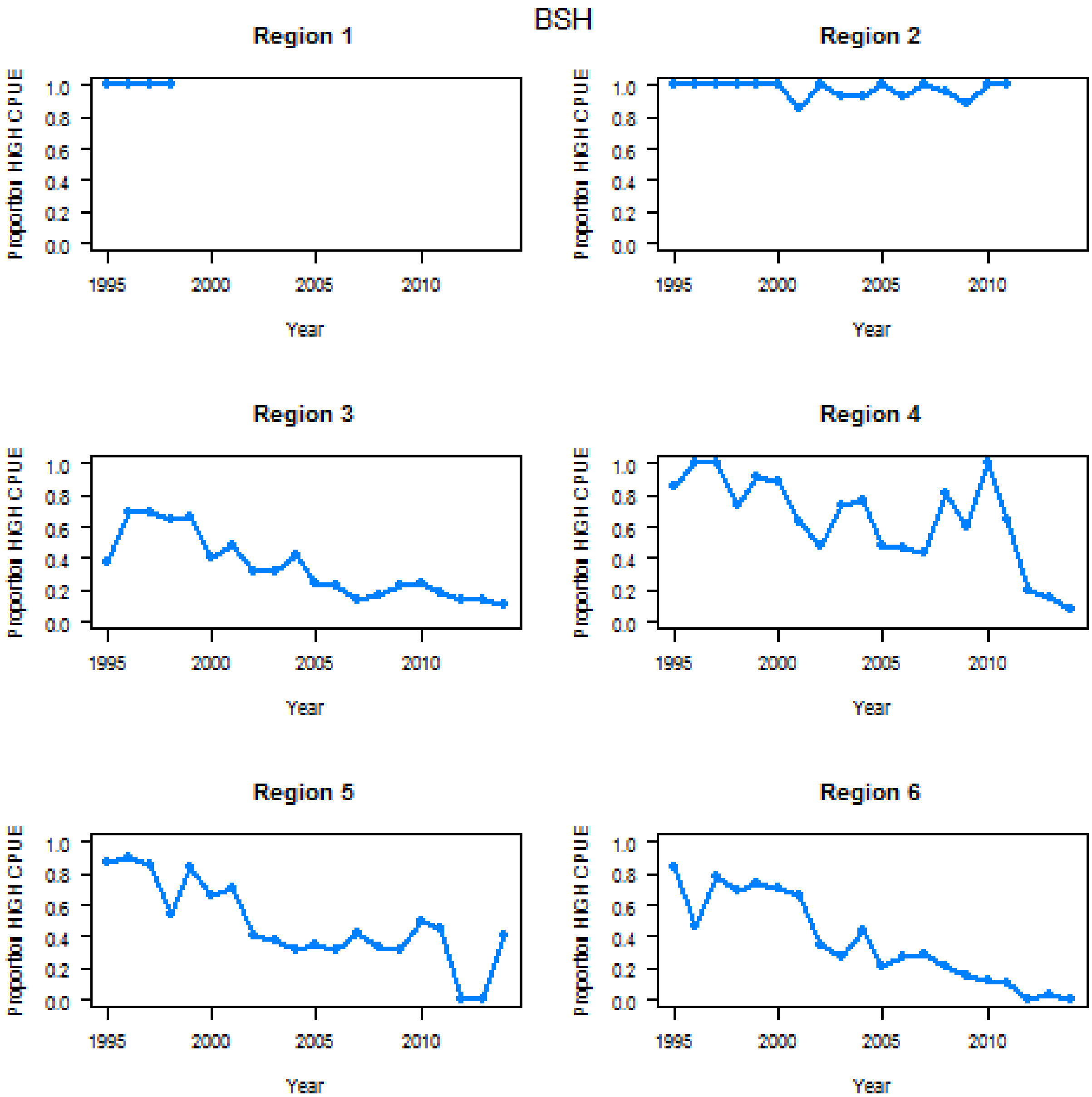

Figure 10: Blue shark distribution indicators. Proportion of 5 degree squares having CPUE greater than 1 per 1000 hooks region, observer data.

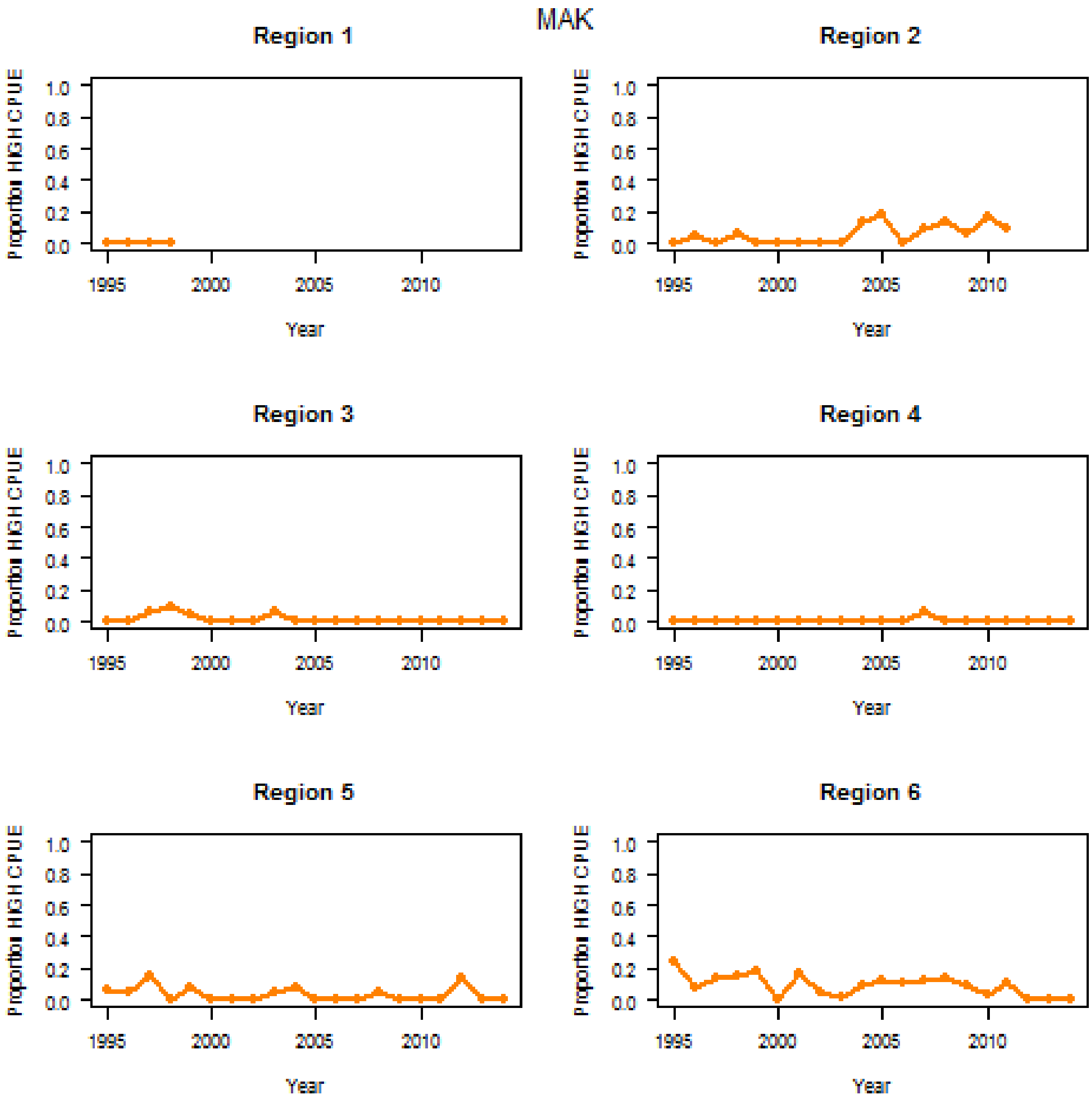

Figure 11: Mako shark distribution indicators. Proportion of 5 degree squares having CPUE greater than 1 per 1000 hooks region, observer data.

3.3.3 Mako Shark

3.3.4 Silky Shark

3.3.5 Oceanic Whitetip Shark

3.3.6 Thresher Shark

3.4 Conclusions

4 Species Composition Indicator Analyses

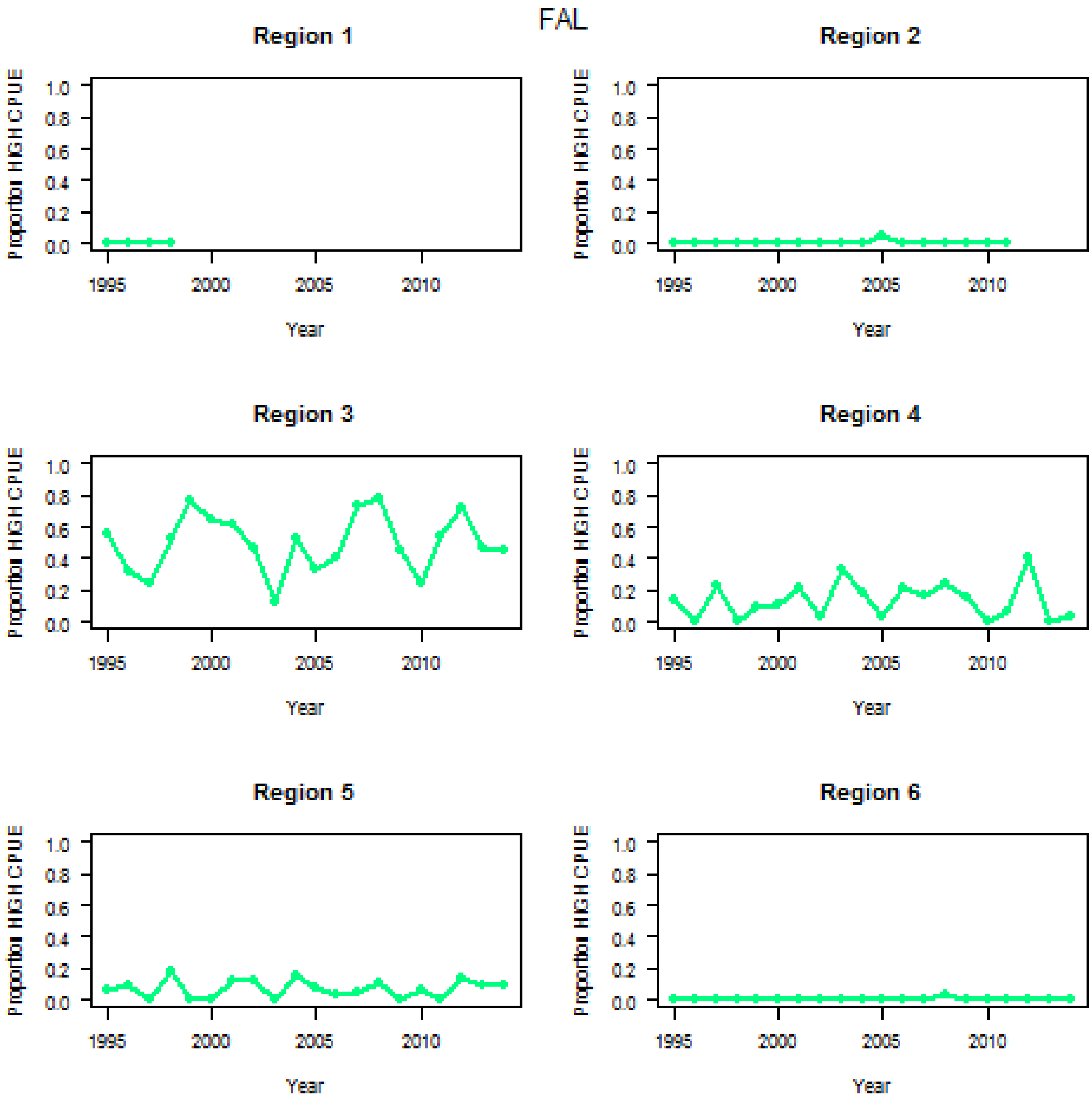

Figure 12: Silky shark distribution indicators. Proportion of 5 degree squares having CPUE greater than 1 per 1000 hooks region, observer data.

al. 2011), stock assements (Rice et al. 2014, Rice et al.2013, Rice et al.2012) (cite the standardization papers cite ISC work?). The developments presented here include additional analyses of the Secretariat of the Pacific (SPC) data holdings for silky caught in longline and purse seine fisheries in the Western and Central Pacific Ocean (WCPO), though we note that some previous data (Japan) was not available for this effeort. Standardized catch per unit of effort (CPUE) series are developed for the main shark species.

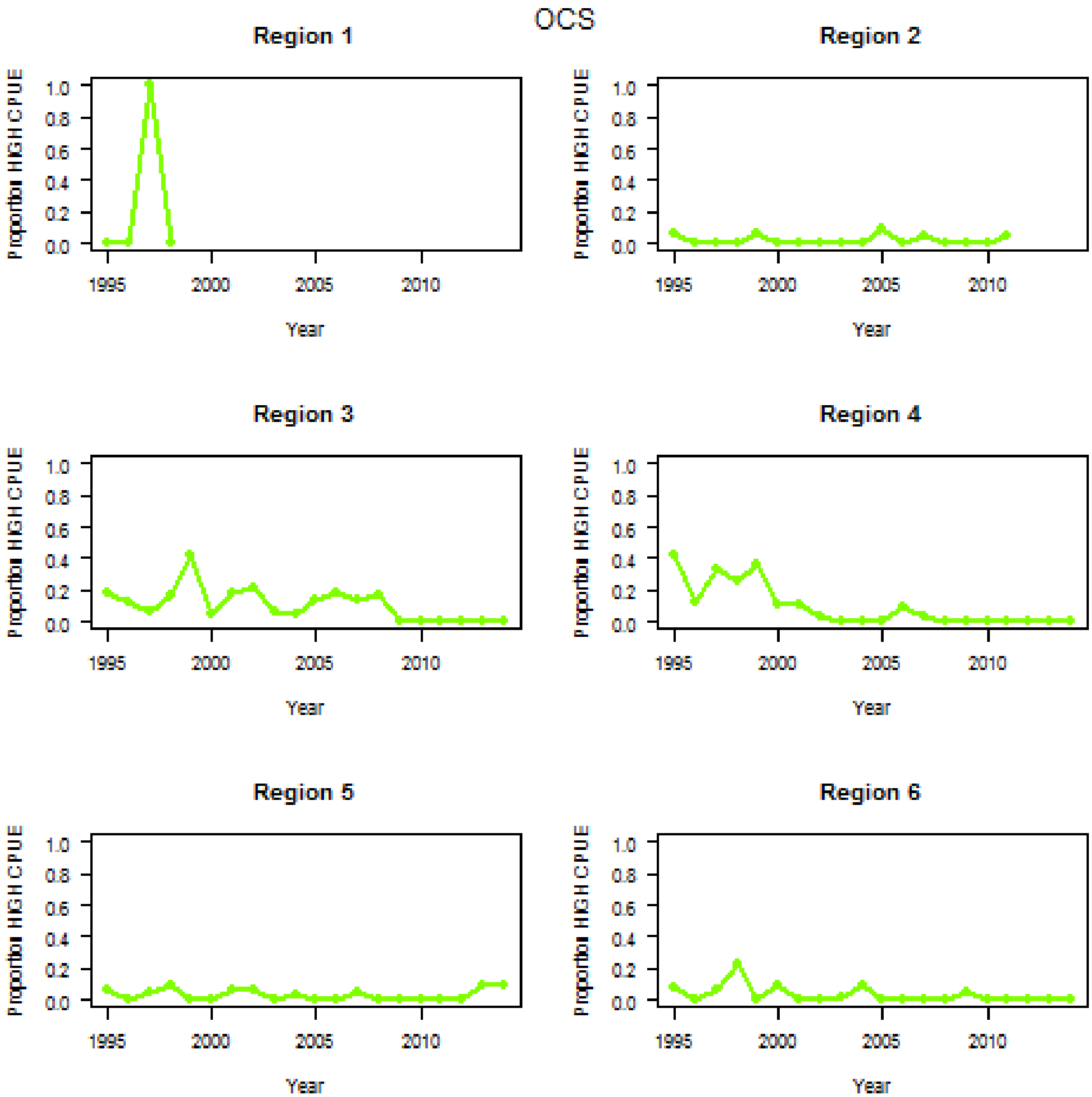

Figure 13: Oceanic whitetip shark distribution indicators. Proportion of 5 degree squares having CPUE greater than 1 per 1000 hooks region, observer data.

The framework for the analysis is not to construct inputs for stock assessment or estimate catch, it is designed to illustrate general population trends via catch rate. It is recommended that infrence to develop catch estimates or other stock assessment inputs be conducted independently. The SPC longline observer database contains records from 1985 to recent years, however silky sharks were not routinely identified to species until 1995, hence the dataset used in this analysis spans the years 1995-2014. Recent work by Clarke et al. (2011) noted gaps in observer data in terms of time and space continuity, reporting rate, and

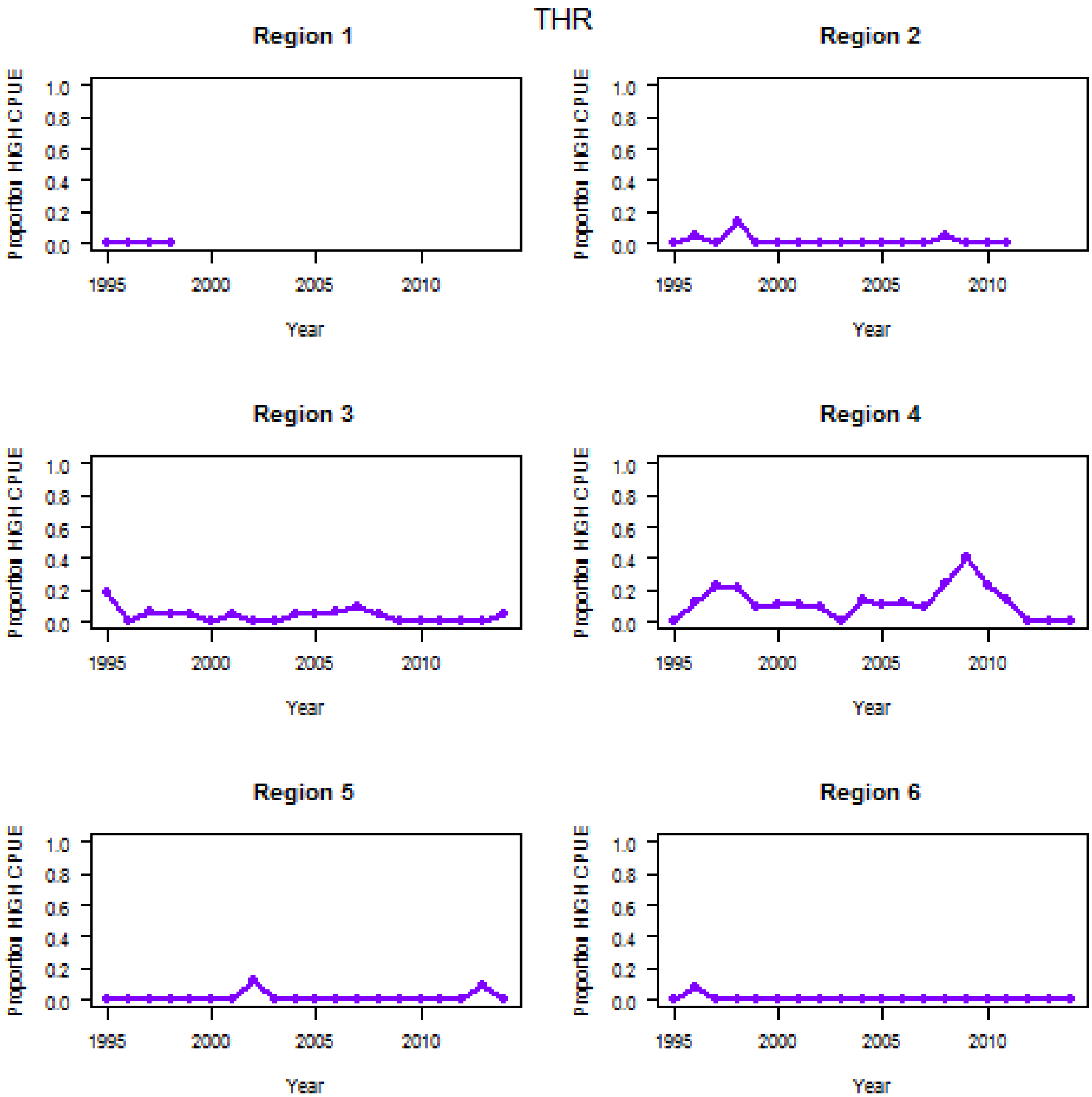

Figure 14: Thresher shark distribution indicators. Proportion of 5 degree squares having CPUE greater than 1 per 1000 hooks region, observer data.

identification with respect to sharks. Silky and oceanic white tip sharks are observed mainly in the equatorial waters in the purse seine fishery (Figure 1), and from about -25??S to 25??N in the longline fishery (Figure 1). Silky and oceanic white tip sharks have been assessed (Rice et al 2012, Rice et al 2013) as a single stock in the WCPO, and are presented in this analysis ass one stock (not regionally). Thresher, mako and blue sharks are more common in cold and temperate waters, and generally believed to constitute two seperate stocks, in the north and south. Blue shark in the north pacific have been subject to multiple stock assessments

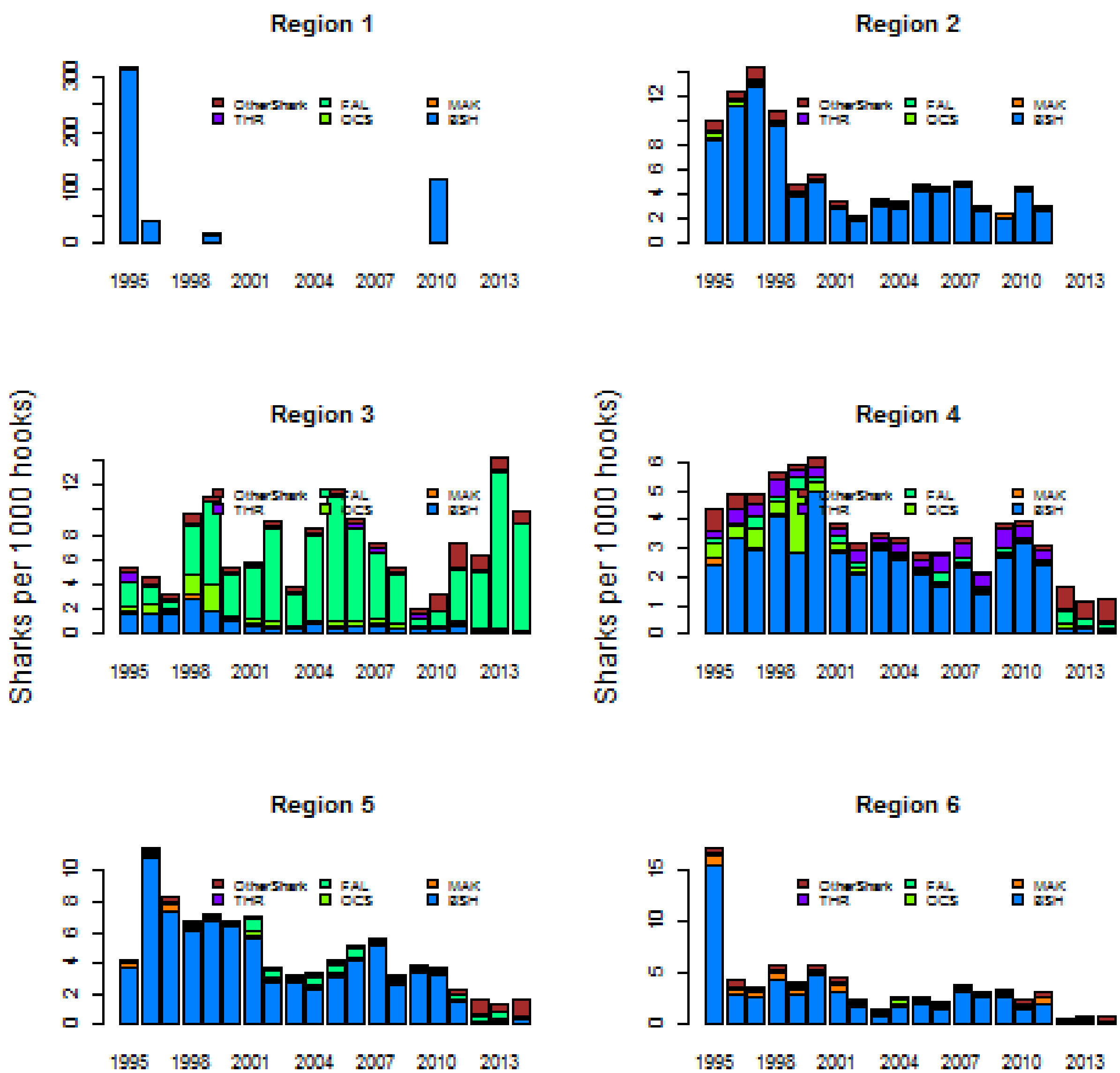

Figure 15: Catch Composition Indicators. Sharks Per. 1000 hooks by region, observer data.

as a single stock. These temperate species stocks will be presented as individual stocks.

CPUE data for species such as sharks often have a large proportion of observations (or sets) with no catch, and also include observations with large catches when areas of higher densities are encountered; this is typical of bycatch species (Ward and Myers 2005). The signals from the nominal CPUE data can be heavily influenced by factors other than abundance and therefore a procedure to standardize CPUE data for changes in factors (e.g. fishing technique, season, bait type) that do not reflect changes in abundance is usually recommended. Nominal CPUE data for bycatch can be more variable than expected (i.e., overdispersed) with many outlying data points from uncommonly high catch rates. These outlying data points can sometimes be a function of shark targeting.

5.2 Methods

This analysis follows the work of Clarke et al., (2011, 2011b), Walsh and Clarke (2011), Rice and Harley (2013) however the regions for this study differ slightly. Because silky sharks are tropical species this led to the analysis being considered for one region, from 25??S to 25??N and bordered on the east and west by the WCPFC Statistical Area. A comprehensive overview of the observer logsheet data and a characterization of the fisheries in which each species is caught is presented in the preious sections, what follows is a summary of the methods used in this analysis.

The data were validated and trimmed (records with missing values for key explanatory variables removed) to include only relevant data from the species 'core' habitat. This was done to reduce the already excessive number of zeros in the data, i.e. zero catch where you would not reasonably expect to catch silky sharks.

Because silky sharks are an epi-pelagic tropical species, all sets that occurred in water colder than 25

Latitude and longitude were truncated to the nearest 1

Although a much smaller proportion of the overall dataset (6.5% of the sets), the targeting sets represent significant shark catch (82% of the total silky shark catch). Therefore the dataset was examined with respect to variables relating to whether sharks were the intentional target of the set. Silky shark CPUE was plotted as a function of the variables sharkline, shark bait, shark target against date of set (Figure 3). Inspection of these covariates led to the separation of shark-targeting sets and non-targeting (bycatch) sets. Shark targeting sets were deemed to be sets where the observer had marked that the set was intentionally targeting sharks of any species, whether shark bait was used, or whether shark lines were used. The results of these filtering rules are in Table XXX.

Purse Seine data preparation

The only restriction placed on the purse seine observer data was that the set occurred within the rectangle defined by

CPUE methodology

CPUE is commonly used as an index of abundance for marine species. However, it is important that raw nominal catch rates be standardized to remove the effects of factors other than abundance. Further, catch data for non-target species (and sharks in particular) often contain large numbers of observed zeros as well as large catch values which need to be explicitly modelled (Bigelow et al. 2002; Campbell 2004, Ward and Myers 2005; Minami et al. 2007). Standardized CPUE series for all fisheries (bycatch and target longline; associated and un-associated purse seine fisheries) were developed using generalized linear models. In the longline analyses the number of hooks in a set was the effort measure, whereas for purse seine it was simply the set. It is notoriously difficult to come up with accurate estimates of the true effort that relates to a purse seine set (Punsly, 1987).

POverview of GLM Analyses

The filtered datasets were standardized using generalized linear models (McCullagh and Nelder 1989) using the software package R (www.r-project.org). Multiple assumed error structures were tested including; The delta lognormal approach (DLN) (Lo et al. 1992, Dick 2006, Stefansson 1996, Hoyle and Maunder 2006): this approach is a special case of the more general delta method (Pennington 1996, Ortiz and Arocha 2004), and uses a binomial distribution for the probability w of catch being zero and a probability distribution f(y), where y was log(catch/hooks set), for non-zero catches. An index was estimated for each year, which was the product of the year effects for the two model components,

The negative binomial (Lawless 1987): is typically more robust to issues of overdispersion (overdispersion can arise due to excess zeros, clustering of observations, or from correlations between observations) was also used. This model has been advocated as a model that is more robust to overdispersion than the Poisson distribution (McCullagh and Nelder 1991), and is appropriate for count data (Ward and Myers 2005), but does not expressly relate covariates to the occurrence of excess zeros (Minami et al. 2007).

Mixture models such the zero inflated Poisson (ZIP) and zero inflated negative binomial (ZINB) (Zuur 2009, Cunningham and Lindenmayer 2005, Welsh et al. 2000): these models are useful for modelling counts of rare species when the number of zero observations is larger than expected. Zero inflated models are a process similar to the delta approach in which the presence or absence of the catch is modelled orthogonally to the size of the catch (Welsh et al 2000), however unlike the delta approach the count data can include zeros. These zeros could result from predator satiation, competition for hooks, or disinterest (called true zeros) as opposed to design errors, sampling errors, observer errors or zeros resulting from sampling outside the habitat range (called false zeros). The total probability of a zero count is then, Therefore, the probability distribution for the zero inflated Poisson is equal to: Where yi is the size of the catch of the ith set, and distributed Where yi is the size of the catch of the ith set, and distributed Under this parameterization the mean of the negative binomial is ?? and the variance is The main advantage of the zero inflated approach is that these techniques can model the overdispersion in both the zeros and the counts as opposed to just the counts (negative binomial) and deal with overdispersion better than other models (quasi Poisson). Each model was fit to the data set independently and all variables used in the models were included as categorical factors except the response variables for catch and the effort (silky and SILKYCPUE) and the offset variable (hook_est); these variables were included in the model as continuous variables (Table 1). Model selection began with regression trees and piecewise ANOVA models for each model (De'ath and Fabricius 2000, Zuur 2009). The Akaike information criterion (AIC) was used as a metric to score the results and determine the final models for each data set. Model specific fitting criteria and model diagnostics resulted in different variables being chosen for different data sets and model types. Multiple methods of calculating the indices of abundance and confidence intervals exist depending on the model type (Shono H. 2008, Maunder and Punt 2004). In this study estimates were calculated by predicting results based on the fitted model and a training data set that included each year effect and the mean effect for each covariate (Zuur et al 2009). Confidence intervals were calculated as SE, where SE is the standard error associated with the predicted year effect term. Appendices hold the model diagnostics

5.3 Results

5.3.1 Blue Shark

Figure 16: Blue shark CPUE indicators. Proportion of positive sets, observer data.

5.3.2 Mako Shark

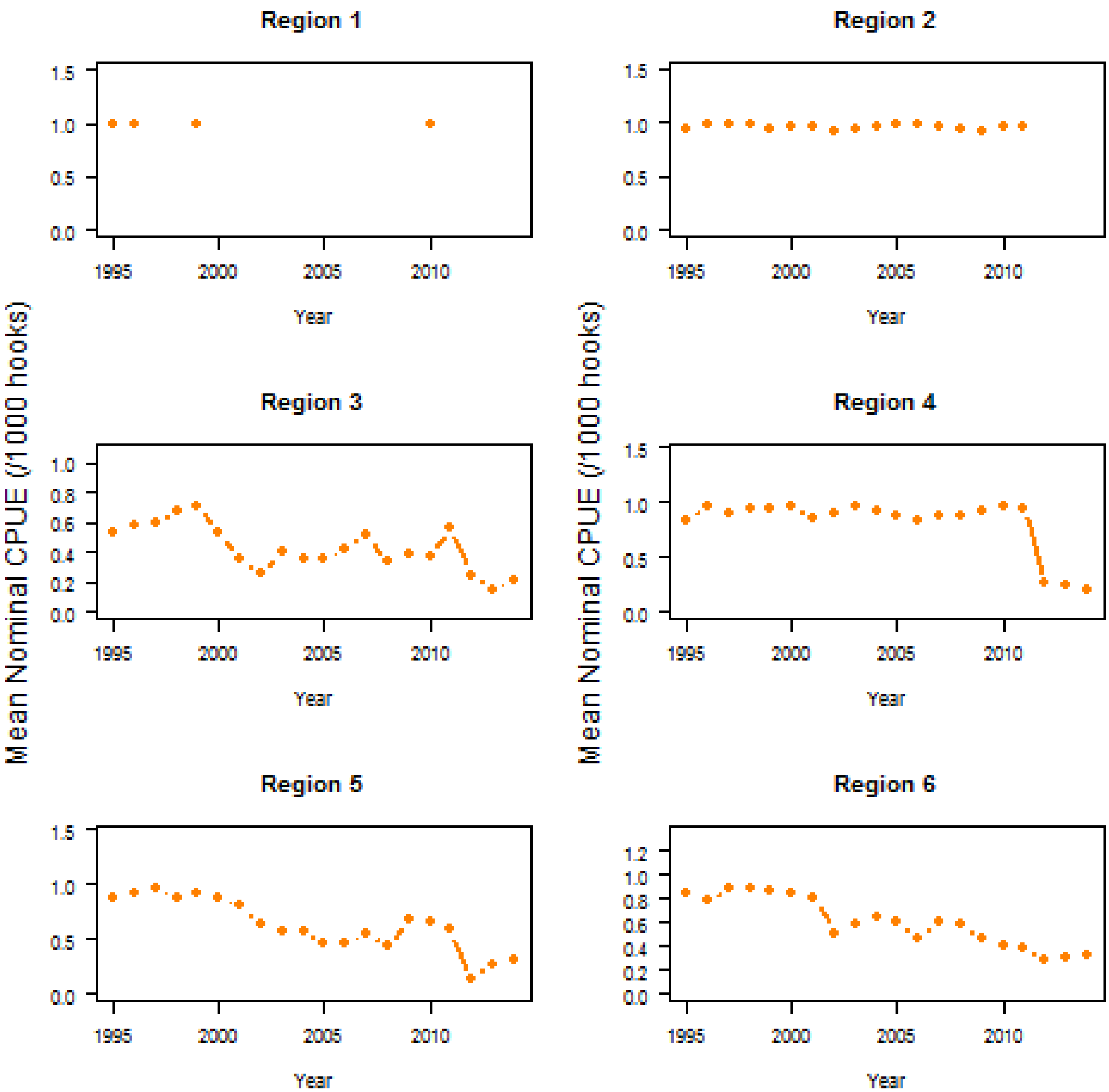

Figure 17: Blue shark CPUE indicators. Nominal CPUE, sharks per 1000 hooks, observer data.

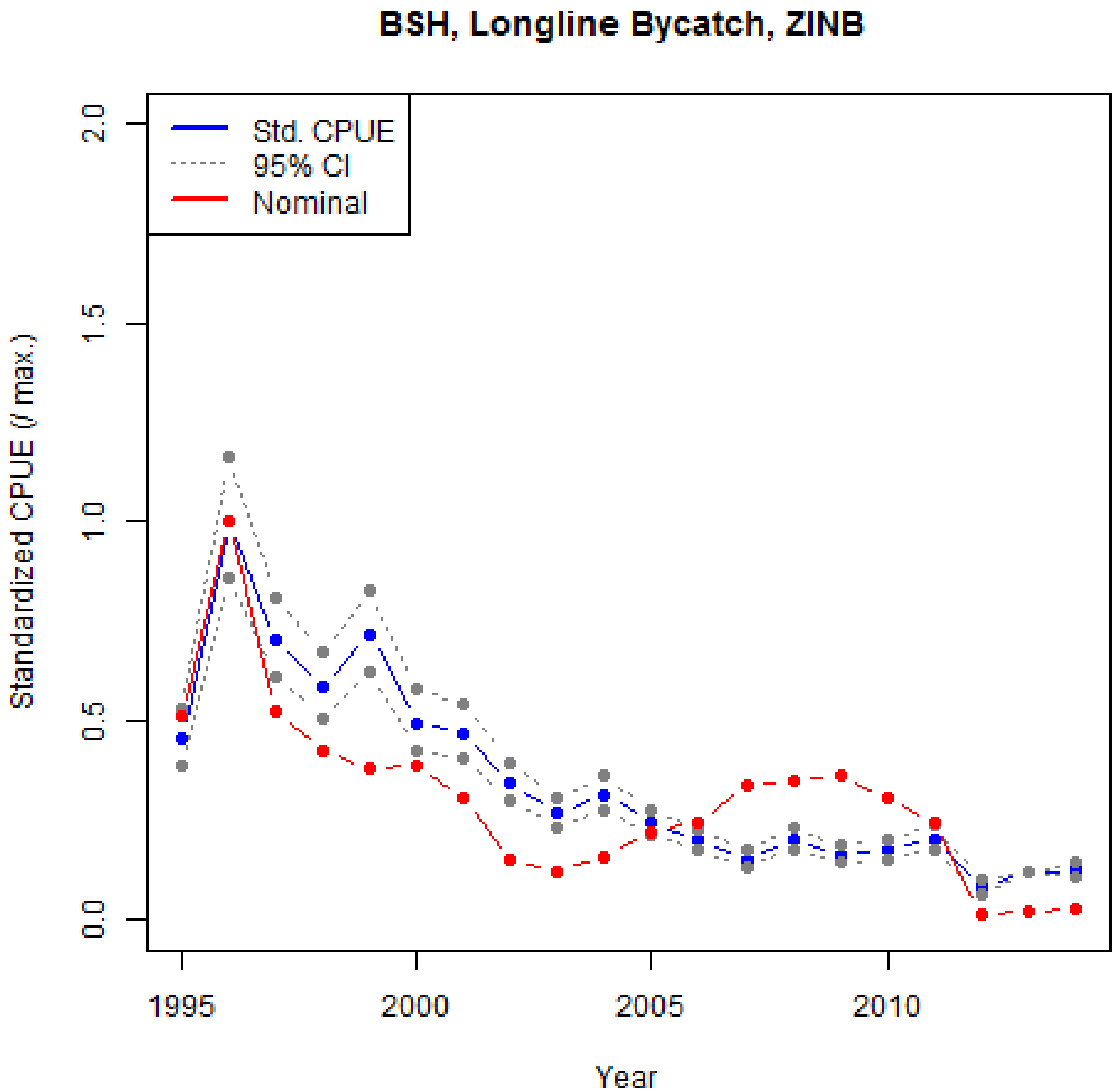

Figure 18: Blue shark CPUE indicators. Standardized CPUE, zero inflated negative binomial Southern Hemisphere, observer data.

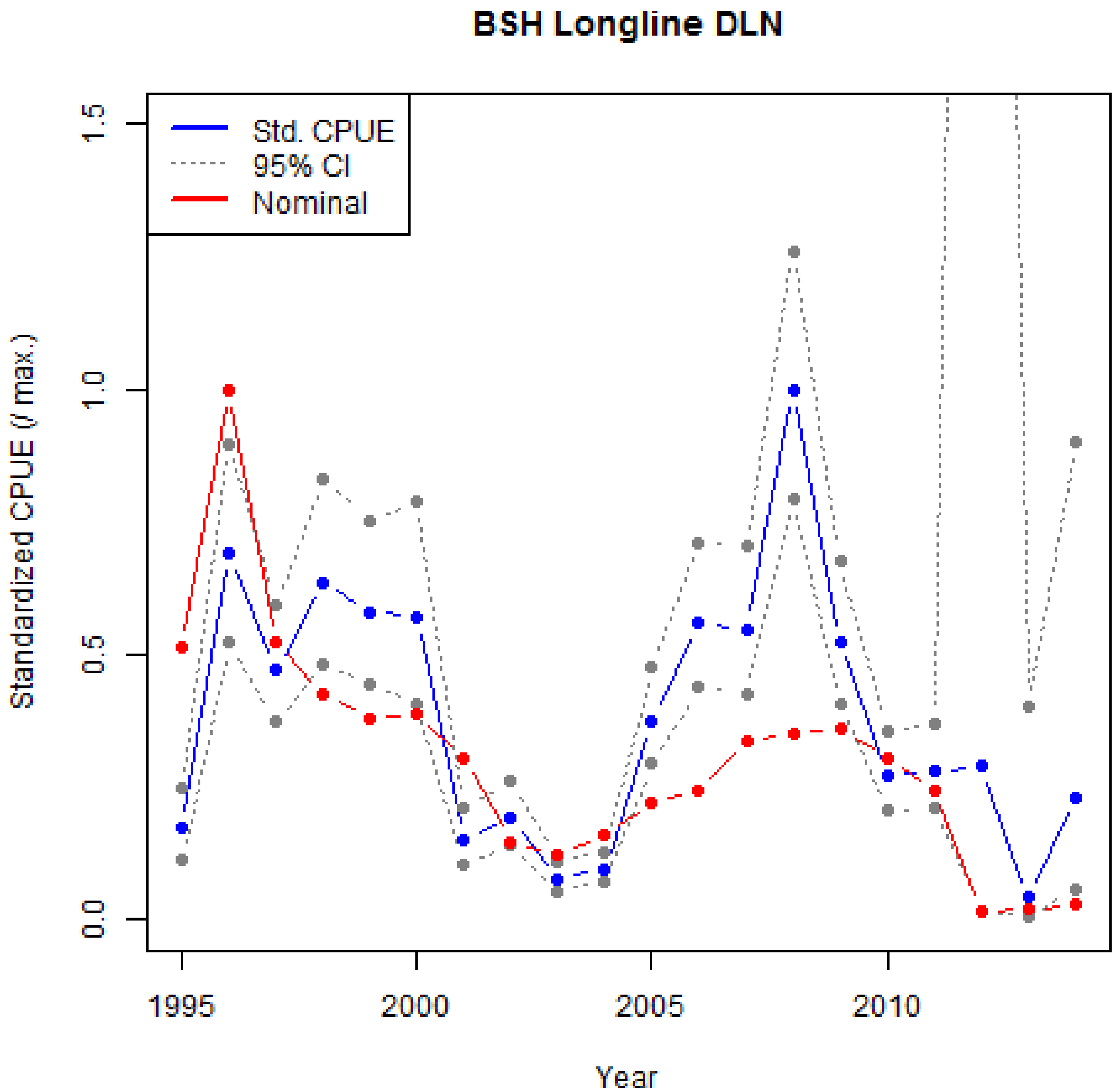

Figure 19: Blue shark CPUE indicators. Standardized CPUE (delta lognormal) and nominal CPUE, Southern Hemisphere, observer data.

Figure 20: Mako shark CPUE indicators. Proportion of positive sets, observer data.

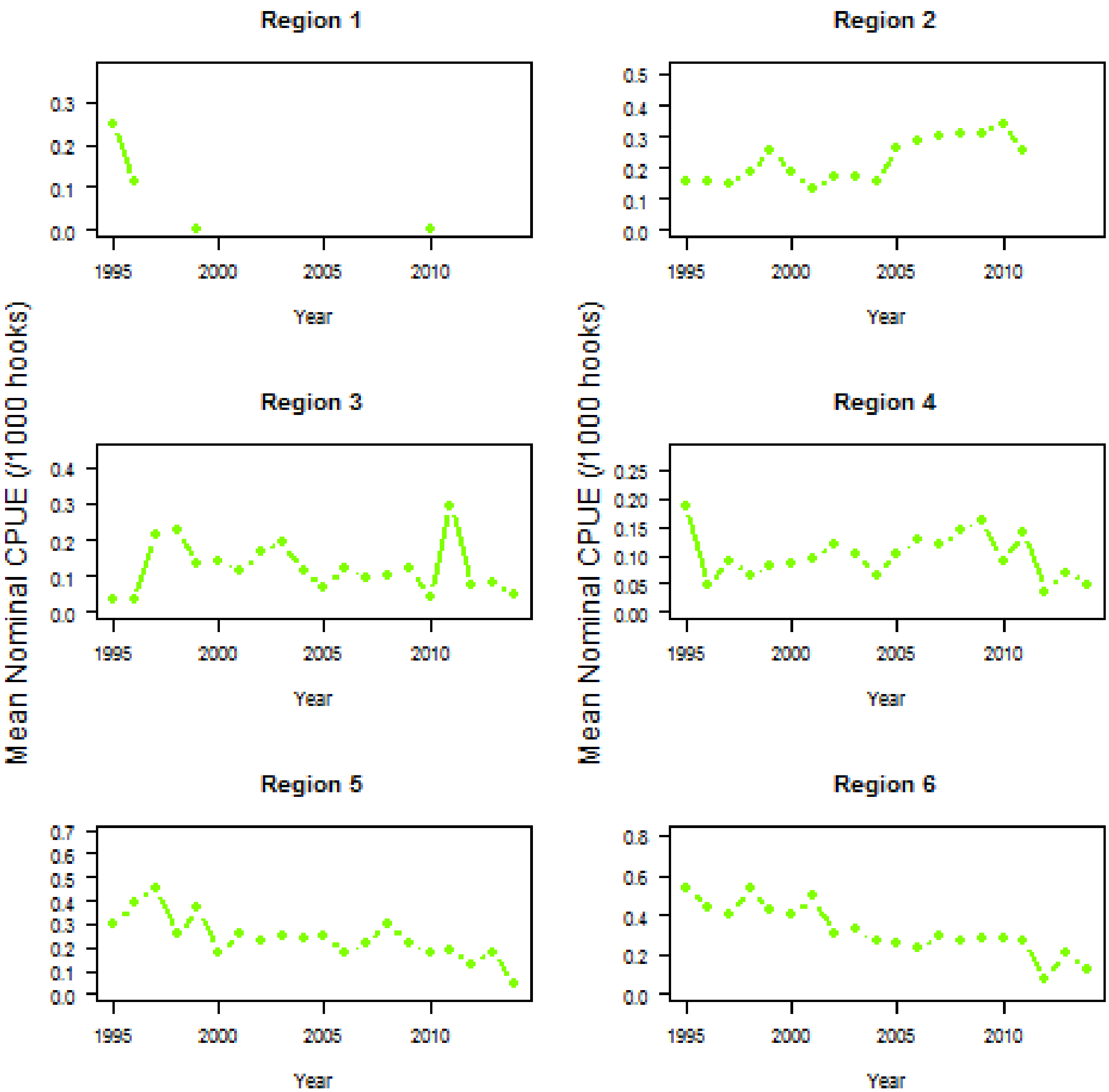

Figure 21: Mako shark CPUE indicators. Nominal CPUE, sharks per 1000 hooks, observer data.

5.3.3 Silky Shark

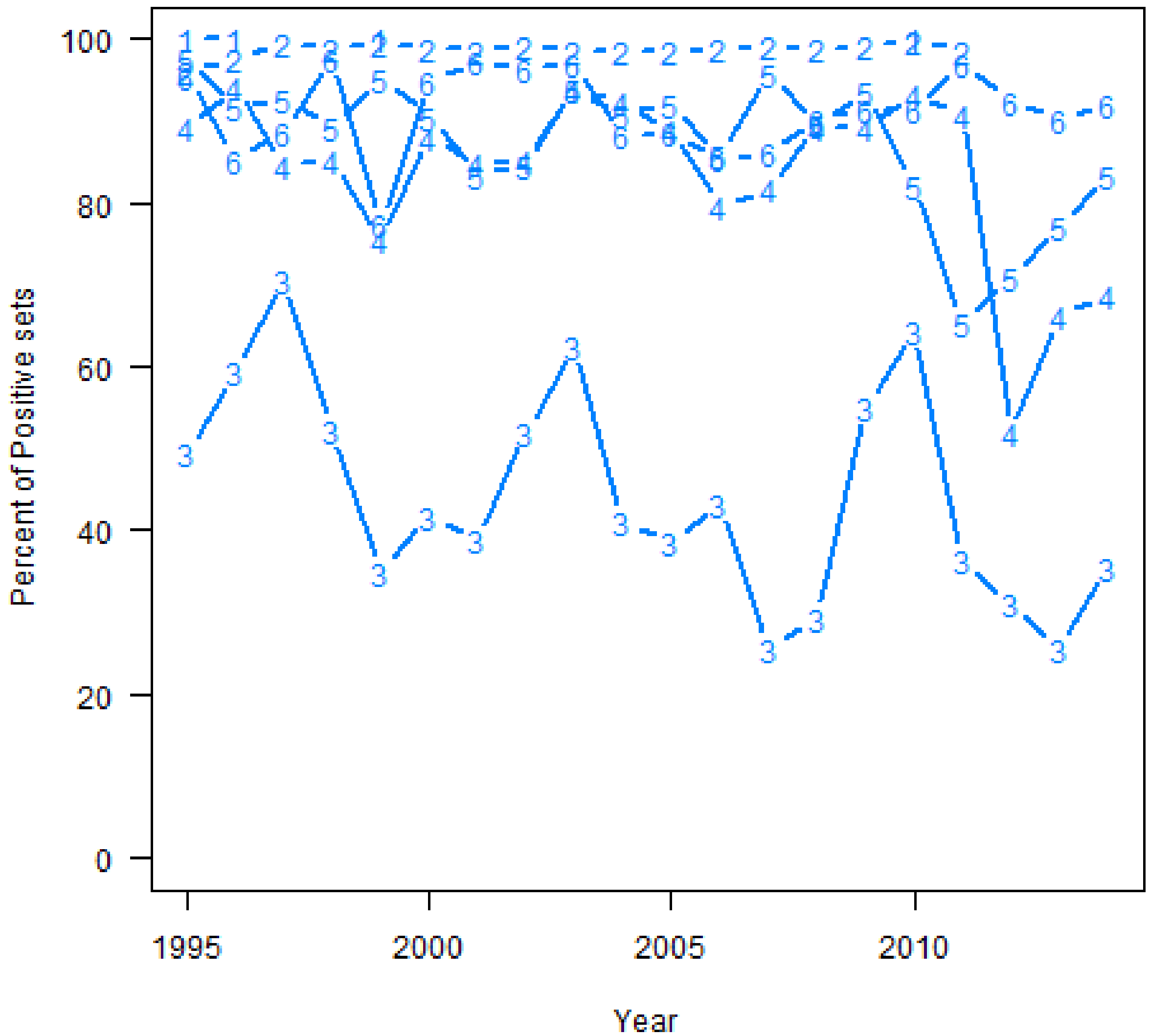

Figure 22: Silky shark CPUE indicators. Proportion of positive sets, observer data.

5.3.4 Oceanic Whitetip Shark

5.3.5 Thresher Shark

5.4 Conclusions

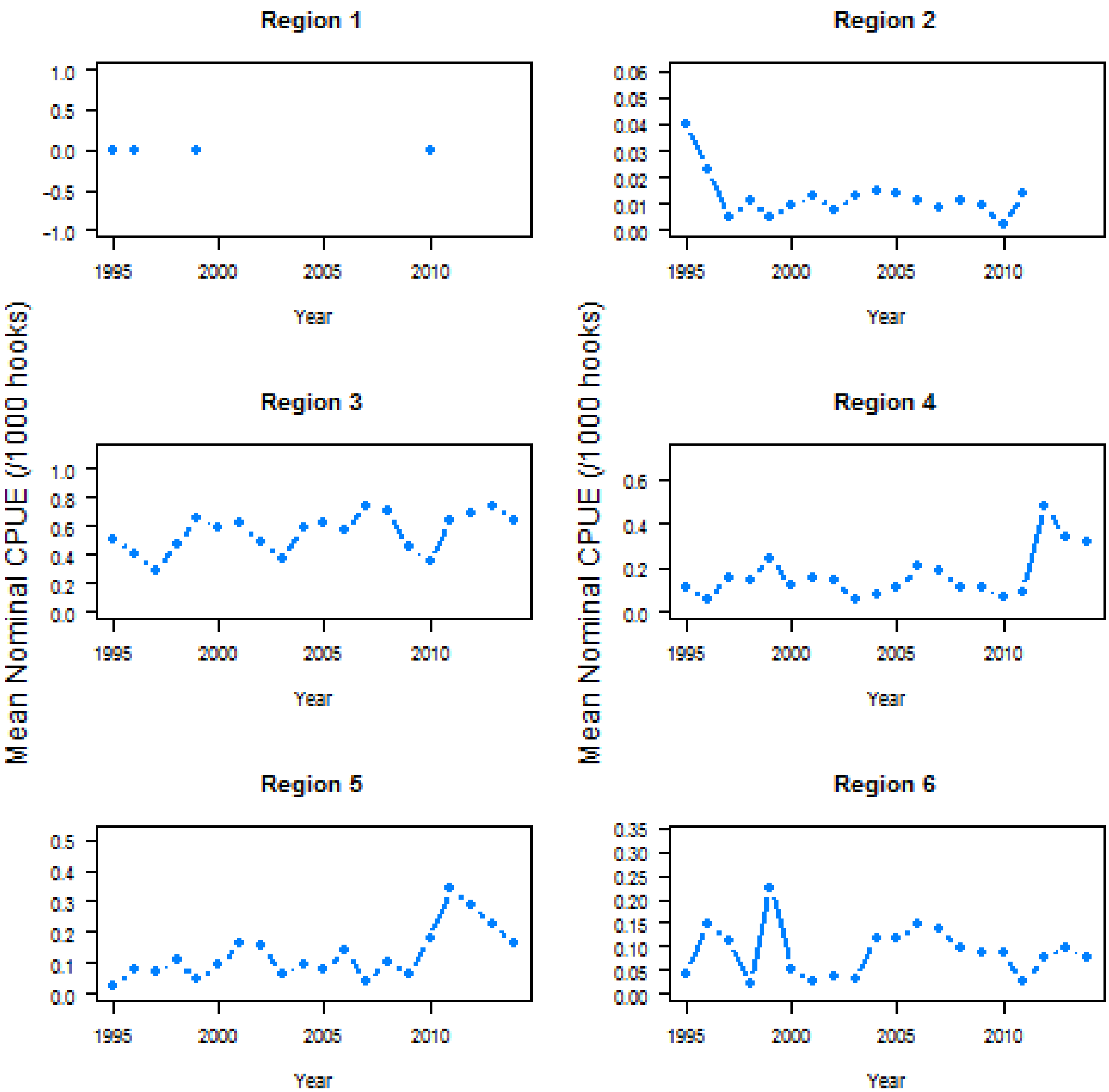

Figure 23: Silky shark CPUE indicators. Nominal CPUE, sharks per 1000 hooks, observer data.

Figure 24: Oceanic whitetip shark CPUE indicators. Proportion of positive sets, observer data.

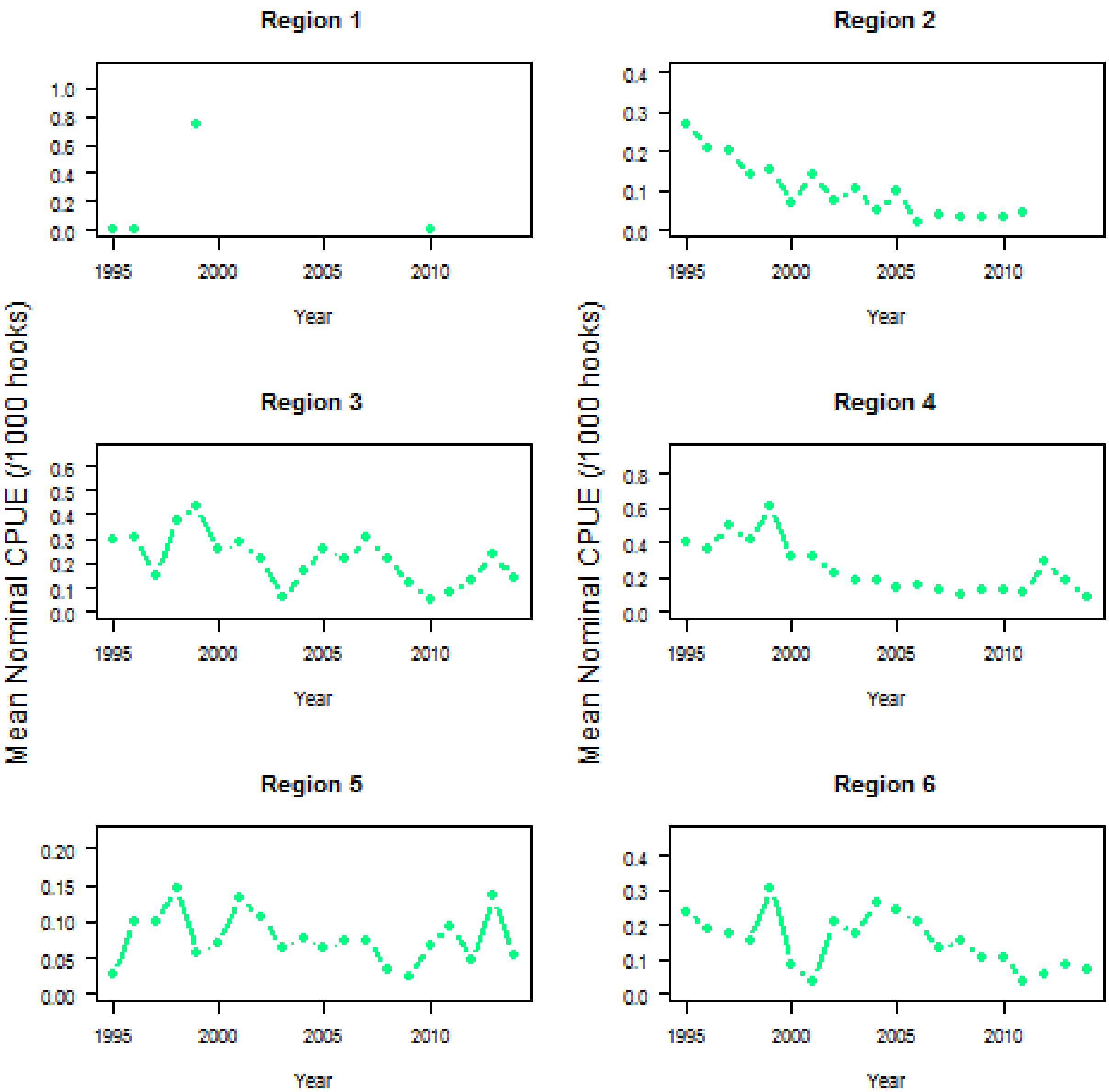

Figure 25: Oceanic whitetip shark CPUE indicators. Nominal CPUE, sharks per 1000 hooks, observer data.

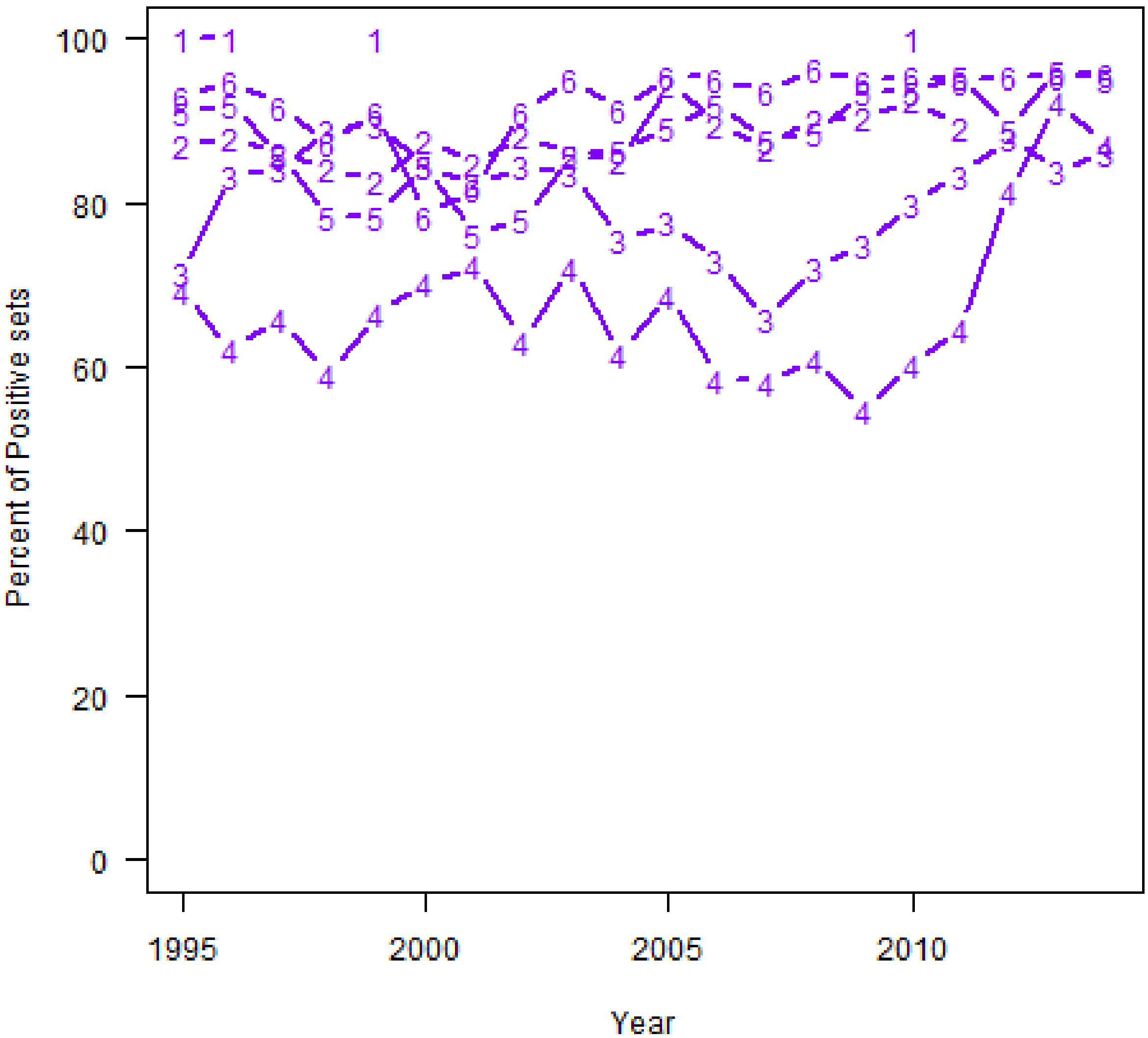

Figure 26: Thresher shark CPUE indicators. Proportion of positive sets, observer data.

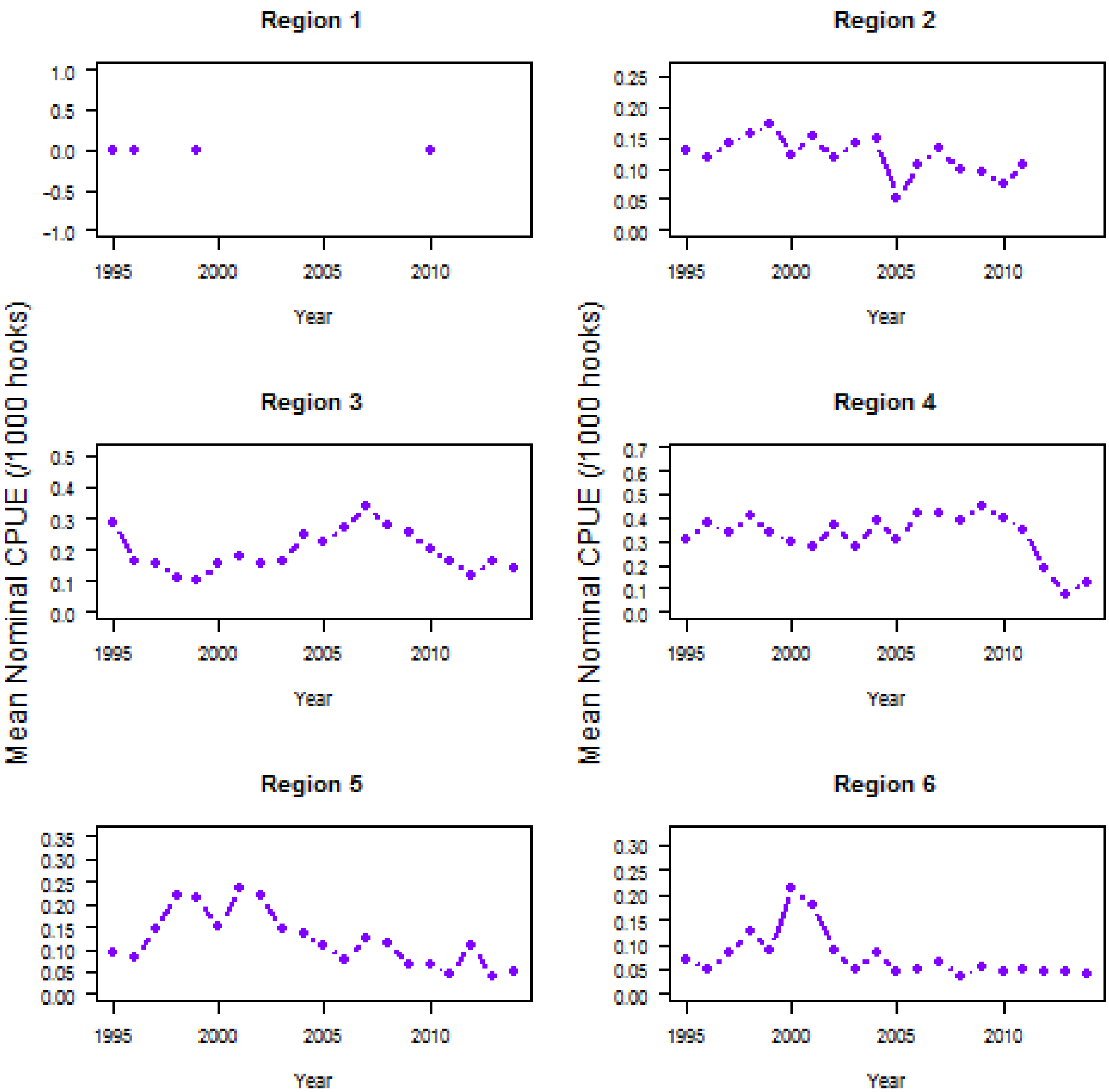

Figure 27: Thresher shark CPUE indicators. Nominal CPUE, sharks per 1000 hooks, observer data.

6 Biological indicator analyses

6.1 Introduction

6.2 Methods

6.3 Results

6.4 Conclusions

7 Feasibility of Stock Assessments

8 Impact of Recent Shark Management Measures

9 Recommendations for Future Indicator Work

10 Management Implications

Acknowledgements

11 Appendices

11.1 CPUE Standardizatoin model diagnostics and extra plots

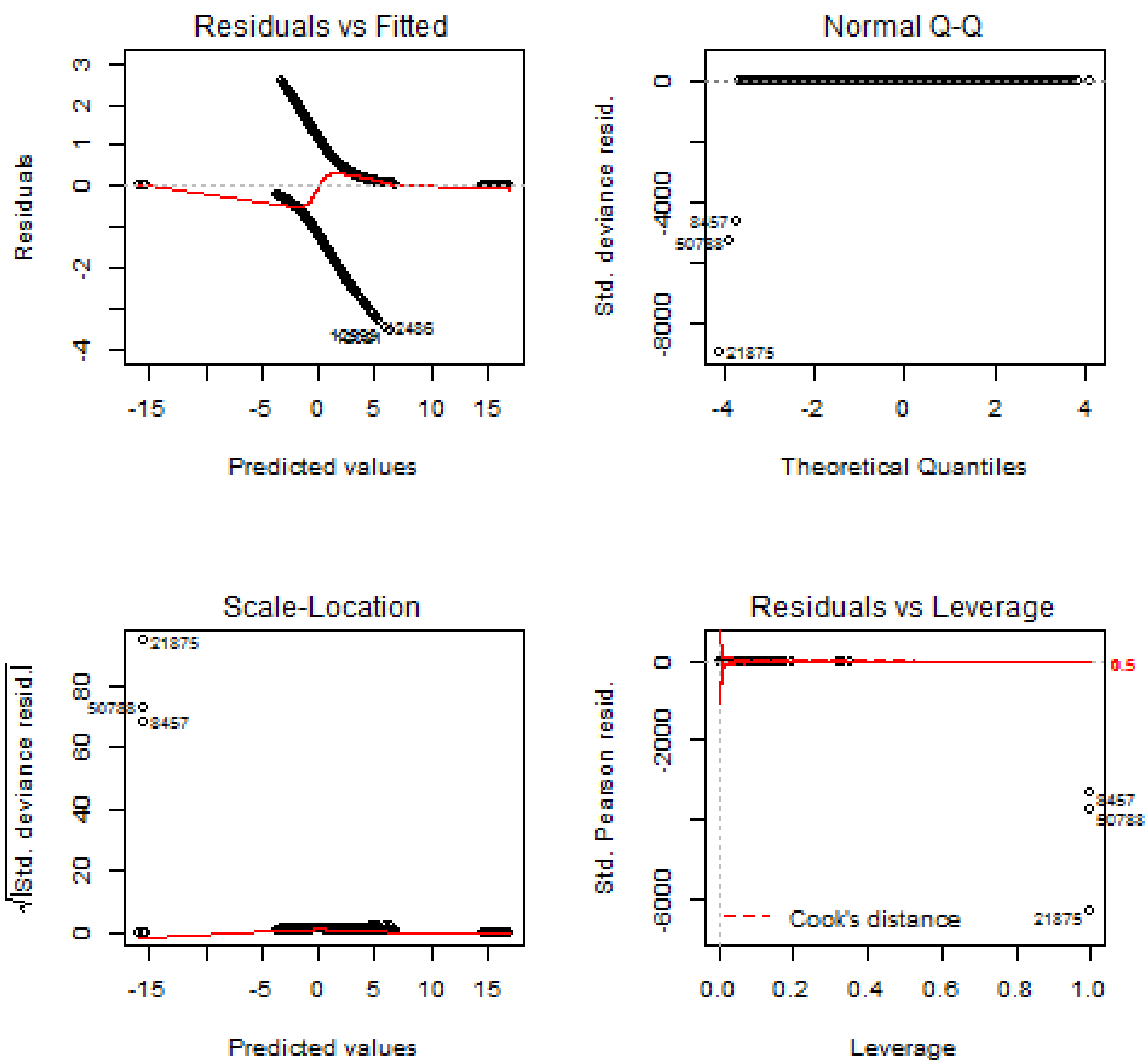

Figure 28: Blue shark CPUE indicators. Standardized CPUE (delta lognormal) model diagnostics binomial component, Southern Hemisphere, observer data.

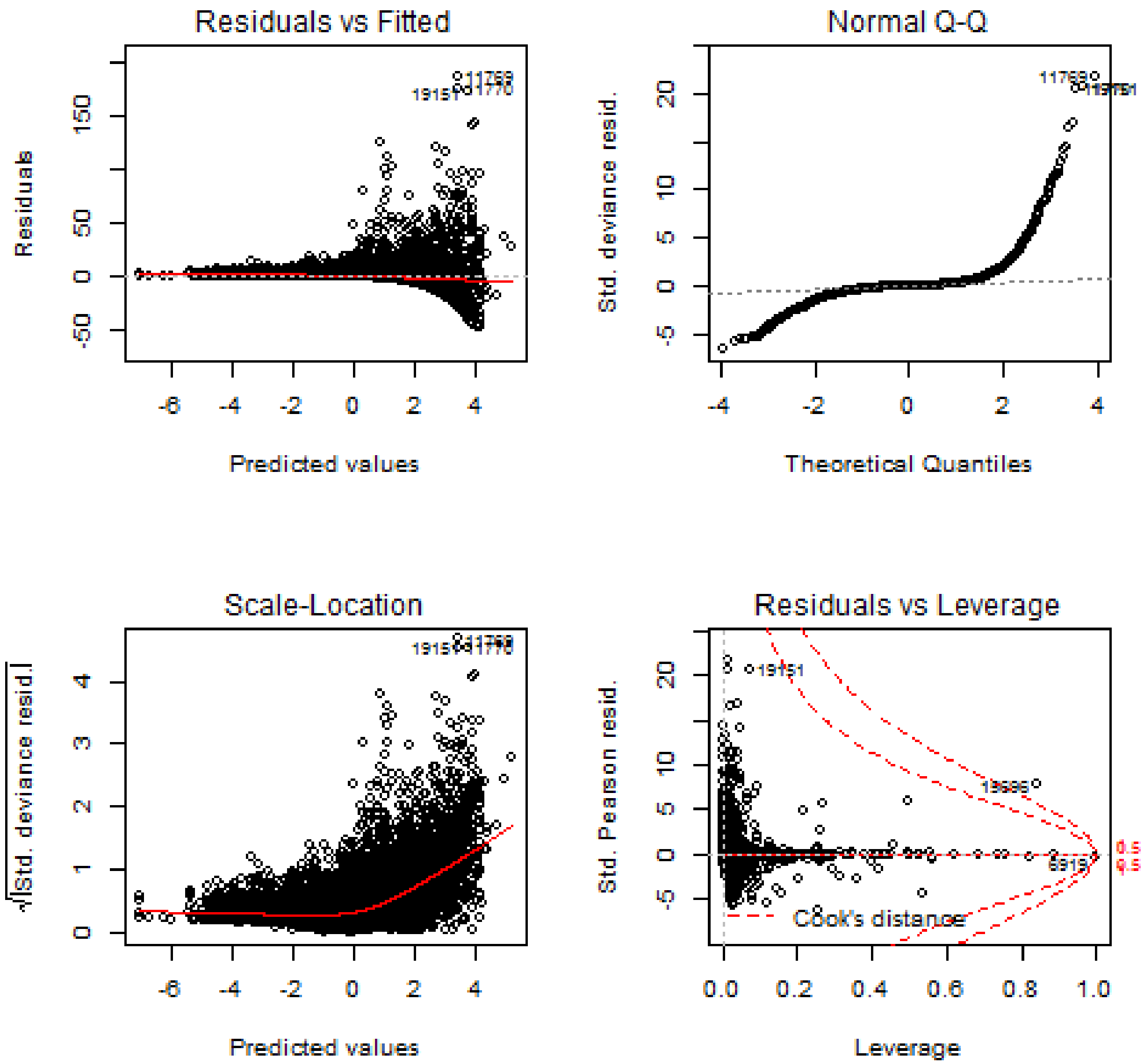

Figure 29: Blue shark CPUE indicators. Standardized CPUE (delta lognormal), model diagnostics- lognormal component, Southern Hemisphere, observer data.