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Potential catch and CPUE series to support a stock assessment of blue shark in the south Pacific Ocean

WCPFC-SC9-2013/SA-WP-04

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Executive Summary

At SC8 in August 2012 SPC was requested to conduct assessments for blue shark in the North and South Pacific Oceans. In developing the critical catch and CPUE inputs for the south Pacific assessment, it became apparent to SPC that data to support the development of catch estimates varied greatly in their quality and coverage, and constructing catch estimates that could be easily understood and accepted by the SC was going to be challenging. This was agreed by the Pre-Assessment Workshop held in April 2013.

Subsequently this paper outlines the nature and extent of data available for the construction of CPUE and catch series for a south Pacific blue shark assessment. We highlight some of the critical gaps in the data and provide some potential catch and CPUE series. The role for the SC is two-fold: 1) to determine if they have sufficient confidence in the available data to request SPC to complete the stock assessment; and 2) provide guidance on which CPUE and catch series should be included in the assessment if one goes ahead.

This paper has presented the estimated catches and standardized CPUE series for blue sharks in the south western central Pacific from longline vessels based on observer, logsheet and aggregate data held by SPC for the years 1990-2011. The data sets all share the same characteristics of poor coverage with respect to space, time, species identification or all three. The analysis was conducted base on five regions for both catch and CPUE, though the Fleet specific CPUE trends correspond only approximately to the catch regions. Further 9 CPUE trends for 8 individual fleets were estimated for 5 regions. Purse seine data was not considered due to extremely low observed catch rates.

The catch estimates in the early years are all quite uncertain and there is a large variation in the catch estimates throughout the 1990s. By the end of the model period, total catch estimates from 5 of the 6 approaches used were in the 90,000-180,000 mt range. While this is a nearly 100 % difference between the lowest and highest (of these lowest 5 models) they all compare more favourably than the Logsheet Raised restricted estimates which is over 500,000 mt in the last 4 years of the estimates. The analysts' recommendations are to use the standardized observer-based catch estimates in a future stock assessment due to the data quality. Because the catch at length data shows region specific differences it is important to bound the uncertainty in the catch by including alternative trends The catch trends derived from aggregated reported data and the logsheet standardized should be included as sensitivities to capture the differences in the magnitude and trend of the region specific catch estimates.

The overall CPUE trends are quite different between the individual fleets, and in any assessment multiple runs would be undertaken based on groupings of similar CPUE trends, as it is generally considered to be incorrect to include both increasing and decreasing trends in the same model run. The fleet specific standardized CPUE trends reflect the underlying nominal data in many of the models indicating that the standardization may have had little effect over the entirety of the time series. Fleet 7 would be the index to use in an assessment associated with catch region 4, a refined estimate from fleet 8 should be used for region 5, along with fleets 1 and 2 for regions 1 and 3. Due to the difference in the standardized CPUE trend based on observer data for Fleet 2 and the standardized CPUE trend resulting from catch estimation for region 2 it is suggested that both trends be included in any future assessment. Additional standardization for the logsheet derived CPUE

trend could improve the index because year trends from GAM with splines on the year effect are usually over-fit with respect to the intra-year variability.

Introduction

At SC8 in August 2012 SPC was requested to conduct assessments for blue shark in the North and South Pacific Oceans. In developing the critical catch and CPUE inputs for the south Pacific assessment, it became apparent to SPC that data to support the development of catch estimates varied greatly in their quality and coverage and constructing catch estimates that could be easily understood and accepted by the SC was going to be challenging.

This issue was discussed with participants at the April 2012 Pre-Assessment Workshop held at SPC in New Caledonia (OFP 2013). This group made the following recommendation "*that work on south Pacific blue shark should focus solely on the determination of plausible catch and CPUE series so that these can be reviewed at SC9 to determine the feasibility of conducting a south Pacific blue shark assessment*". This advice was communicated to the SC Chair and WCPFC Secretariat who agreed to this change in the proposed work plan.

Subsequently the purpose of this paper is to outline the nature and extent of data available for the construction of CPUE and catch series for a south Pacific blue shark assessment. We highlight some of the critical gaps in the data and provide some potential catch series. The role for the SC is two-fold: 1) to determine if they have sufficient confidence in the available data to request SPC to complete the stock assessment; and 2) provide guidance on which CPUE and catch series should be included in the assessment if one goes ahead.

Methods

General approach

Two distinct approaches were used to generate the catch and separately the CPUE time series that we are proposing as candidates for inclusion in the stock assessment, note that CPUE series are a secondary output of the catch estimation, these CPUE series have been examined and reported as well.

The general approach for the construction of catch time series was based around the aggregate estimates of longline fishing effort by quarter and 5x5 degree area. These are the best estimates of total longline fishing effort. The critical task was then to generate a spatial 'layer' of CPUE which could be multiplied across the aggregate effort data to provide the catch estimates. These spatial CPUE layers were not necessarily using the same data / fleets used for the CPUE series mentioned below. In the following sections you will see that we have come up with multiple approaches to estimate the spatial CPUE layer – and it is this layer which causes the differences in the estimated catch series (as the underlying effort was the same).

For both exercises we divided the south Pacific region up into five sub-regions (Figure 1). This was done based on detailed analysis of patterns in fish sizes, sex ratios, CPUE, and fleet dynamics which was presented to the Pre-Assessment workshop (OFP 2013) and will form an integral part to the documentation in any subsequent assessment. For constructing CPUE series, we identified fleets within regions that had consistent reporting of blue shark catches and then standardised their catch rates using all available covariates. Multiple fleets were associated with region 3 & 4 based on the initial analysis of catch at length and historical reporting.

Further, this analysis focuses on estimated CPUE and catch from longline fisheries. Estimation of the catch of blue shark in purse seine fisheries is not included in this analysis because it is very low compared to longline catches (based on examination of blue shark purse seine CPUE). Any final assessment is also likely to include catch estimates from the high seas driftnet fishery that operated during the late 1980s-early 1990s, but this issue has not been addressed at this stage.

Finally, operational logsheet data was available for Spanish vessels that predominantly fished in region 5. These logsheets included reporting of blue shark catches in weight. This fleet will be modelled separately in the assessment and subsequently data for this fleet were excluded from any of the modelling described below and their effort was removed from the aggregate catch and effort layer.

In the remainder of this section we describe the different data sources that are available and their coverage and potential shortcomings, then describe the approaches used to generate CPUE and catch series.

Data sources

The primary source of catch information regarding sharks is the SPC held observer data which, despite low coverage in all regions (Table 1) has a significant amount of information regarding operational characteristics as well as the fate and condition of sharks caught. In addition to the observer data, SPC holds operational logsheet and aggregate data on shark catches by longline fisheries. The operational data submitted to the SPC are at a higher spatial resolution, and are preferred for catch estimation, but in practice the utility is limited by the lack of data provision by species for shark (Table 2), especially in region 1 where the majority of the longline effort occurs (Figure 2). Aggregate coverage rates are on par with the coverage rates of the operational logsheet data sets, although coverage differs greatly by region (Table 3). Historical coverage rates are poor partly because prior to February 2011 sharks were not amongst the species for which data provision was required (WCPFC 2013); since that time, data provision for 13 species designated by WCPFC as key shark species is mandatory[2]. Under CMM 2007-01, required levels of Regional Observer Programme (ROP) coverage in longline fisheries are set to rise to 5% from June 2012 in most areas, but annual average values have been <1% in recent years (for the entire WCPO). With some notable exceptions (e.g. northeast and southwest of Hawaii), most observed sets occurred within Exclusive Economic Zones (EEZs). A thorough explanation of the SPC held fisheries data and its utility for shark related analyses can be found in Clarke et al. (2011).

Construction of CPUE series for scaling aggregate longline effort data

In this section we describe the construction of individual catch series by region based on the intuitive assumption that *Catch = CPUE * Effort*. The methodology used here is the same as in Lawson (2011) and Rice (2012), developing catch time series that result from the application of each area specific

[2] Whale sharks are not included in the list of species under the scientific data provisions, but reporting is required under CMM2012-04.

CPUE series (surface) to the total effort on a 5˚x5˚ scale. Region specific CPUE surfaces based on the observer data, the operational data, and the aggregate data were used to construct several alternative catch series as described below. For the analysis based on the observer data and logsheet data, where generalized additive models were used to create the CPUE surfaces that allowed construction of region specific CPUE trends, a brief discussion of the use of these CPUE series as indices of abundance is included at the end of this report alongside a more traditional CPUE standardization analysis.

Observer data

The observer dataset was standardized using generalized additive models (Zuur et al. 2012) using the software package R (www.r-project.org). 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. Catch data for non-target species (sharks in particular) often contain a large number of sets with zero catch as well as sets with substantial catch. These phenomenon need to be explicitly modelled (Bigelow et al. 2002 Minami et al. 2007). Standardized CPUE series for all regions were developed using generalized linear models. For longline analyses, effort was defined as the number of hooks fished in a set.

The delta lognormal approach (DLN) (Lo et al. 1992, Dick 2006, 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, $(1-w) * E(y|y \neq 0)$.

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

An annual CPUE surface was predicted for the fishery based on the delta lognormal (DLN) model. For each region (except region 5 which did not have sufficient observer data) a delta lognormal generalized additive model (GAM) was used to estimate year and spatial CPUE effects. Basis splines were used for latitude and longitude as well as year[3] as a feature of all regional models, and other variables (e.g. hooks between floats, vessel name, and SST) were included where they were supported by the model as categorical factors. Model selection the he Akaike information criterion (AIC) and forward selection starting with the minimal model where covariates were only *year*, *lat* and *lon.*

A surface of overall annual effort based on the SPC OFP effort records (Williams and Terawasi 2011) was then created by proportioning the effort to 5˚x5˚ square based according to the reported latitude and longitude. Catch estimates by region were calculated by multiplying the CPUE surface (predicted CPUE in numbers of blue sharks per 1000 hooks for each 5 degree square and year) by the effort surface with respect to space (latitude and longitude) and time. This produced an annual catch

[3] Typically year effects are estimated as categorical variables, but due to the limited degrees of freedom available to estimate the spatial surfaces we took this approach.

surface (Figure 3 provides an example of this approach), which was summed to provide an annual catch estimate (Figure 4).

When additional variables were included in the standardization (e.g. vessel), a median coefficient was used in the prediction. Some general model diagnostics are provided in Appendix 1. The nominal and n standardized year effects by region are presented in Figure 5.

Operational level data

The approach to estimate catch based on the operational level was similar to what was used for the observer data where delta lognormal generalized additive models (GAM) were used to estimate year and spatial CPUE effects. Basis splines were used for latitude and longitude as well as year effect due to the lack of data in both time and space, catch was calculated as the summed product of the area (5˚x5˚ cell) effect and effort for that cell (Figure 6). Region 5 was not modelled with the GAM due to lack of data.

In addition to the spatial smoothing approach described above, two simpler approaches were also used to estimate alternative catch estimates from the logsheet data. First the nominal CPUE for each year and region were scaled to aggregate effort to produce one set of catch estimates (Figure 7). Second we repeated the calculation of nominal CPUE based on a subset of the operational data. This subset used flags for which there were at least five consecutive years with more than five records of blue shark reported. We did not include all data for those flags identified above – just those data within the run of consecutive years reporting, annual nominal CPUE based on the restricted dataset was then scaled by aggregate effort to calculate overall catch (Figure 8).

Region specific CPUE trends for the overall nominal CPUE and subset of data from nations reporting BSH at least 5 times for 5 years are presented in Figures 9 and 10. The CPUE trends based on the DLN models (Figure 11) were calculated as the average predicted year effect across all cells, and are presented alongside the nominal region specific CPUE trend, normalized by their respective means. The DLN models are based on the minimally adequate data starting with the restricted logsheet data base and adding data on a region by region basis until the models converged, general model description and diagnostics are presented in Table 5 and Appendix 2, respectively.

Analysis of Aggregate level data

A similar approach to that used for the simple operational level data analysis was used to incorporate the available reports of blue sharks catches in the aggregate catch and effort data. Figure 12 shows the total reported BSH catch in the south Pacific by region.

We estimated catch based on the aggregate CPUE data from flags for which there were at least five consecutive years with more than five records of blue shark reported. We did not include all data for those flags identified above – just those data within the run of consecutive years reporting. Annual CPUE was calculated then scaled by aggregate effort to produce a 'scaled up' version of the aggregate catch data (Figure 13). No effort was made to standardize the nominal aggregate CPUE due to lack of identifying covariates and the aggregated nature of the data (Figure 14).

Analysis of Spanish longline data

Data from the Spanish longline fleet was submitted to the WCPFC without information on effort, but full information on the catch of blue shark, in metric tons as well as some operational characteristics.

Because this is not easily comparable it is presented as is, on its own (Figure 15), note that this is both the majority of the effort (and hence catch) in Region 5.

Analysis of SPC held observer data to produce CPUE indices

As noted above, for constructing CPUE series, we looked for fleet / regions which had consistent reporting of blue shark catches, reasonable levels of data, and caught similar sized fish (i.e. we can combine fleets within a region if the selectivity profile is likely to be the same). We indentified eight fleets based on these investigations (Table 7).

Negative binomial models were used to standardize the fleet specific data on a fleet specific basis (Table 7 with models for each fleet, Figure 17). Fleet 8 (Spanish LL) lacked the effort information so this fleet was also modelled with linear mixed effects models with a lognormal error structure and a response variable of blue shark catch+1. The negative binomial modelling of Fleet 8 (Figure 18) had decent diagnostic plots but further investigation into more sophisticated methods for dealing with the lack of effort is warranted. General model diagnostics are presented in Appendix 3.

Discussion

This paper has presented the estimated catches and standardized CPUE series for blue sharks in the south western central Pacific from longline vessels based on observer, logsheet and aggregate data held by SPC for the years 1990-2011. The data sets all share the same characteristics of poor coverage with respect to space, time, species identification or all three. The analysis was conducted base on five regions for both catch and CPUE, though the Fleet specific CPUE trends correspond only approximately to the catch regions. Further 9 CPUE trends for 8 individual fleets were estimated for 5 regions. Purse seine data was not considered due to extremely low observed catch rates.

The catch estimates in the early years are all quite uncertain and there is a large variation in the catch estimates throughout the 1990s. By the end of the model period, 5 of the 6 models were in the 90,000- 180,000 mt range. While this is a nearly 100 % difference between the lowest and highest (of these lowest 5 models) they all compare more favourably than the operational raised restricted estimates which is over 500,000 mt in the last 4 years of the estimates. The analysts' recommendations are to use the standardized observer-based catch estimates in a future stock assessment due to the data quality. Because the catch at length data shows region specific differences it is important to bound the uncertainty in the catch by including alternative trends. The catch trends derived from aggregated reported data and the logsheet standardized should be included as sensitivities to capture the differences in the magnitude and trend of the region specific catch estimates.

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REFERENCES

Bigelow K. A., Hampton J., & Miyabe N. (2002) Application of a habitat-based model to estimate effective longline fishing effort and relative abundance of Pacific bigeye tuna (*Thunnus obesus*). Fisheries Oceanography 11: 143-155.

Clarke, S., Harley, S., Hoyle, S. and Rice, J. (2011) An indicator-based analysis of key shark species based on data held by SPC-OFP. WCPFC-SC7-2011/EB-WP-01

Dick E. J. (2006) Delta_glm. [1.7.2]. Santa Cruz, CA, USA, NOAA.

Hoyle S. D. & Maunder M. N. (2006) Standardisation of yellowfin and bigeye CPUE data from Japanese longliners, 1975-2004. IATTC Working Group on Stock Assessments. 6th Meeting, SAR-7-07.http://www.iattc.org/PDFFiles2/SAR-7-07-LL-CPUE-standardization.pdf . 2006.

Lawson, T. (2011) Estimation of Catch Rates and Catches of Key Shark Species in Tuna Fisheries of the Western and Central Pacific Ocean Using Observer Data. WCPFC-SC7-EB-IP-02.

OFP. (2013) Report from the SPC pre-assessment workshop, Noumea, April 2013. WCPFC-SC9-3/SA-IP-01.

Lo N. C. H., Jacobson L. D., & Squire J. L. (1992) Indices of relative abundance from fish spotter data based on delta-lognormal models. Canadian Journal of Fisheries and Aquatic Sciences 49: 2515-2526.

Minami, M. Lennert-Cody, C.E., Gao, W. , Román-Verdesoto, M. (2007) Modeling shark bycatch: the zero-inflated negative binomial regression model with smoothing. Fisheries Research 84: 210-221.

Oceanic Fisheries Programme. 2013. Report from the SPC pre-assessment workshop, Nouméa, April 2013. WCPFC-SC9-2013/SA-IP-01

Ortiz, M., Arocha, F. (2004) Alternative error distribution models for standardization of catch rates of non-target species from a pelagic longline fishery: billfish species in the Venezuelan tuna longline fishery. Fish. Res. 70, 275–297.

Pennington, M. (1996) Estimating the mean and variance from highly skewed marine data. Fish. Bull. 94, 498–505

Rice, J. (2012) Alternative catch time series for oceanic whitetip and silky sharks in the Western and Central Pacific Ocean. WCPFC-SC8-SA-IP-12.

WCPFC (2013) SCIENTIFIC DATA TO BE PROVIDED TO THE COMMISSION. (http://www.wcpfc.int/node/602)

Williams, P., and Terawasi, P. (2011) Overview of tuna fisheries in the western and central Pacific Ocean, including economic conditions – 2010. WCPFC-SC7-2011/GN WP-1

Zuur A.F., Saveliev A.A., Ieno, E.N. (2012) Zero inflated models and generalized linear mixed models with R. Springer, NY, NY.

Figures.

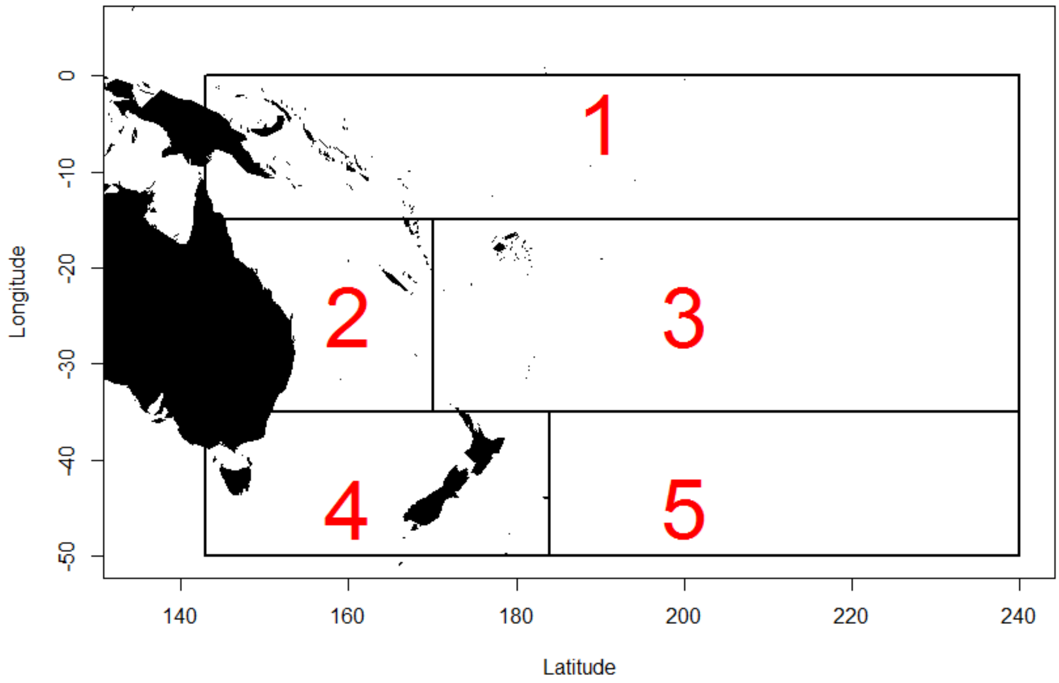


Figure 1. South Pacific Ocean and sub-areas indentified through the analysis of CPUE and size data for the definition of fisheries. These regions were used for catch estimation.

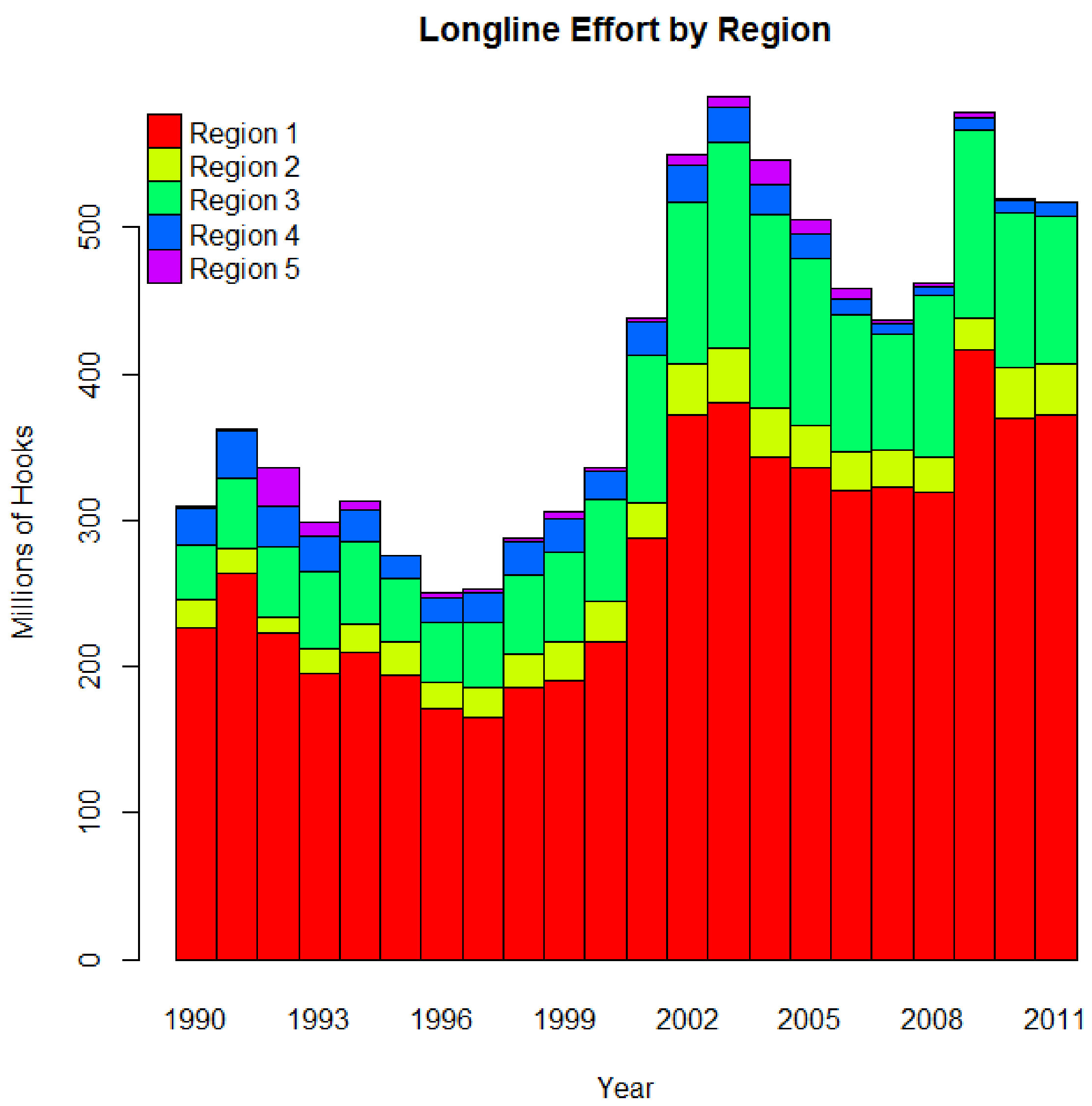


Figure 2. Longline effort by region (1990-2011).

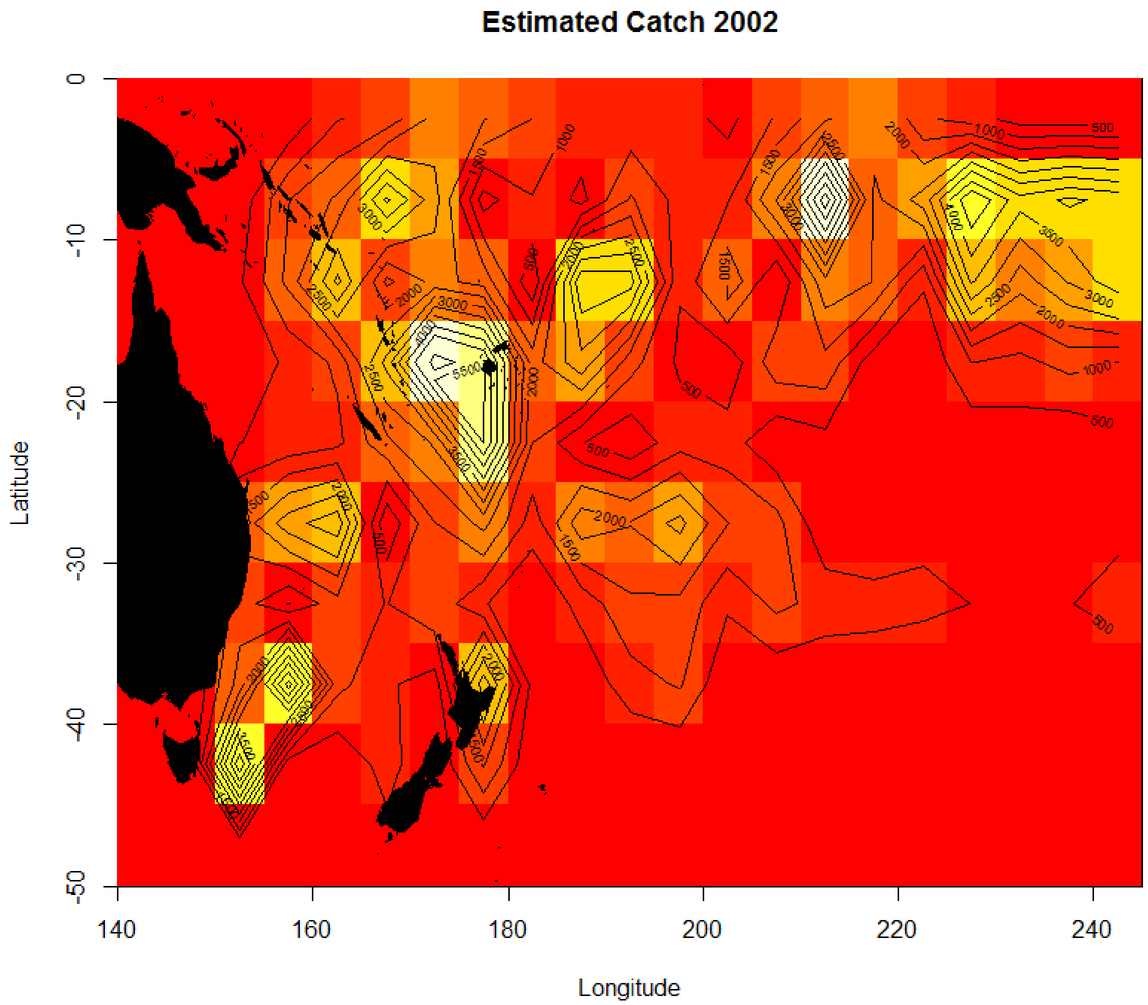


Figure 3. Example of the spatial surface of estimated catch that comes from the aggregate catch and effort data and the estimated CPUE spatial surface. This specific example is from observer data for 2002 for the entire south Pacific Ocean.

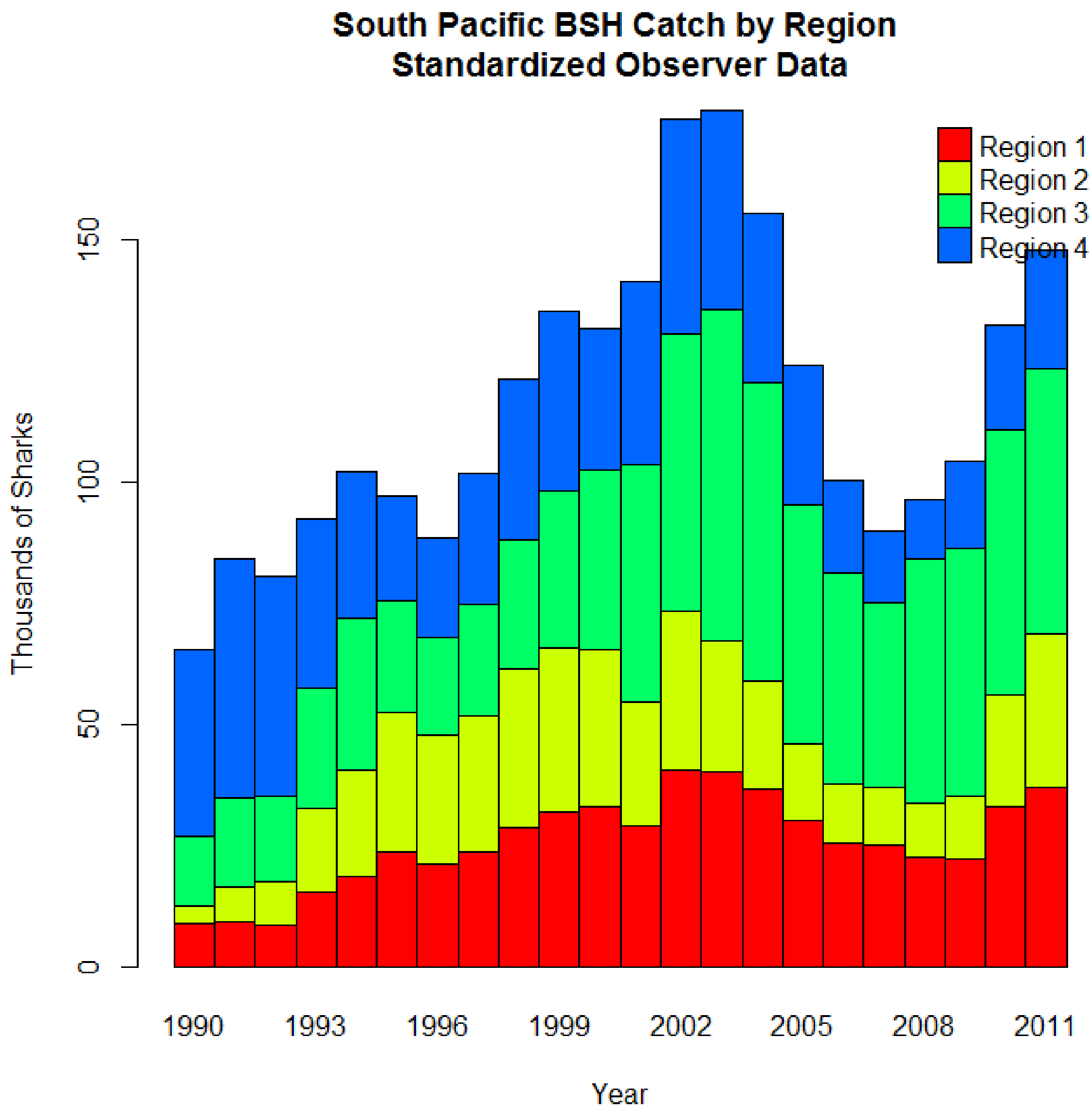


Figure 4. Catch estimates in 1000's of sharks for regions 1,2,3,4 based on the DLN modelling of observer data.

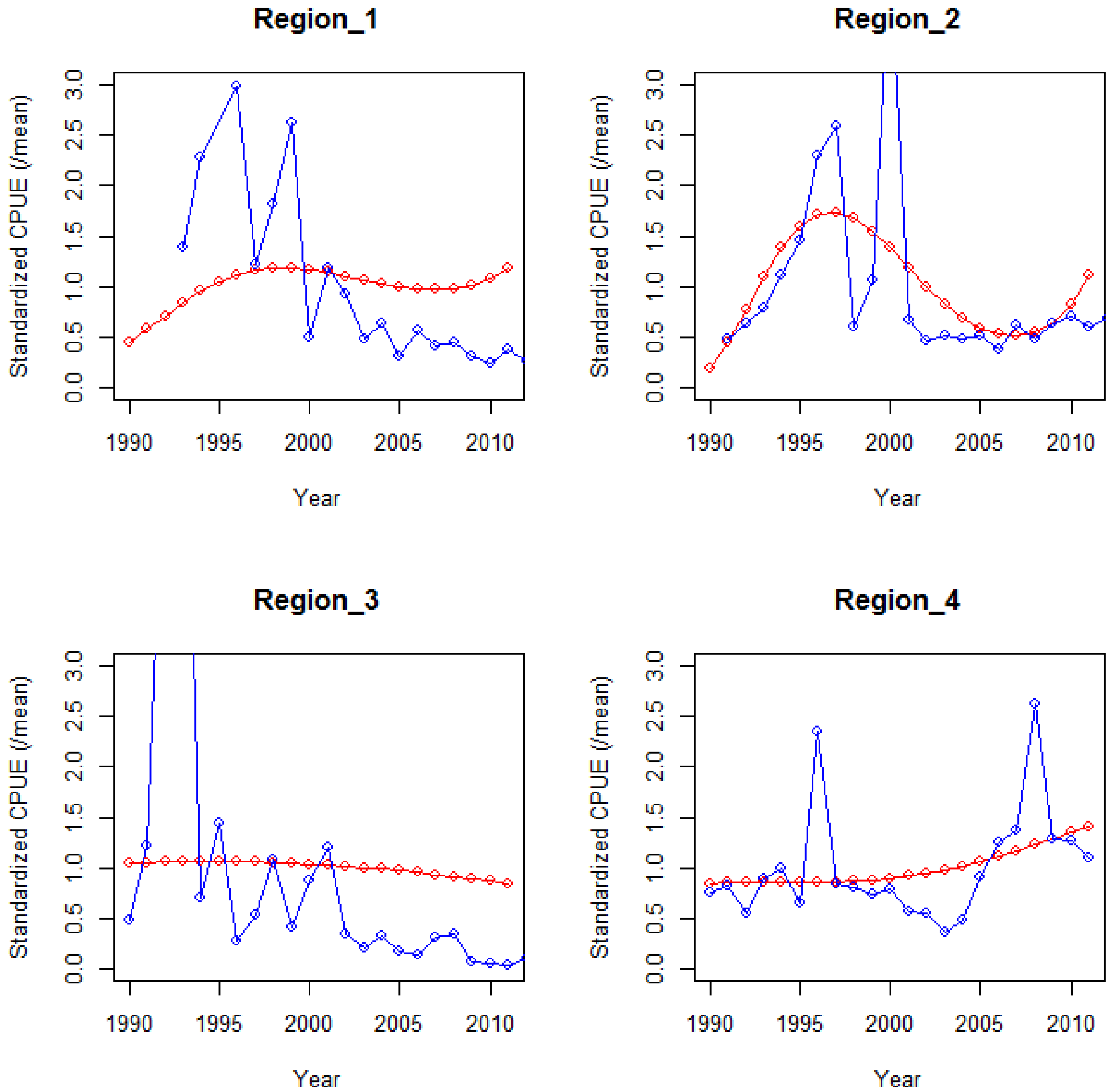


Figure 5. Nominal CPUE (blue) and basis spline year effects (red) from the DLN estimation of CPUE based on observer data. Each series is standardised to its mean.

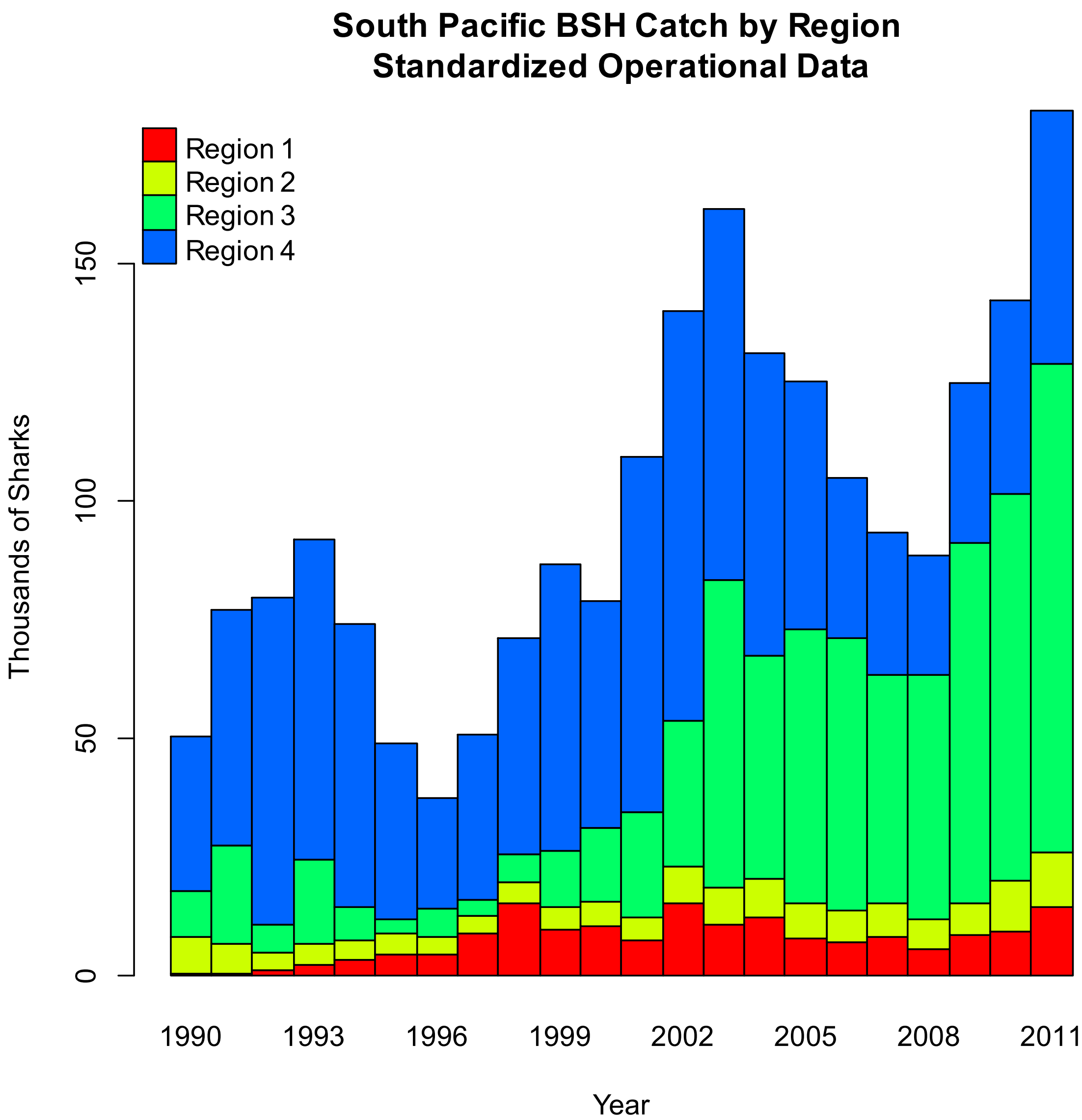


Figure 6. Catch estimates in 1000's of sharks for regions 1,2,3,4 based on the DLN modelling of operational logsheet data.

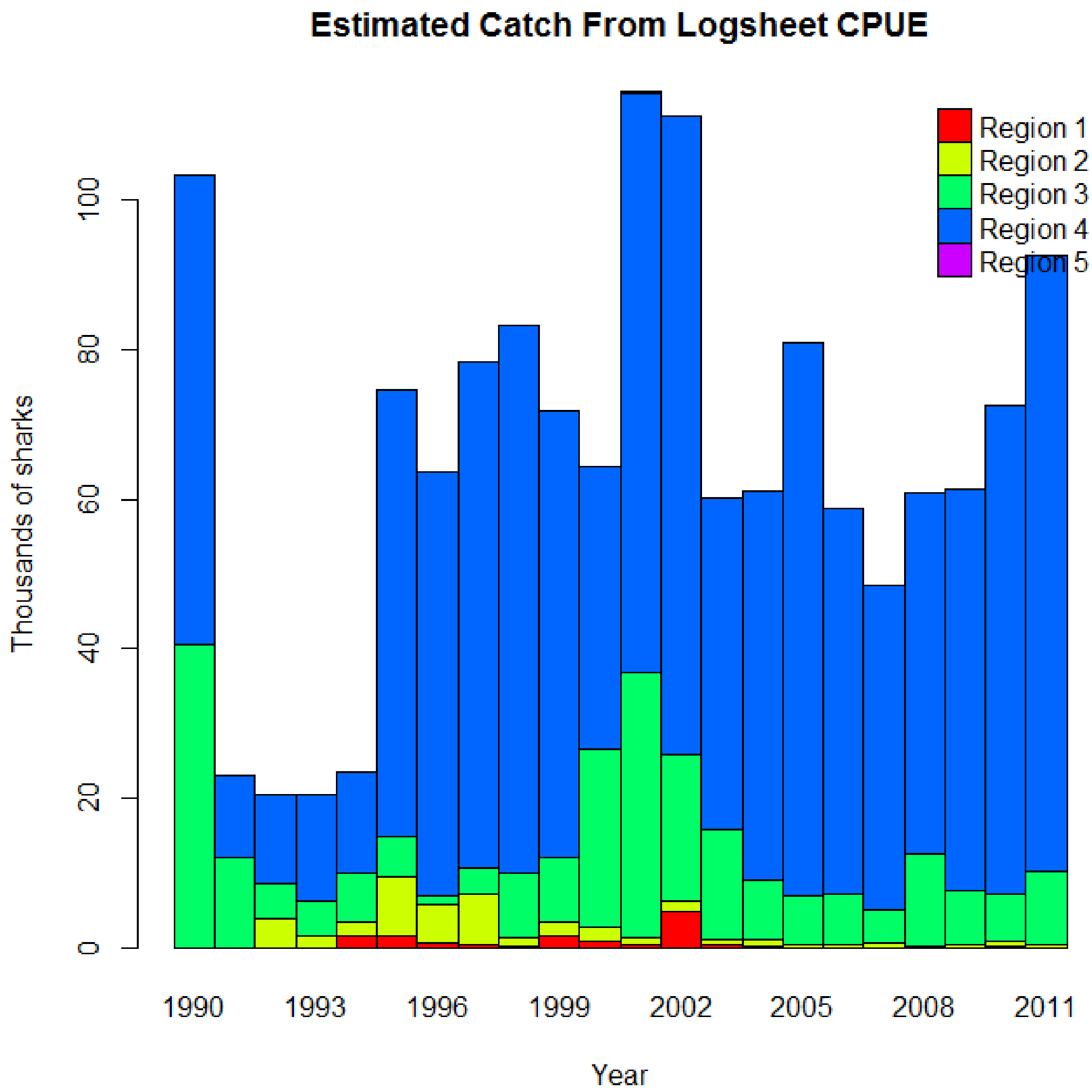


Figure 7. Catch estimates in 1000's of sharks for regions 1-5 based on the nominal CPUE calculated from the full operational logsheet dataset.

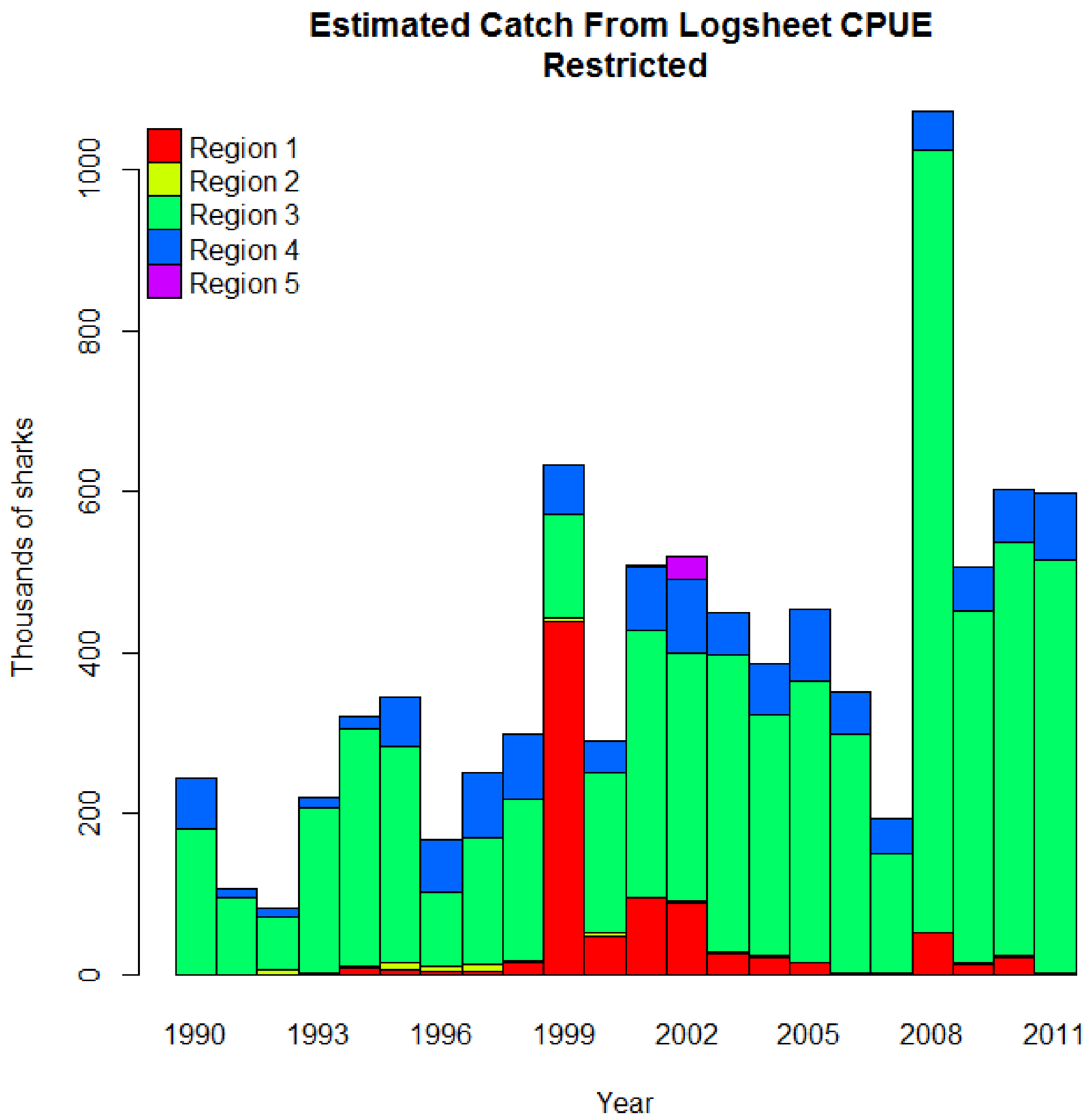


Figure 8. Catch estimates in 1000's of sharks for regions 1-5 based on the nominal CPUE calculated from the restricted operational logsheet dataset based on only those nations that had five years of 5 or more records

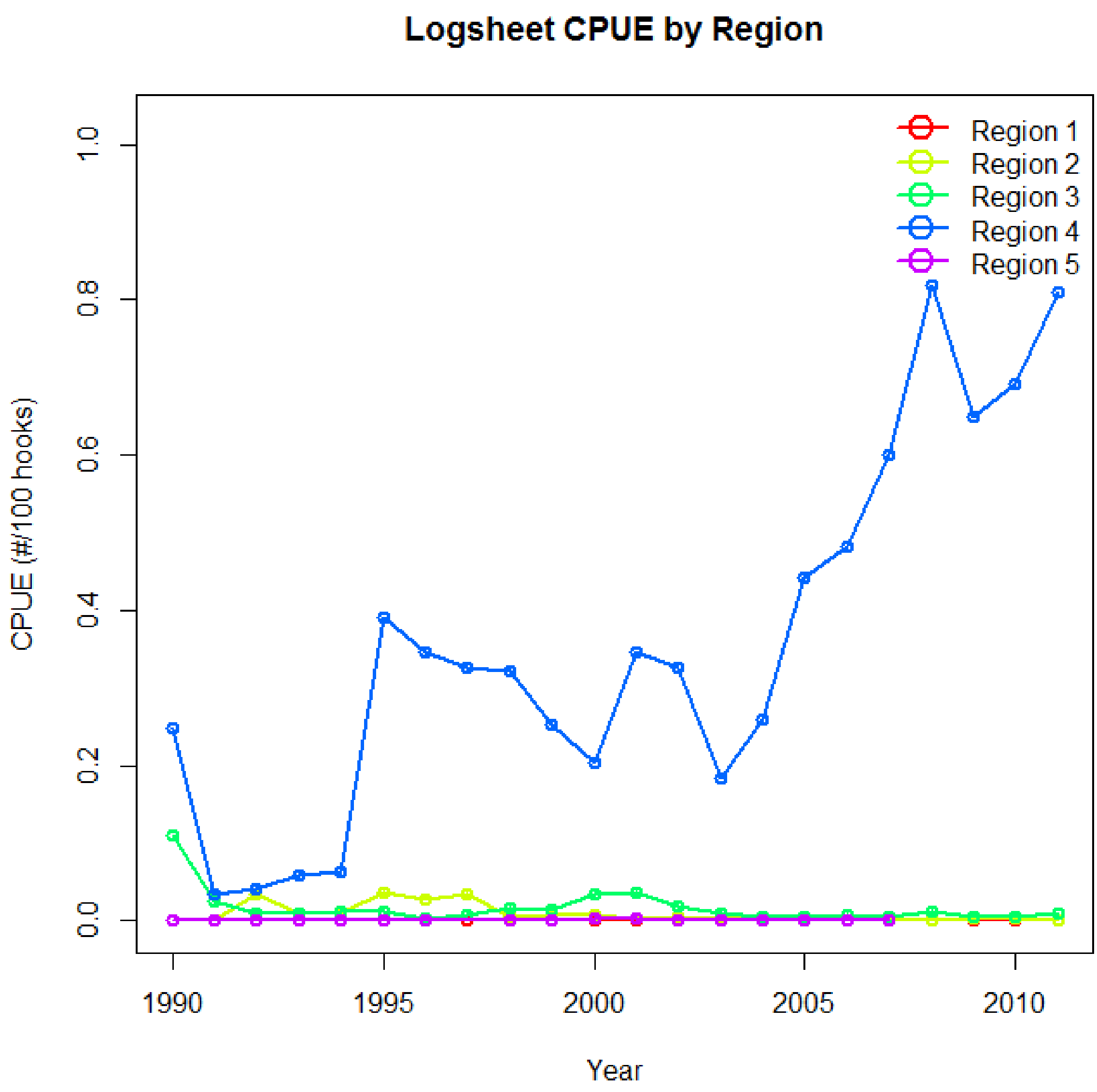


Figure 9. Nominal logsheet CPUE for regions 1-5.

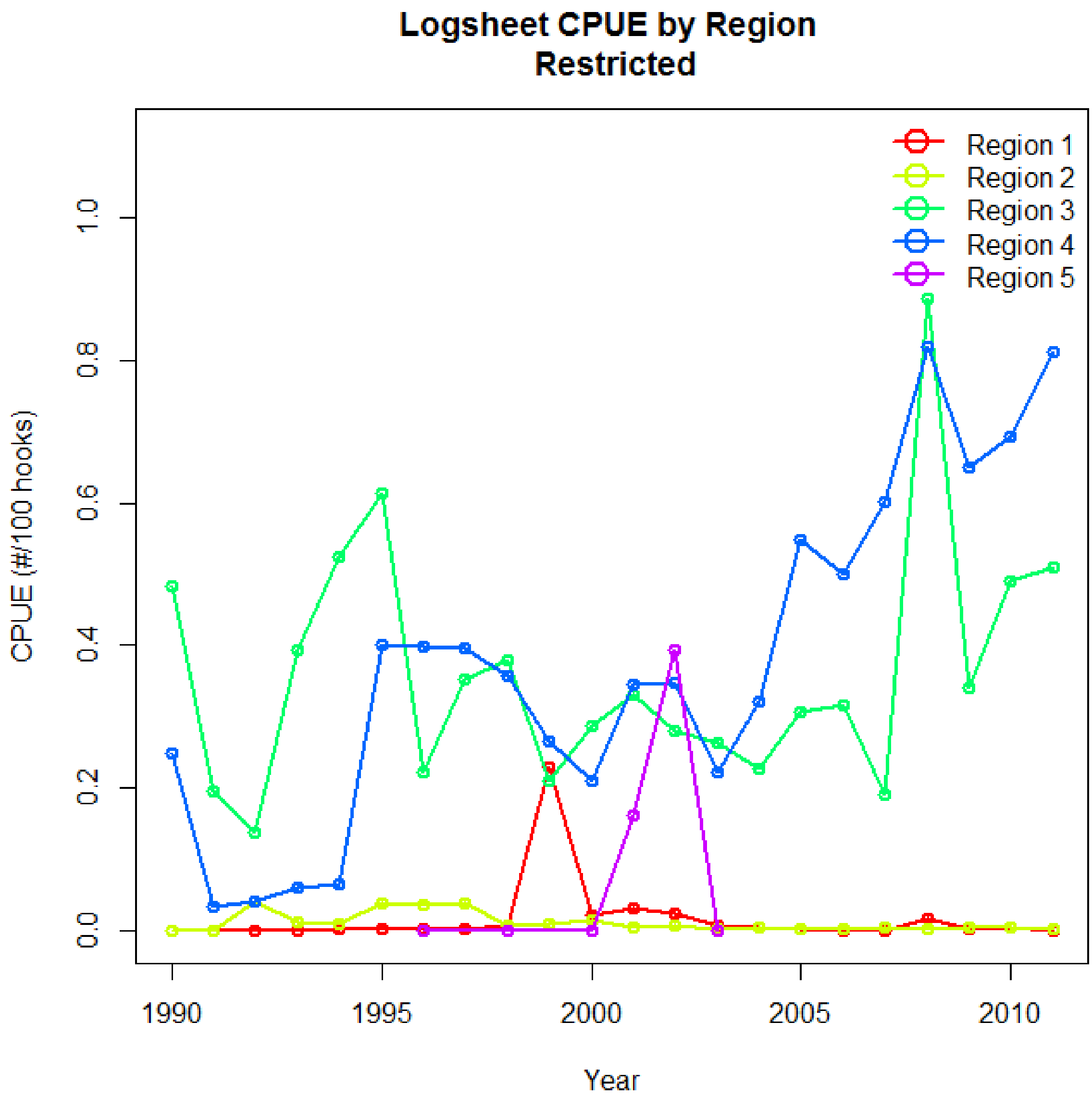


Figure 10. Nominal logsheet CPUE for regions 1-5 for the restricted data set with only nations reporting BSH at least five times for 5 years.

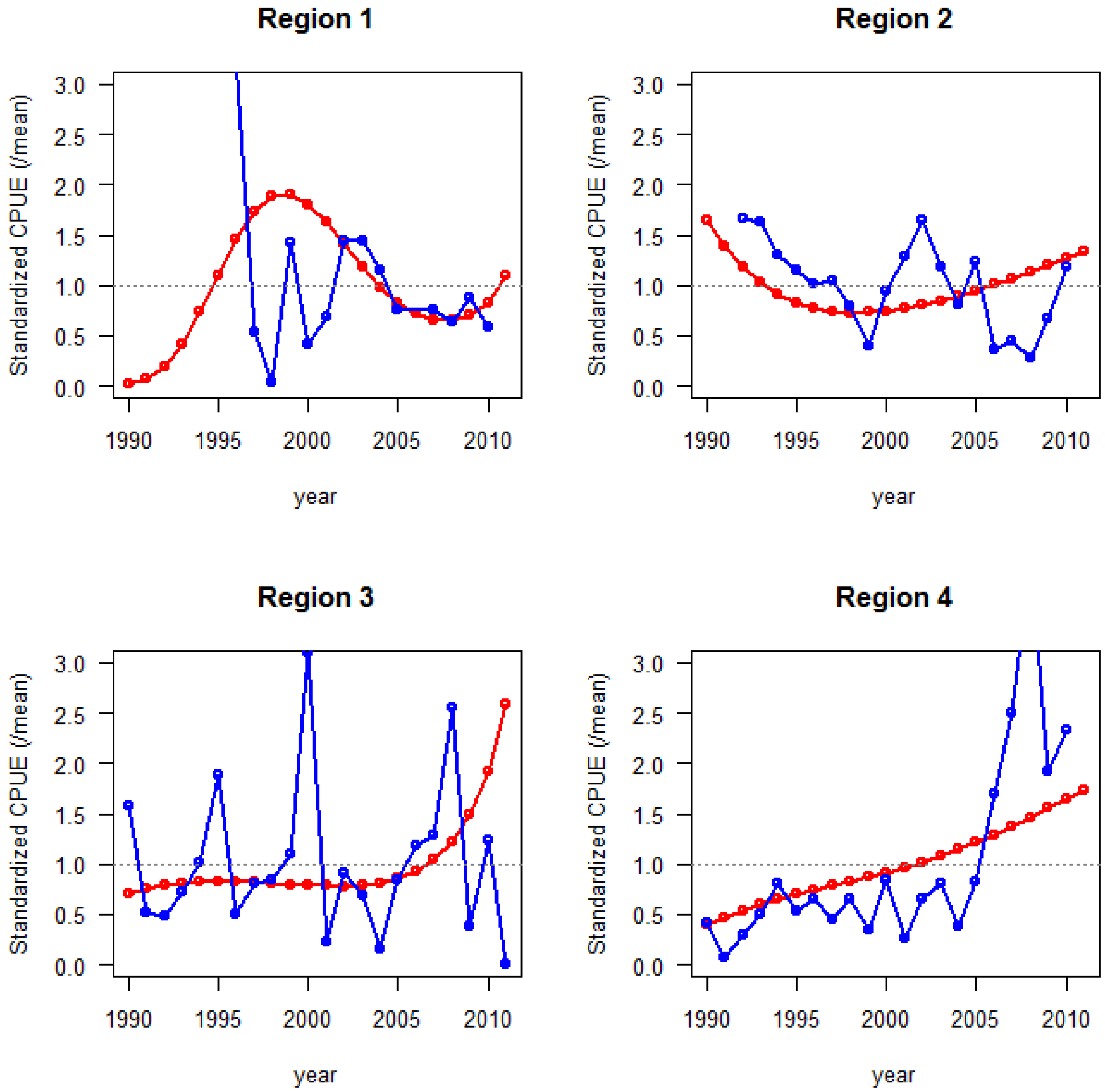


Figure 11. Nominal CPUE (blue) and basis spline year effects (red) from the DLN estimation of CPUE based on operational data. Each series is standardised to its mean.

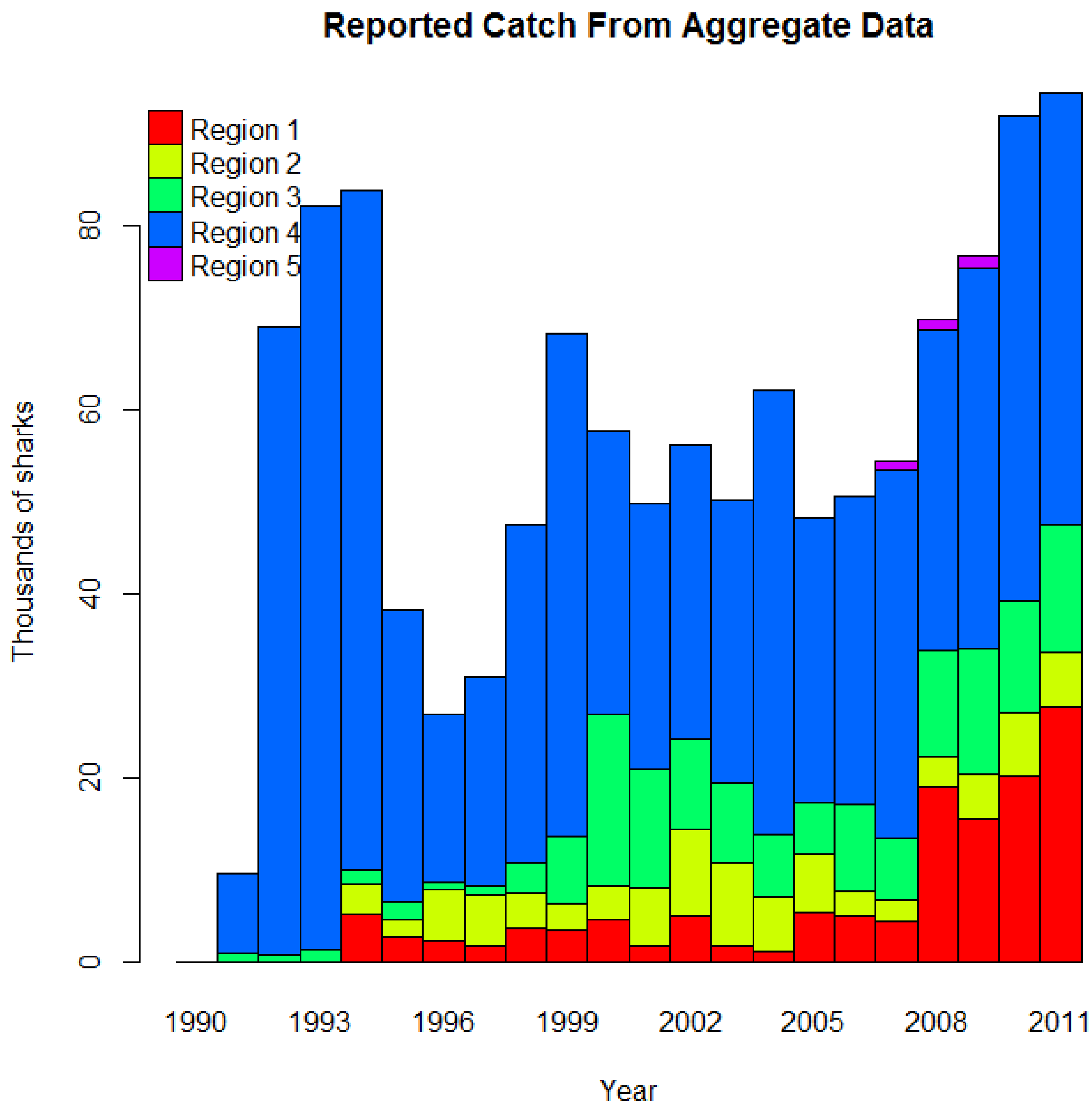


Figure 12. Reported catch in 1000's of sharks for regions 1-5 from aggregate catch and effort data.

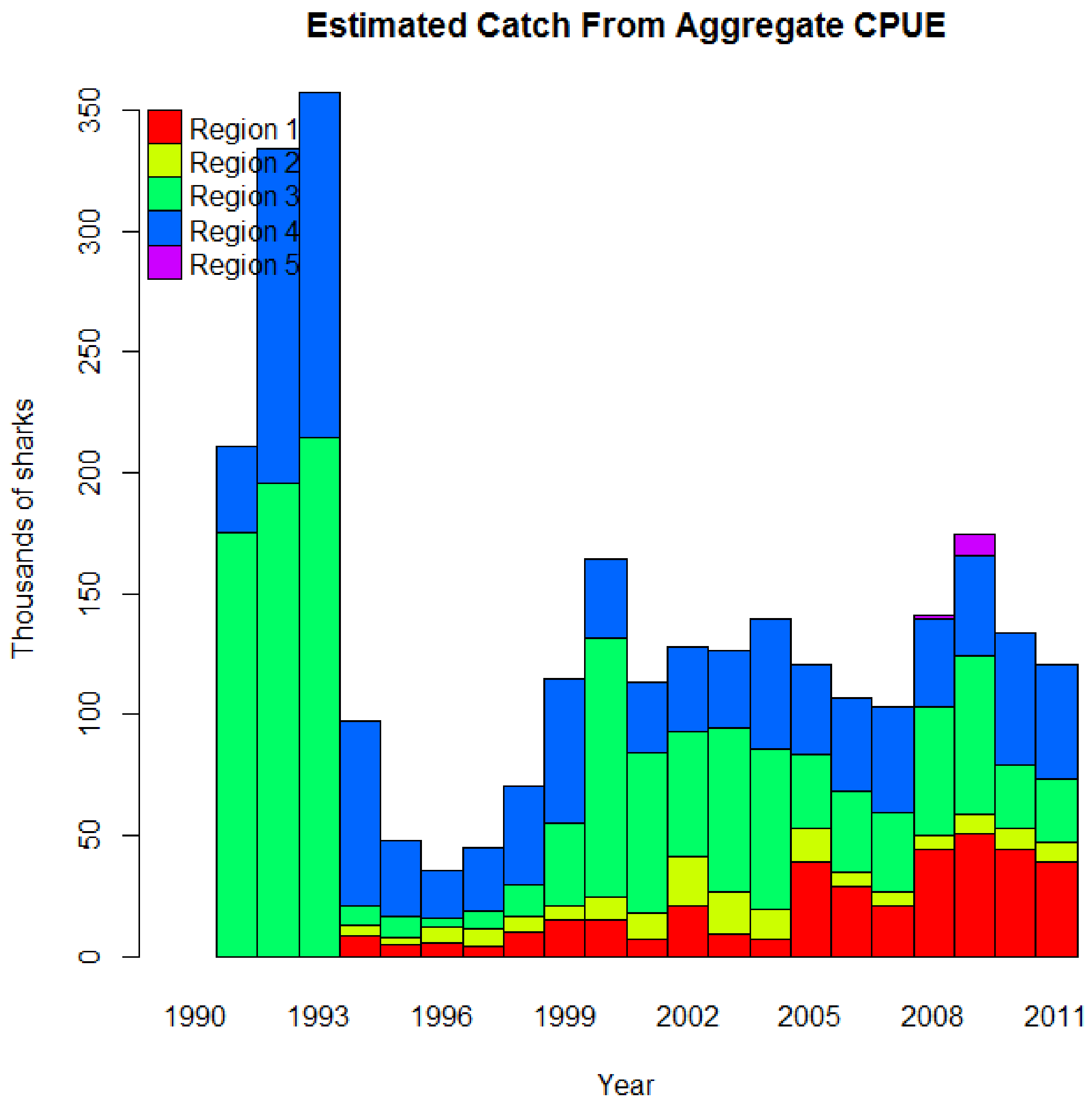


Figure 13. Estimated catch in 1000's of sharks for regions 1-5 from aggregate catch and effort data based on nominal catch rates for those countries that reported BSH catch.

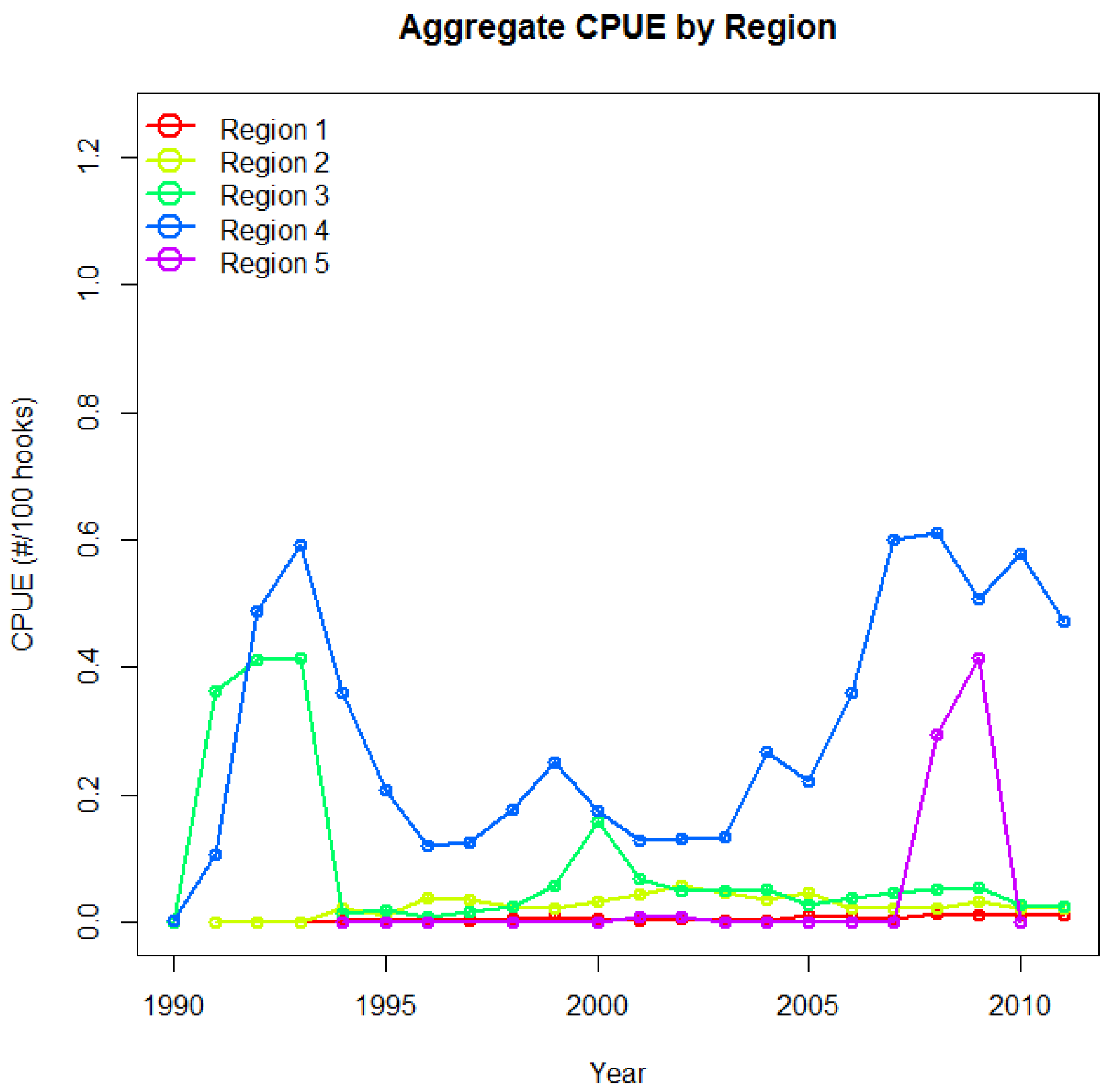


Figure 14 Nominal aggregate CPUE for regions 1-5 for the restricted data set with only nations reporting BSH at least five times for 5 years.

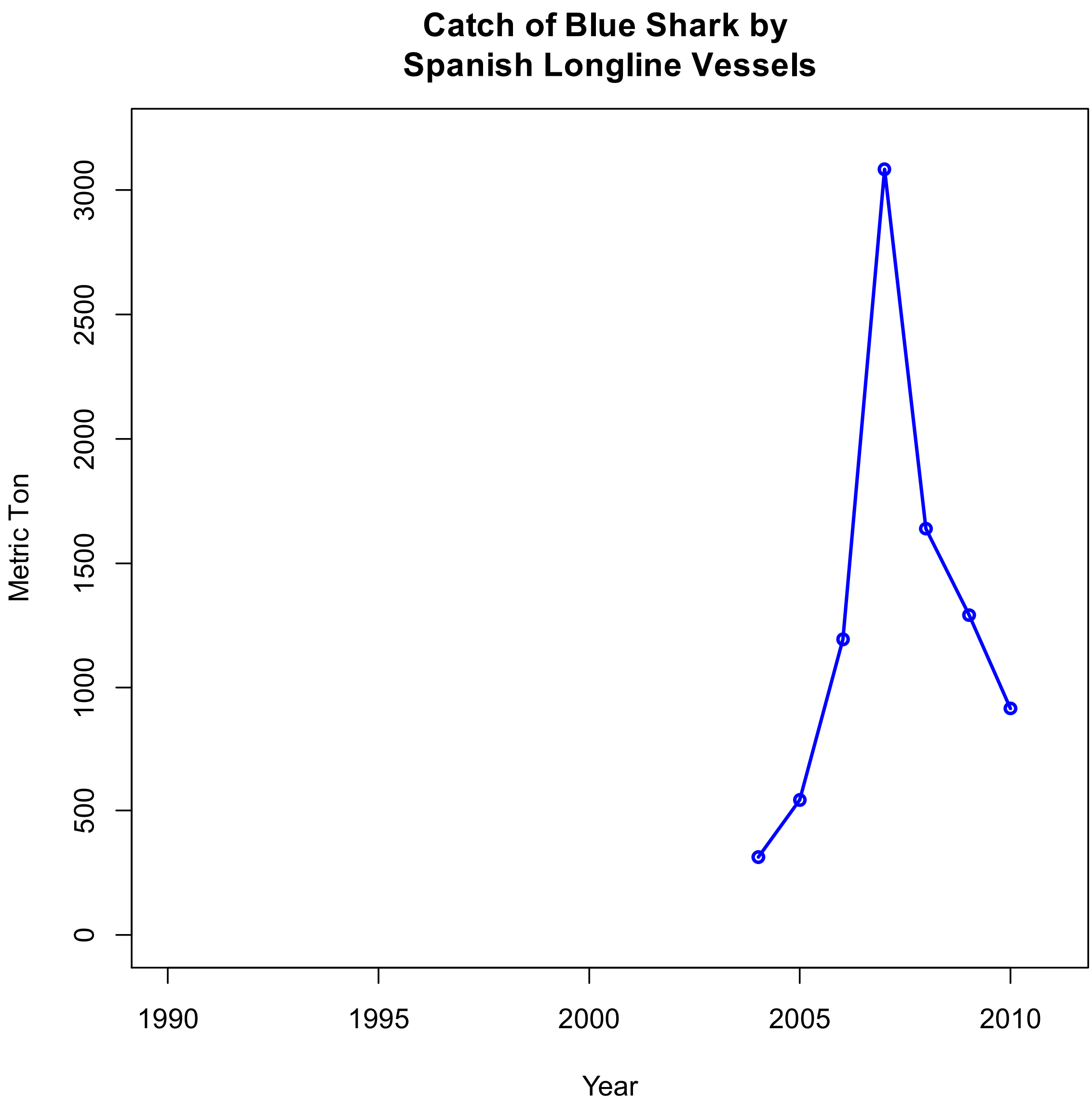


Figure 15: Reported catch of blue shark by Spanish longline vessels.

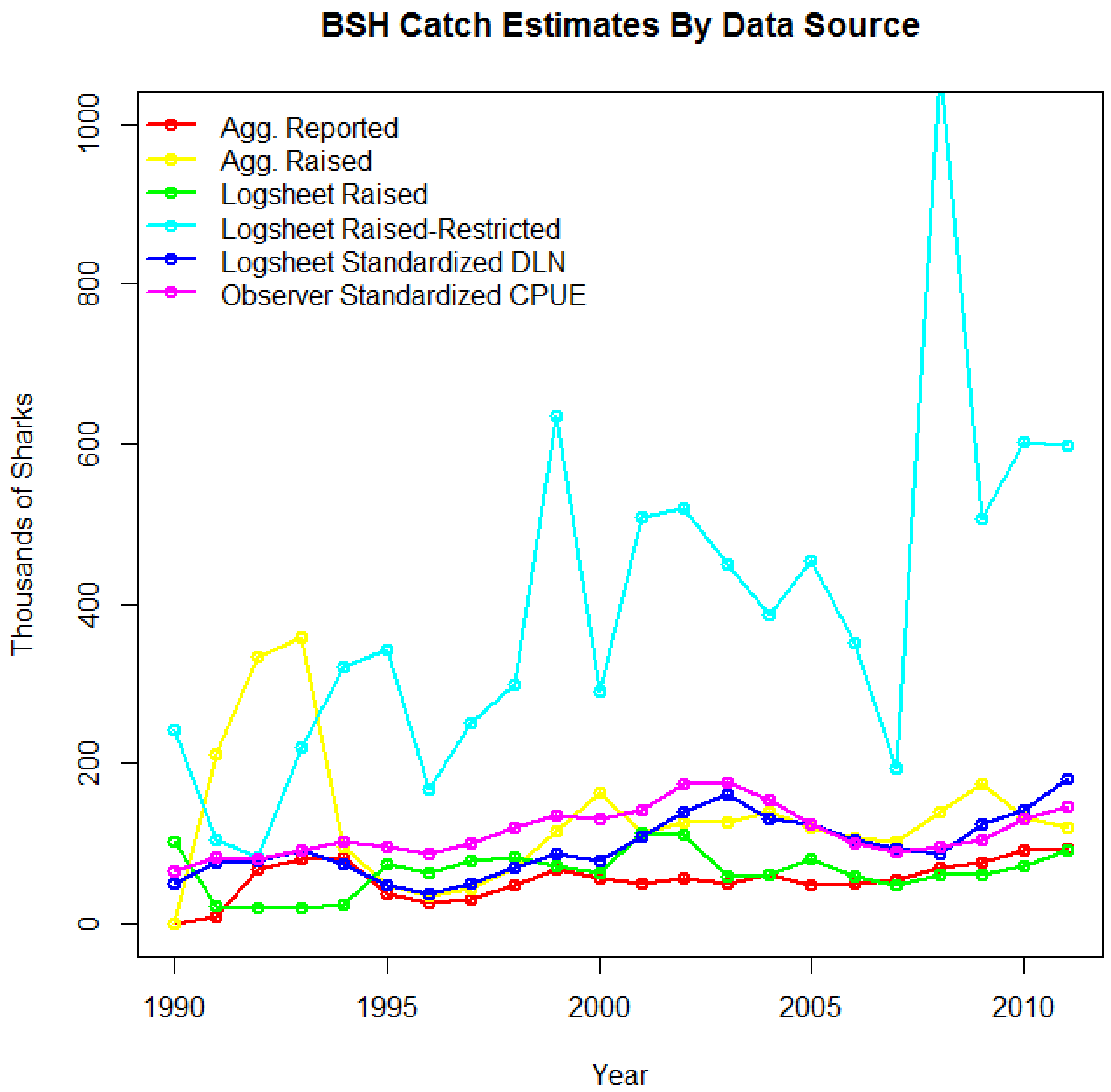


Figure 16 Comparison of catch estimates by data source and estimation method.

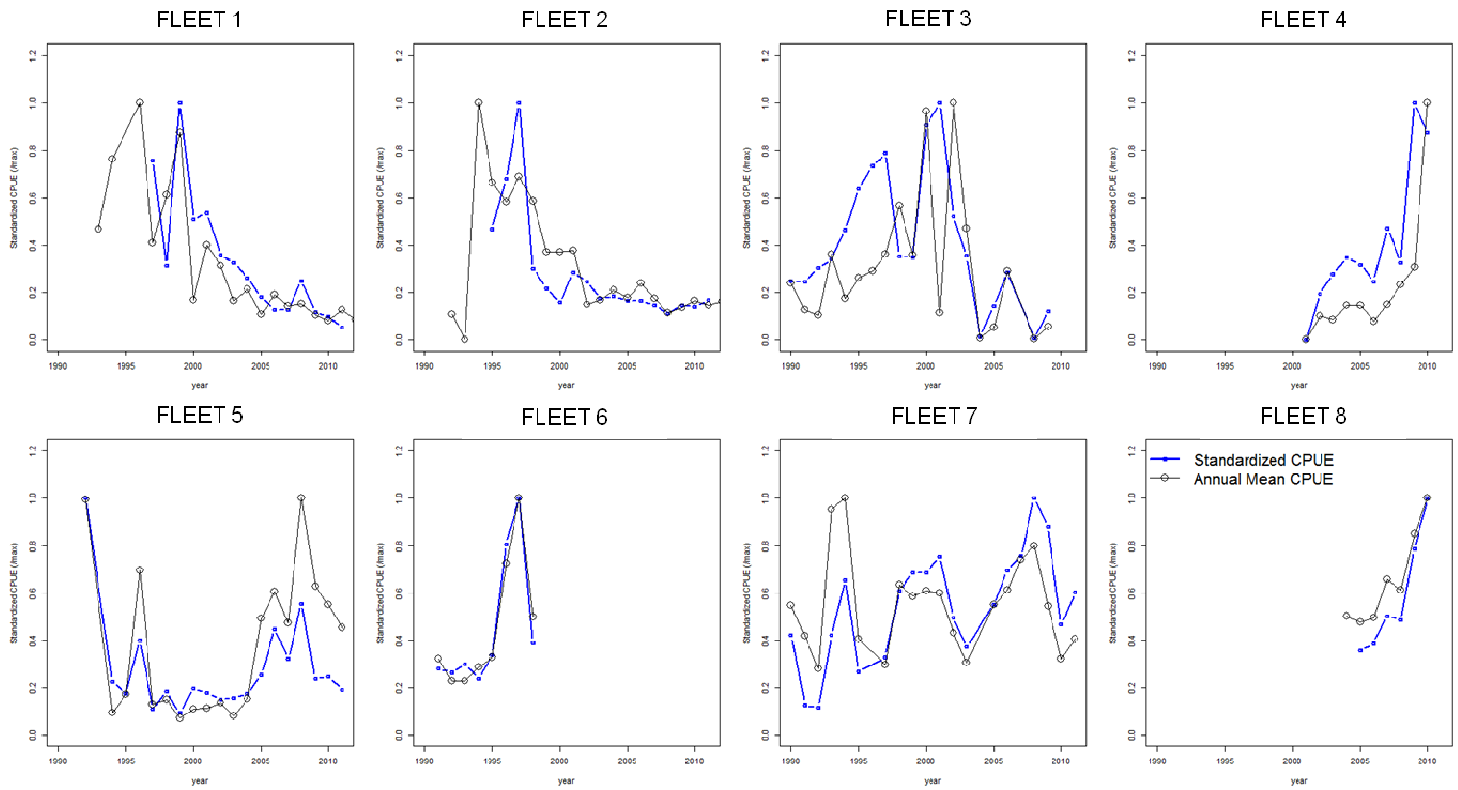


Figure 17. Standardized CPUE and nominal trends based on NB standardization of SPC held observer data (Fleets 1-7, and Linear Mixed Effects model for Fleet8).. See Table 7 for details of the fleets.

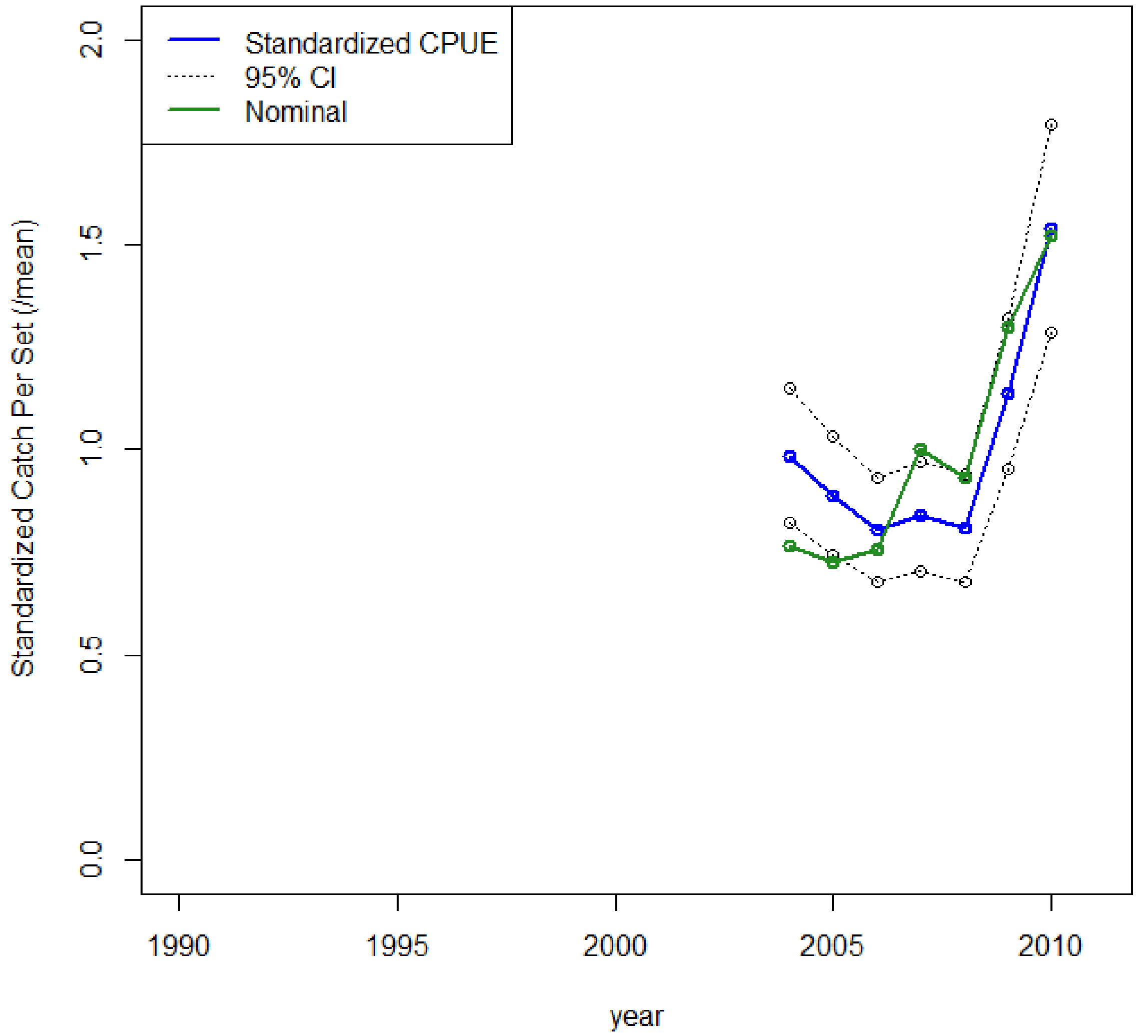


Figure 18. Standardized CPUE and nominal trends based on negative binomial model standardization of Spanish longline data

TABLES

Table 1: Observer coverage rates by region in the longline fishery based on the number of hooks fished. * denotes years in which some data have been provided by Spain, but effort in hooks was not provided.

	Region				
	1	2	3	4	5
1990	0.00%	0.00%	0.00%	1.70%	0
1991	0.00%	2.60%	0.10%	4.30%	0
1992	0.00%	5.60%	0.10%	5.90%	0
1993	0.00%	2.60%	0.10%	11.30%	0
1994	0.00%	1.90%	0.10%	7.90%	0
1995	0.00%	1.80%	0.30%	8.10%	0
1996	0.00%	3.60%	0.50%	3.30%	0
1997	0.20%	2.90%	0.20%	6.00%	0
1998	0.30%	0.20%	0.30%	4.70%	0
1999	0.20%	0.20%	0.30%	4.60%	0
2000	0.20%	0.00%	0.10%	3.50%	0
2001	0.30%	0.20%	0.10%	4.30%	0
2002	0.60%	0.30%	0.20%	3.20%	0
2003	0.40%	1.10%	0.70%	5.80%	0
2004	0.40%	1.50%	0.50%	8.00%	*
2005	0.50%	1.60%	0.70%	4.90%	*
2006	0.40%	1.30%	1.60%	6.30%	*
2007	0.20%	2.00%	1.10%	12.10%	*
2008	0.20%	2.80%	1.50%	6.60%	*
2009	0.10%	3.20%	0.90%	12.20%	*
2010	0.10%	1.80%	1.00%	7.10%	*
2011	0.10%	2.20%	0.50%	6.50%	*

Table 2. Logsheet coverage rates (%) by region that identify sharks to species.

	Region				
	1	2	3	4	5
1990	12.60	84.20	20.52	79.50	44.94
1991	8.90	64.31	17.63	67.70	NA
1992	7.38	88.25	24.61	71.95	8.95
1993	12.28	63.77	32.08	77.94	17.16
1994	23.31	60.43	23.85	61.85	17.76
1995	27.39	62.07	35.48	62.96	NA
1996	25.14	49.96	34.00	33.28	26.54
1997	25.81	71.95	29.22	26.41	NA
1998	23.78	49.62	32.83	24.25	13.21
1999	40.26	48.57	36.16	27.36	25.55
2000	37.35	58.60	36.16	27.21	13.95
2001	25.52	59.90	34.24	26.80	27.43
2002	27.32	57.15	49.39	29.62	57.03
2003	28.37	63.14	48.72	36.46	29.18
2004	37.43	67.56	45.15	38.22	38.05
2005	33.98	80.22	63.29	28.59	59.17
2006	37.10	79.59	56.99	29.85	55.89
2007	39.35	75.07	59.21	43.54	74.69
2008	38.43	76.44	51.77	32.42	37.62
2009	36.16	79.75	51.19	31.18	72.36
2010	37.06	42.70	49.84	30.12	44.16
2011	38.79	55.85	57.83	21.47	NA

Table 3. Aggregate data coverage rates (%) by region that identify sharks to species.

	Region				
	1	2	3	4	5
1990	NA	2.61	NA	7.53	NA
1991	0.00	3.84	0.48	22.21	NA
1992	0.00	7.01	0.34	49.30	NA
1993	0.03	3.82	0.69	56.71	NA
1994	16.96	77.65	6.41	96.36	NA
1995	13.11	73.87	11.71	99.77	NA
1996	8.40	81.69	13.16	90.90	NA
1997	9.84	78.92	10.40	87.55	NA
1998	18.02	76.42	16.81	90.15	NA
1999	13.71	65.13	17.30	91.50	NA
2000	15.29	62.69	12.38	93.73	0.58
2001	8.05	79.16	10.25	99.44	0.38
2002	12.44	63.66	36.40	92.40	0.01
2003	11.80	78.33	43.54	94.95	NA
2004	23.80	75.95	46.05	89.88	NA
2005	19.67	74.57	46.50	85.66	NA
2006	24.93	70.37	58.30	86.94	22.96
2007	24.10	81.64	64.38	92.75	4.34
2008	29.46	85.36	54.72	96.71	11.31
2009	29.32	88.93	54.66	98.51	57.65
2010	49.28	93.58	77.42	96.21	6.12
2011	59.10	82.08	69.71	100.00	88.86

Table 4: Generalised additive models used in the construction of CPUE surfaces with the observer data.

Region	Model
1	`log.gam_R1<-gam(BLUECPUE~bs(yy)+bs(quarter)+bs(lon5)+bs(lat5,df=4), data=lg.dat, family=gaussian(link=log), outer.ok = TRUE);` `bin_gam_R_1<-gam(pos~bs(yy)+bs(quarter)+bs(lon5)+bs(lat5),data=tempdata, family=binomial) ;`
2	`log_gam_R_2<-gam(BLUECPUE~bs(yy)+bs(quarter)+bs(lon5)+bs(lat5), data=lg.dat, family=gaussian(link=log), outer.ok = TRUE);` `bin_gam_R_2<-gam(pos~bs(yy)+bs(quarter)+bs(lon5)+bs(lat5), data=tempdata, family=binomial);`
3	`log_gam_R_3<-gam(BLUECPUE~bs(yy)+bs(quarter)+bs(lon5)+bs(lat5), , data=lg.dat, family=gaussian(link=log))` `bin_gam_R_3<-gam(pos~yy+bs(quarter)+bs(lon5)+bs(lat5, data=tempdata, family=binomial`
4	`log_gam_R_4<-gam(BLUECPUE~bs(yy)+bs(quarter)+bs(lon5)+bs(lat5)+hk_bt_flt+SST +ez_id+vesselname, family=gaussian(link=log),` `bin_gam_R_4<-gam(pos ~ bs( yy )+ bs( quarter)+ bs(lon5)+bs(lat5) , data=tempdata, family=binomial)`

Table 5. Generalised additive models used in the construction of CPUE surfaces with the operational data.

Region	Component	Model
1	Binomial	pos ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5)
	Lognormal	cpue ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5) +as.factor(flag)
2	Binomial	pos ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5) +as.factor(flag)
	Lognormal	cpue ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5) +as.factor(flag)
3	Binomial	pos ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5) +as.factor(flag)
	Lognormal	cpue ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5) +as.factor(flag)
4	Binomial	pos ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5) +as.factor(flag)
	Lognormal	cpue ~ bs(yy)+ as.factor(qtr)+ bs(lon5) + bs(lat5) +as.factor(flag)

Table 6. Alternative catch estimates by method for blue shark in the southwest Pacific in thousands of sharks.

	Aggregate Reported	Aggregate Raised	Logsheet Raised	Logsheet Raised-Restricted	Logsheet Standardized DLN	Observer Standardized CPUE
1990	0	1	103	243	51	65
1991	9	211	23	106	77	84
1992	69	334	20	82	80	81
1993	82	357	21	221	92	93
1994	84	97	23	320	74	102
1995	38	48	75	344	49	97
1996	27	36	64	168	37	89
1997	31	45	78	251	51	102
1998	47	70	83	299	71	121
1999	68	115	72	634	87	135
2000	58	164	64	291	79	131
2001	50	113	115	509	109	141
2002	56	128	111	518	140	175
2003	50	127	60	450	162	176
2004	62	139	61	387	131	155
2005	48	121	81	455	125	124
2006	51	107	59	352	105	100
2007	54	103	49	194	93	90
2008	70	141	61	1,072	89	96
2009	77	174	61	505	125	104
2010	92	133	73	603	142	132
2011	94	120	93	597	182	148

Table 7 Fleet partitioning for observer data based CPUE estimation

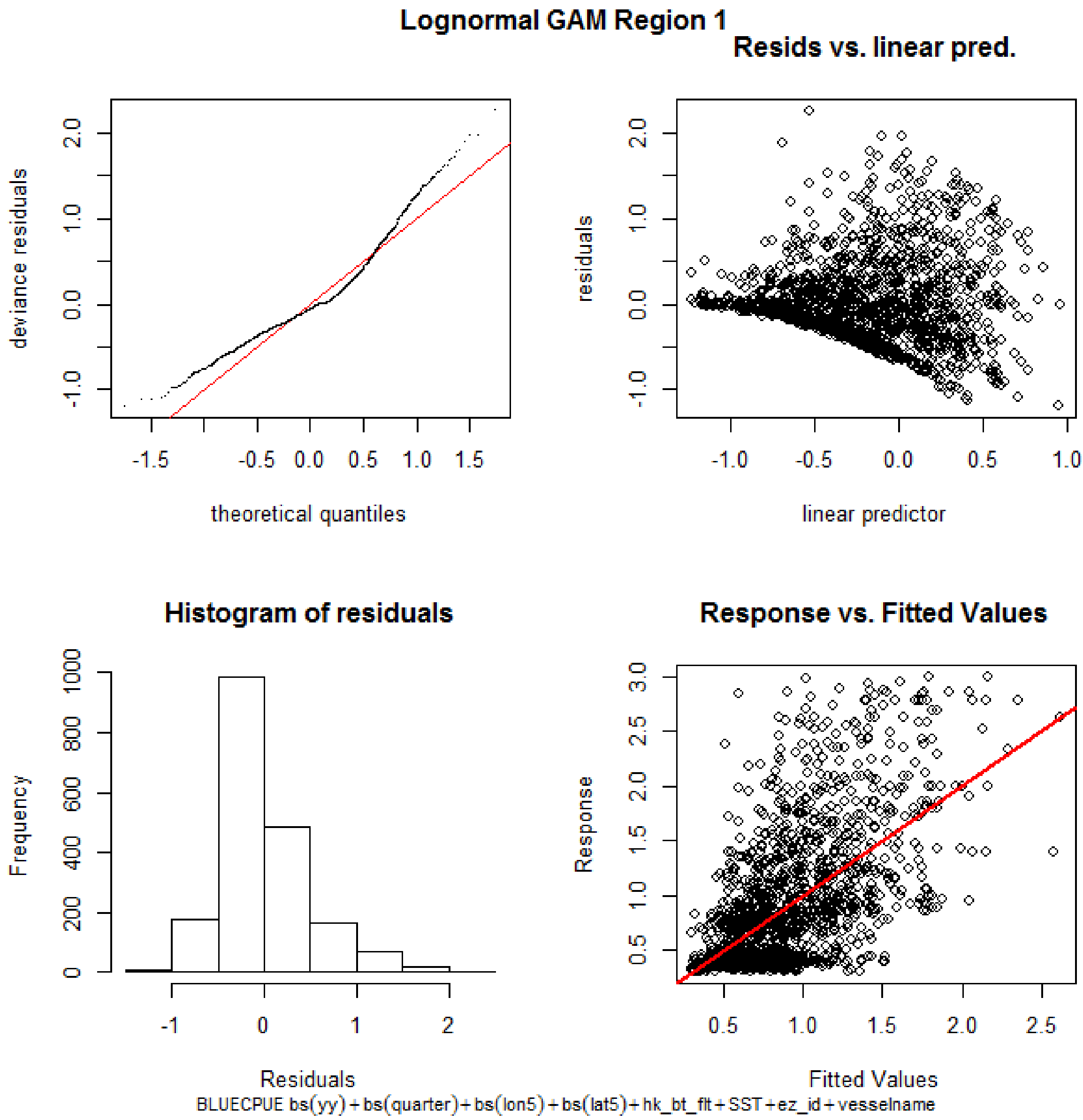
CPUE Fleet #	Fleet Definition	Approximate Catch Region	Fleet Component
1	0˚-15˚S.	1	All Fleets
2	between 15˚S-35˚S.	3	Pacific Island Countires and territories, excluding AU and NZ
3	between 15˚S-35˚S.	3	Distant Water Fishing nations
4	between 15˚S-35˚S.	2	Austrailia Domestic
5	NZ EEZ	4	NZ Domestic
6	South of 35˚S & West of 160W .	4	DWFNS South West
7	South of 35˚S & East of 160W .	4	DWFNS South East
8	South East Pacific	5	Spanish LL

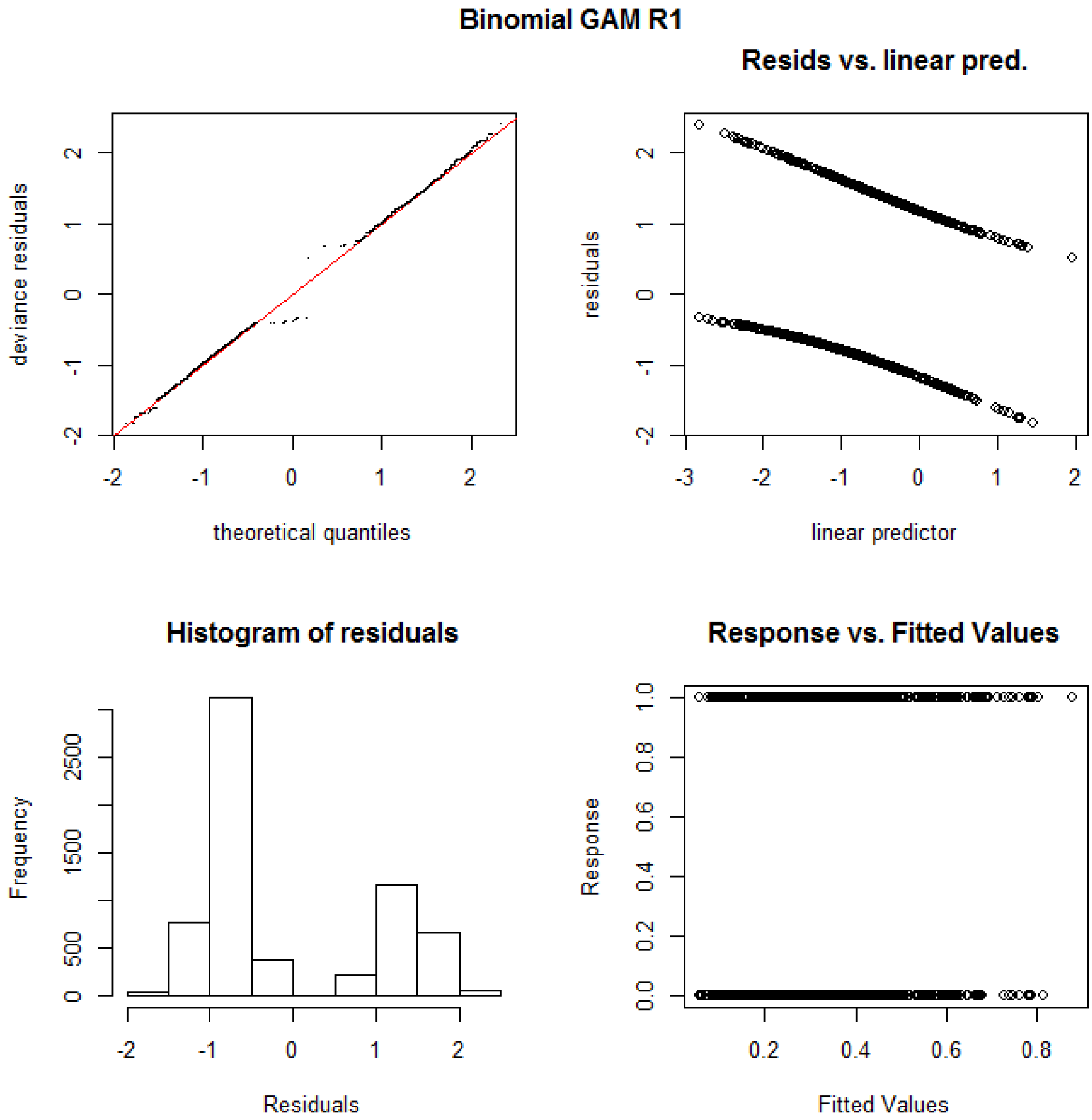
Table 8 Error structure and model definition for observer data based cpue standardization

Fleet	Error Structure	Model
1	GLM-Negative Binomial	blue ~ yy + mm + lat5 + lon5 + TIMECAT + SST + vesselname + flag_id, offset(log(hooks))
2	GLM-Negative Binomial	blue ~ yy + mm + lat5 + lon5 + TIMECAT + SST, offset(log(hooks))
3	GLM-Negative Binomial	blue ~ yy + mm + lat5 + lon5 + TIMECAT + SST, offset(log(hooks))
4	GLM-Negative Binomial	blue ~ yy + mm + lat5 + lon5 + TIMECAT + SST+vesselname, offset(log(hooks))
5	GLM-Negative Binomial	blue ~ yy + mm + lat5 + lon5 + TIMECAT + HPBCAT, offset(log(hooks))
6	GLM-Negative Binomial	blue ~ yy + mm + lat5 + lon5 + TIMECAT + SST, offset(log(hooks))
7	GLM-Negative Binomial	blue ~ yy + mm + lat5, offset(log(hooks))
8	Linear Mixed Effects Model-lognormal	bsh+1 ~ year + (1 | boatid)
8	GLM-Negative Binomial	blue ~ yy + lat5 + boatid

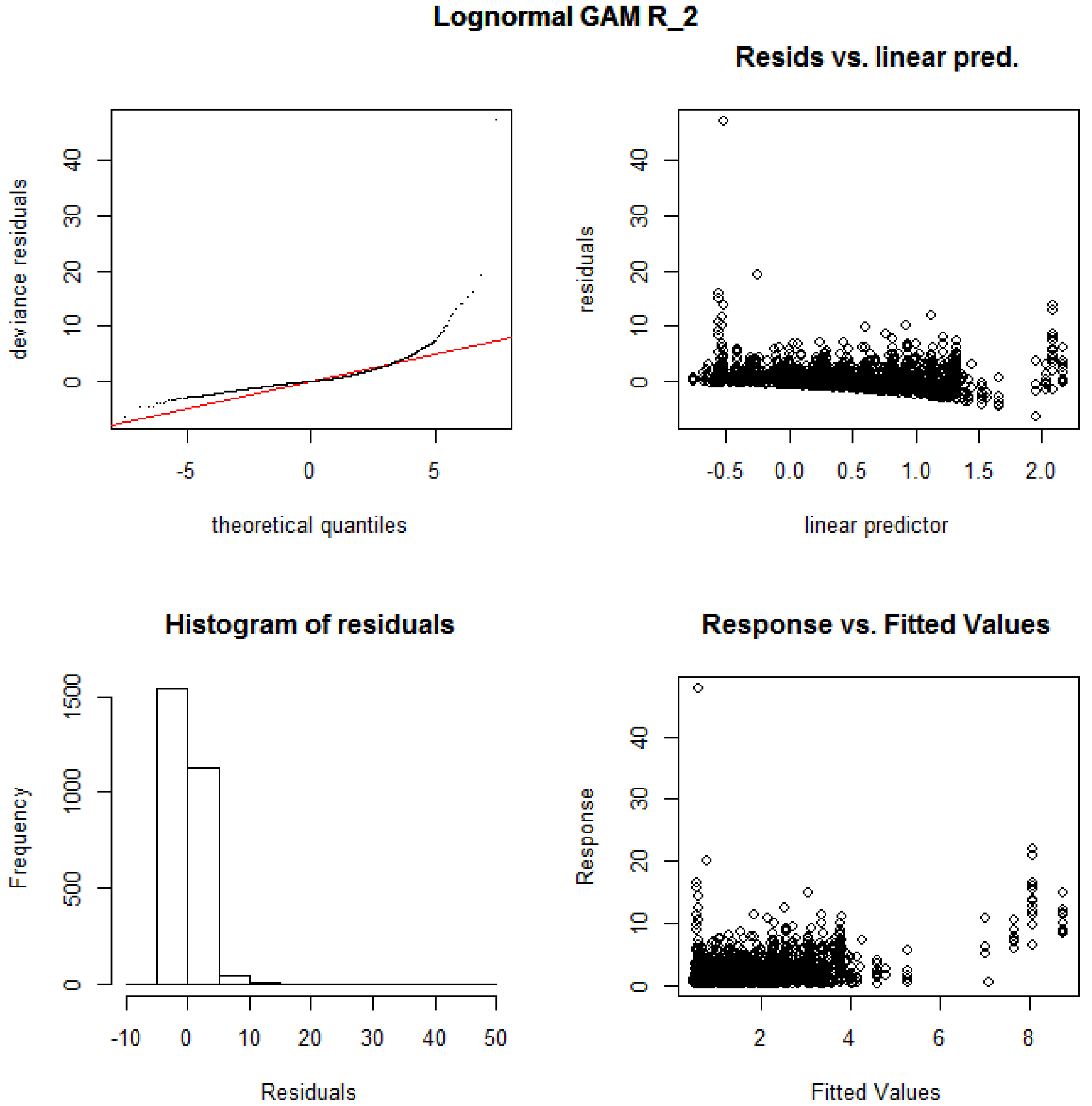
ANNEX 1 Region Specific Models Diagnostic Plots From Observer Data

REGION 1

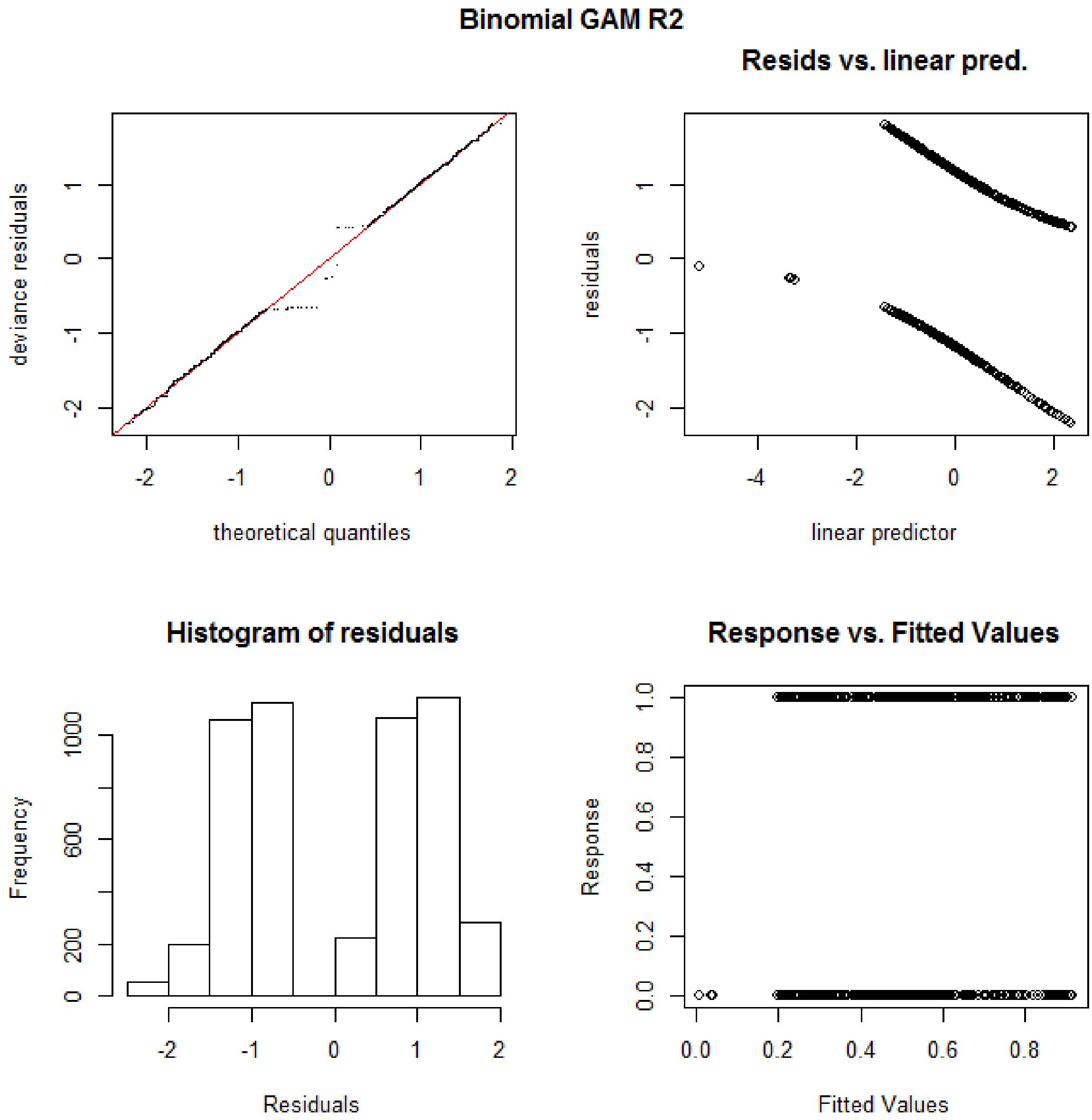



Binomial GAM R1
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values

REGION 2

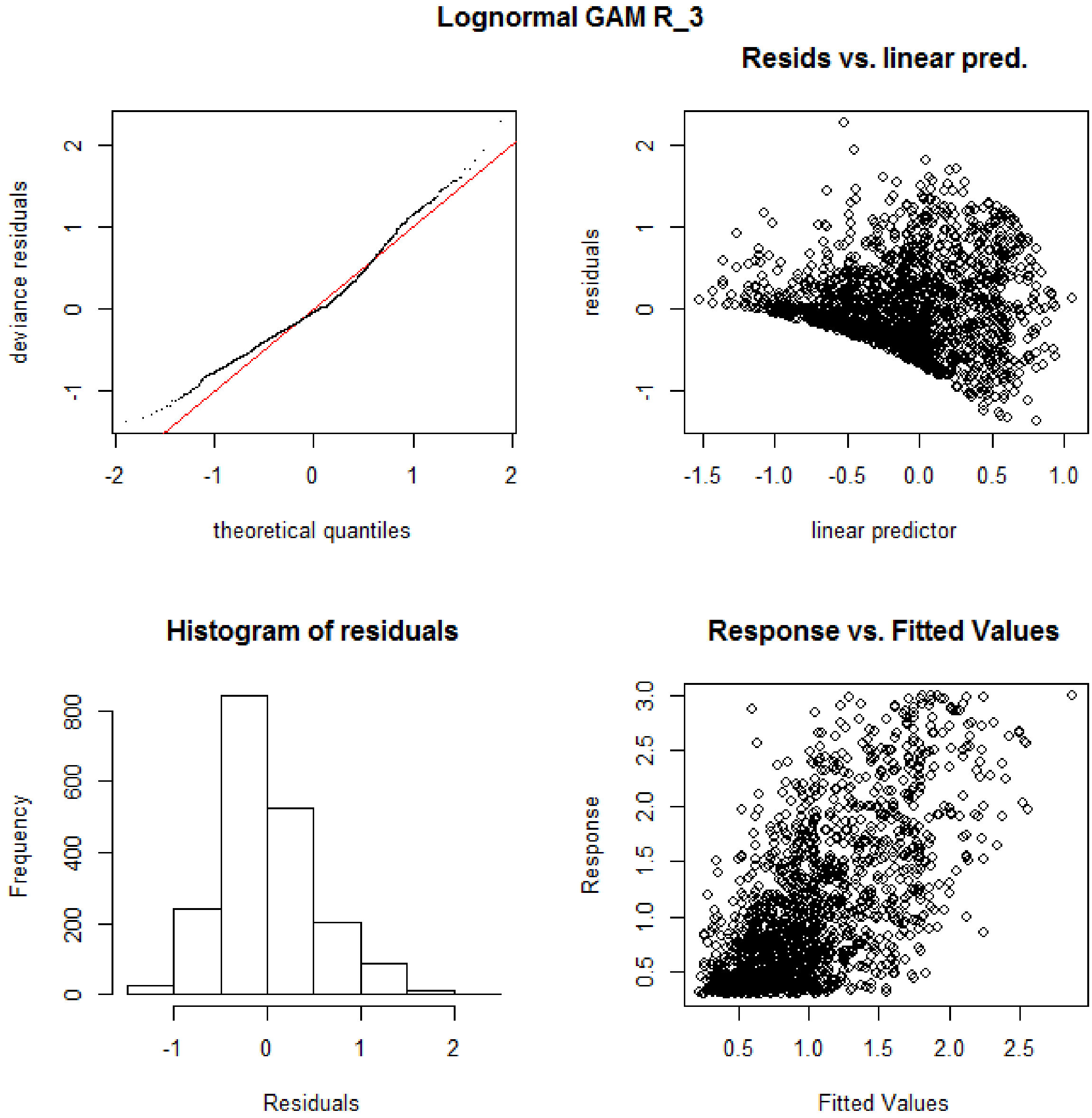


Lognormal GAM R_2
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values

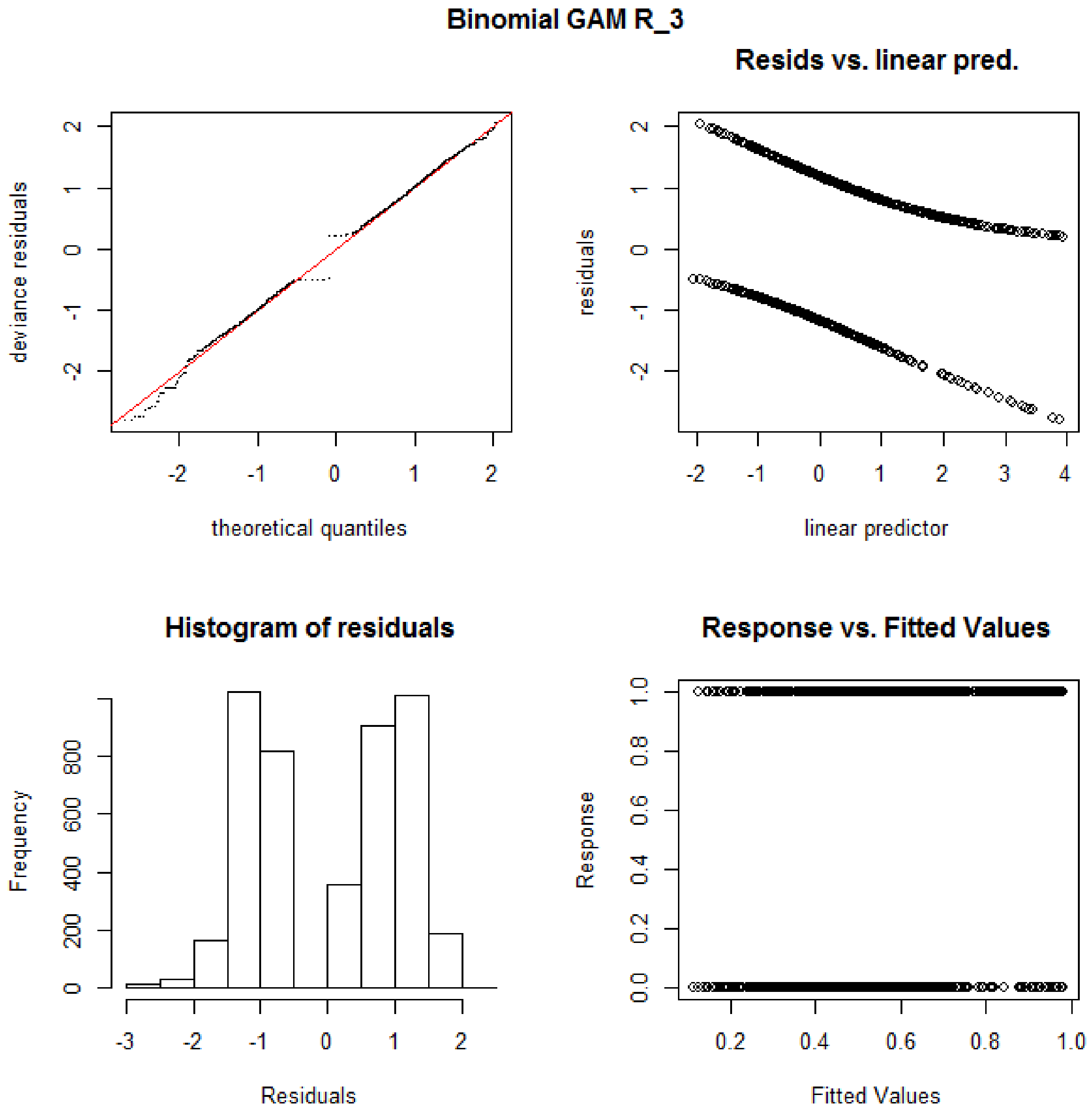


Binomial GAM R2
deviance residuals
theoretical quantiles
Resids vs. linear pred.
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values

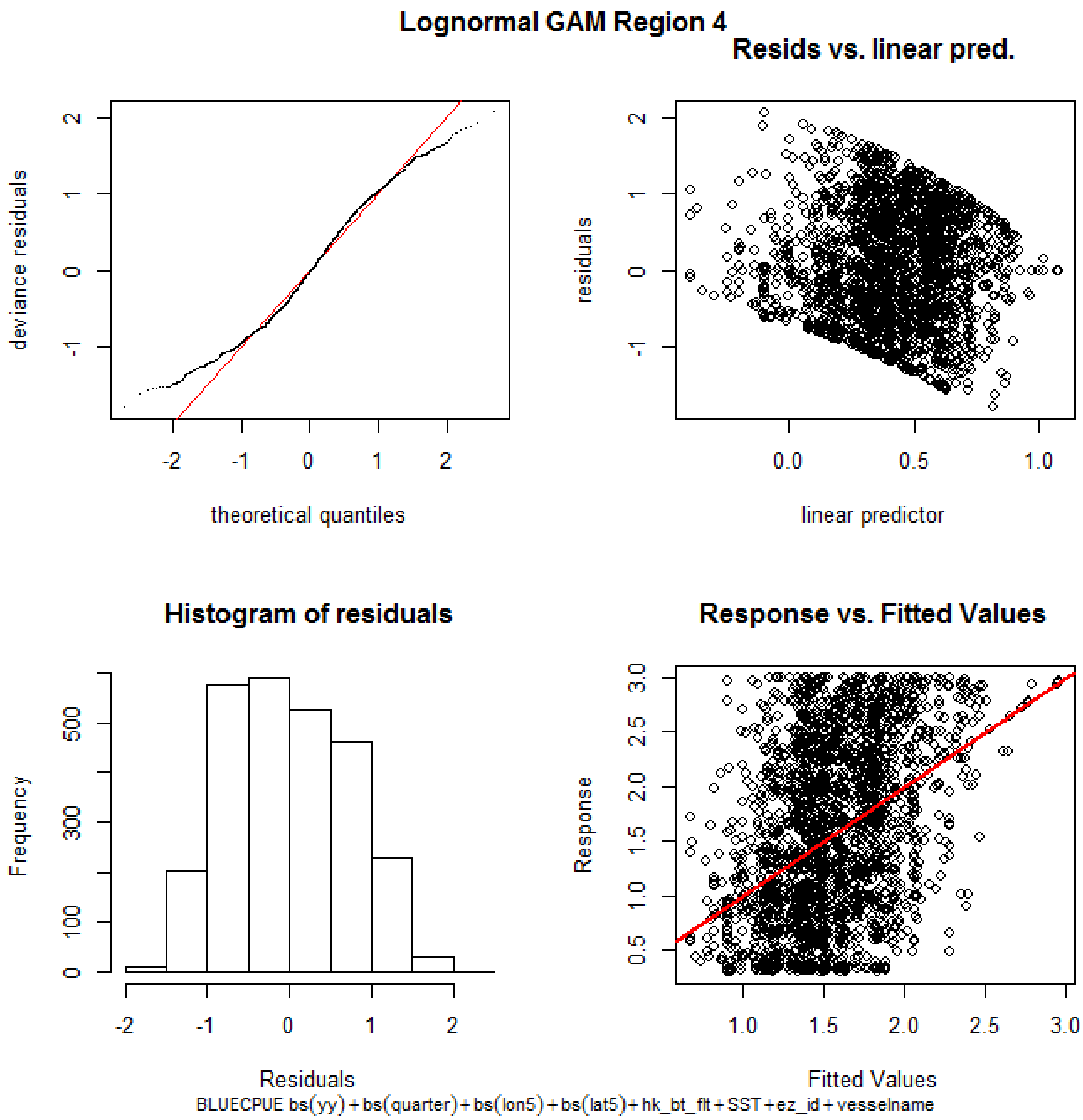
Region 3



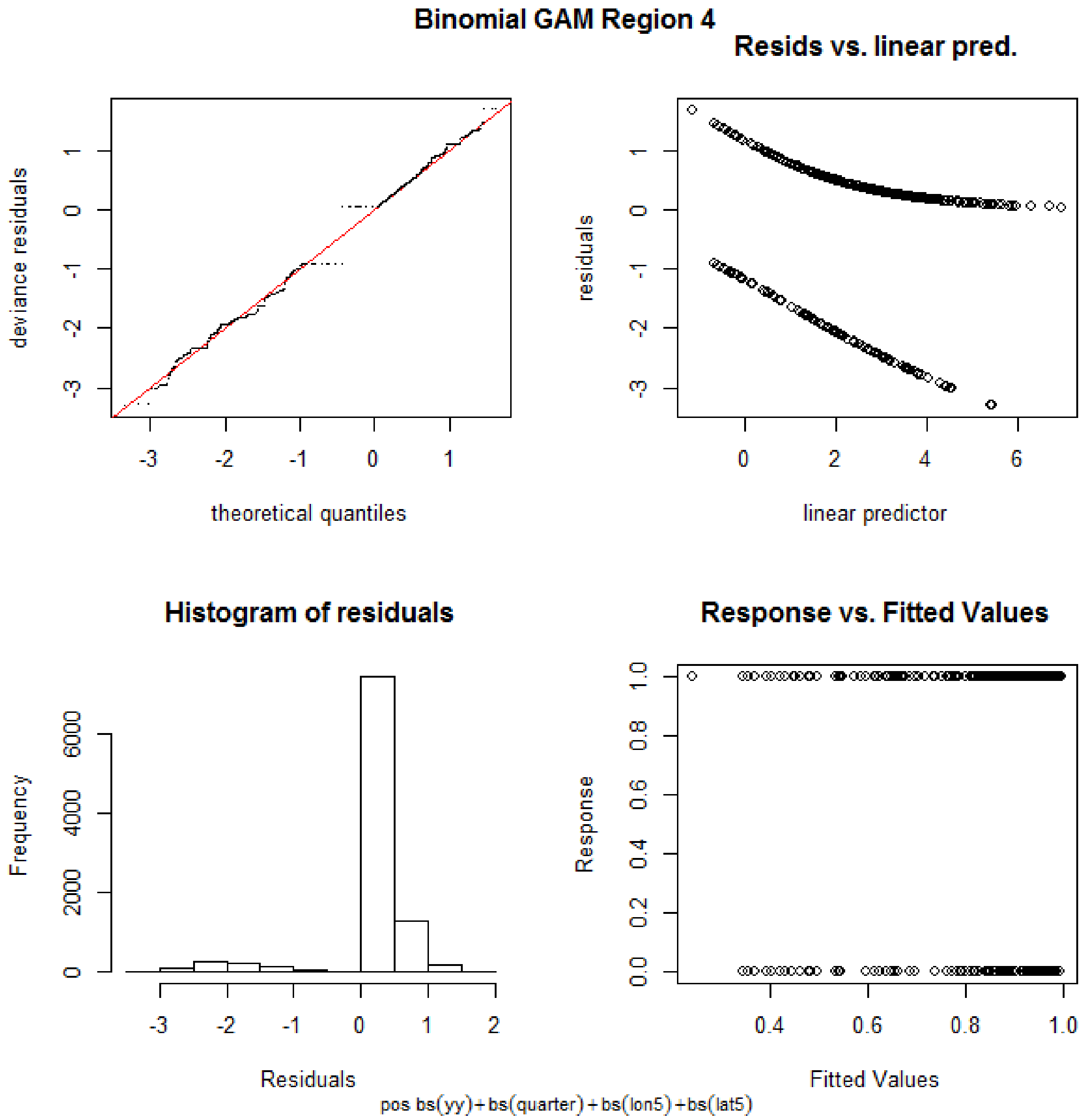
Lognormal GAM R_3
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Response vs. Fitted Values
Frequency
Residuals
Response
Fitted Values


Binomial GAM R_3
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values

Region 4

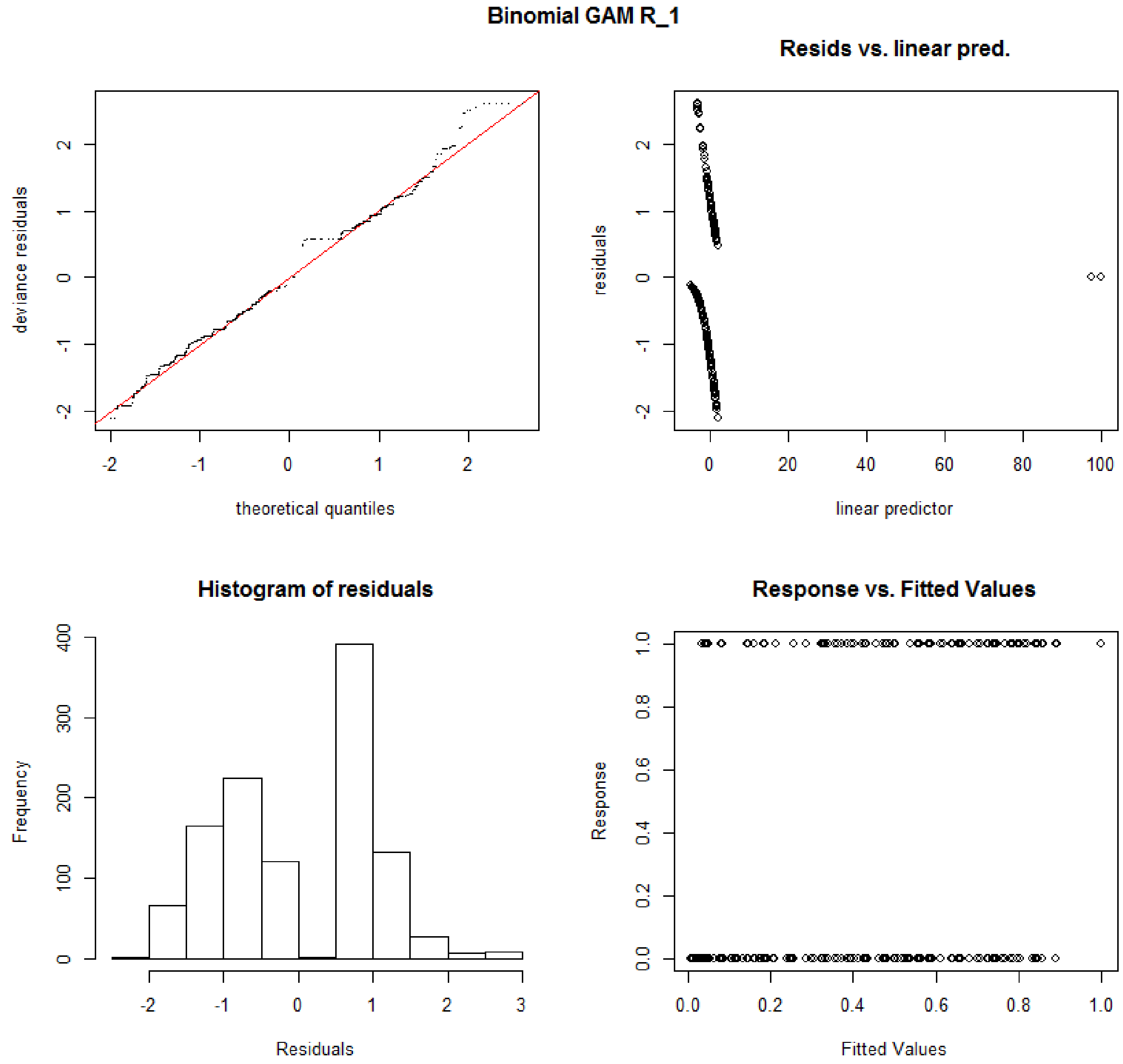


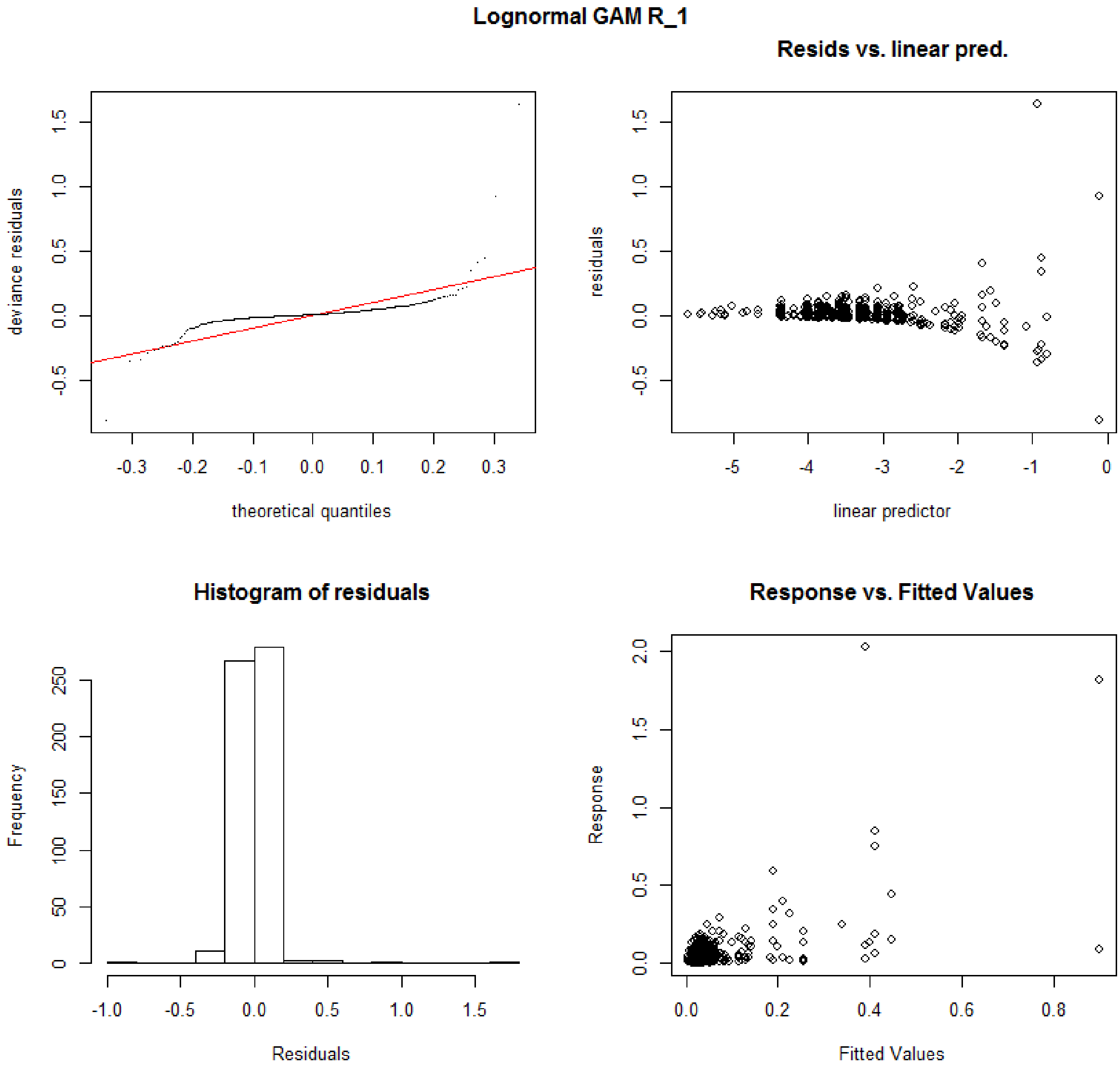
Lognormal GAM Region 4
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Response vs. Fitted Values
Frequency
Residuals
Response
Fitted Values
BLUECPUE bs(yy)+bs(quarter)+bs(lon5)+bs(lat5)+hk_bt_flt+SST+ez_id+vesselname


Binomial GAM Region 4
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values
pos bs(yy)+bs(quarter)+bs(lon5)+bs(lat5)

Appendix 2 Region specific Diagnostic Plots From Operational data.

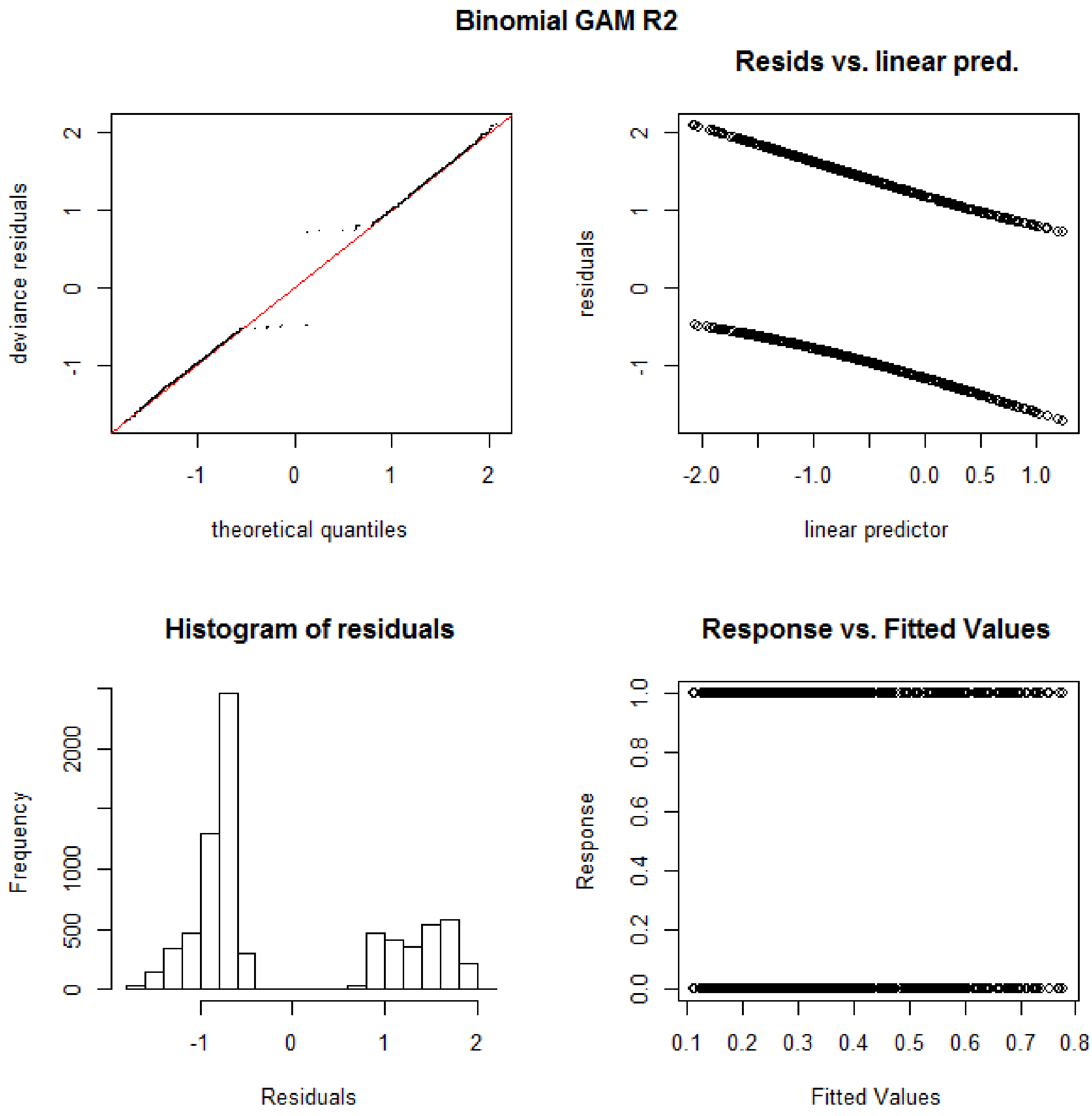
Region 1



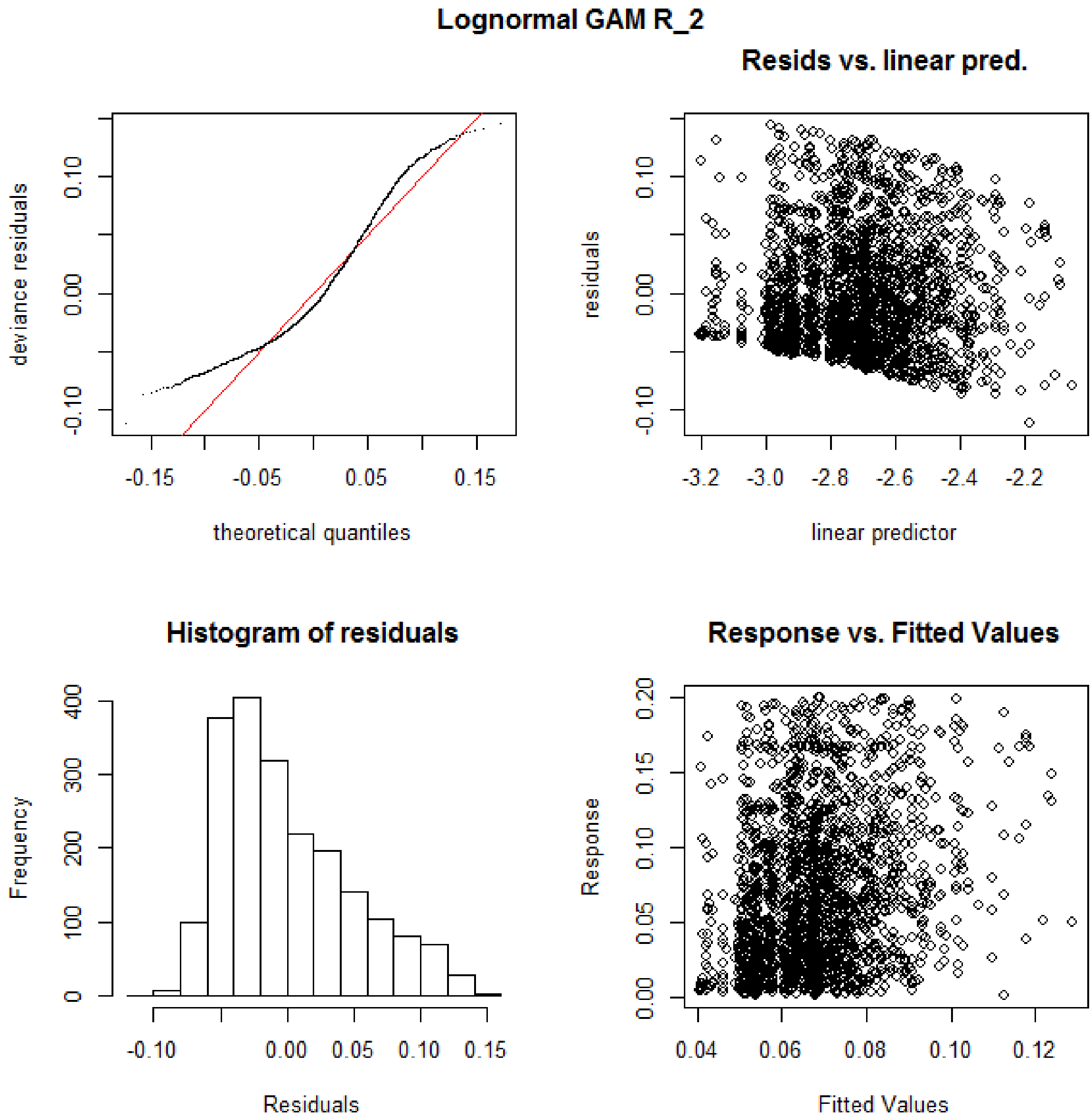


Lognormal GAM R_1
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values

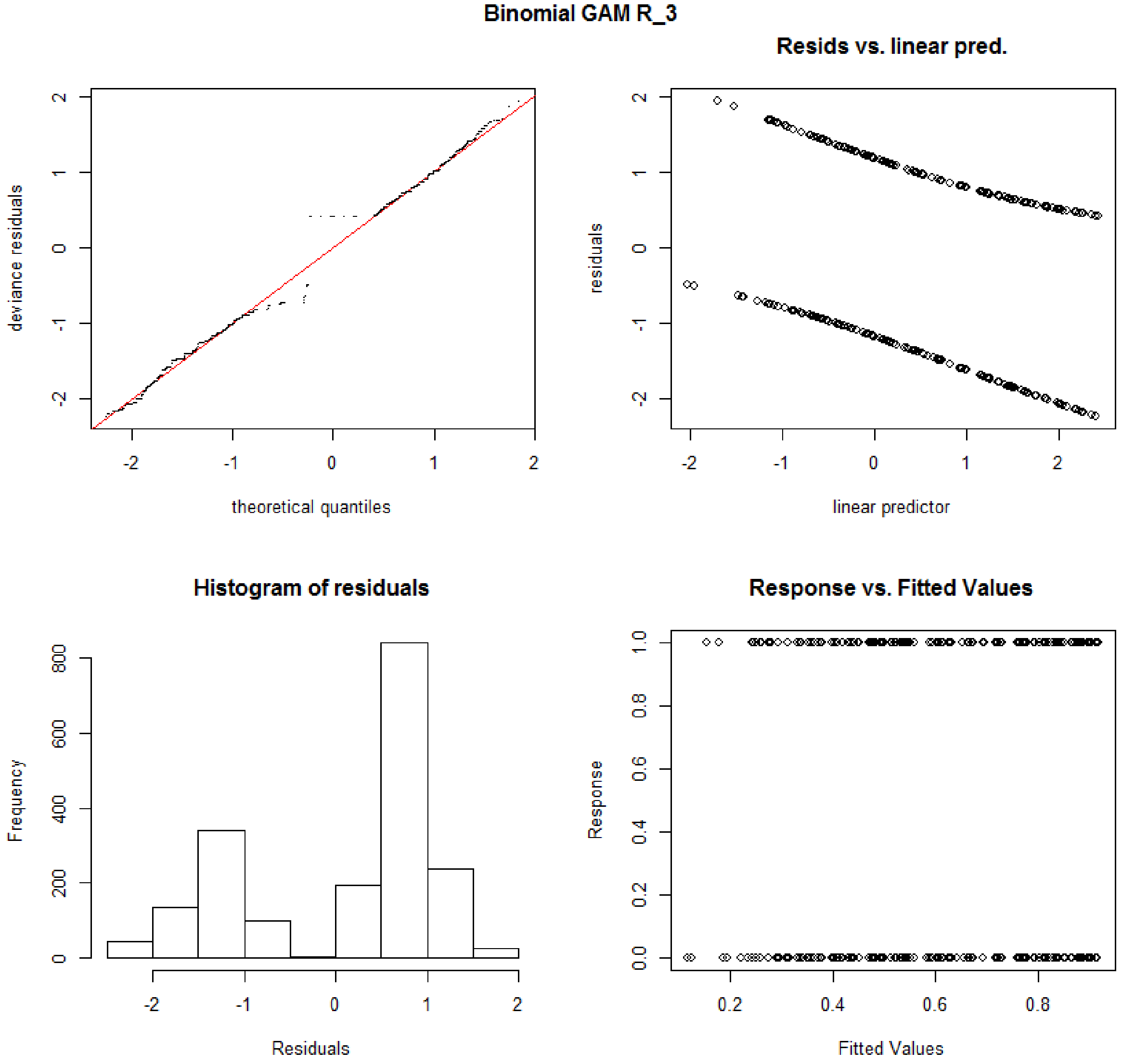
Region 2



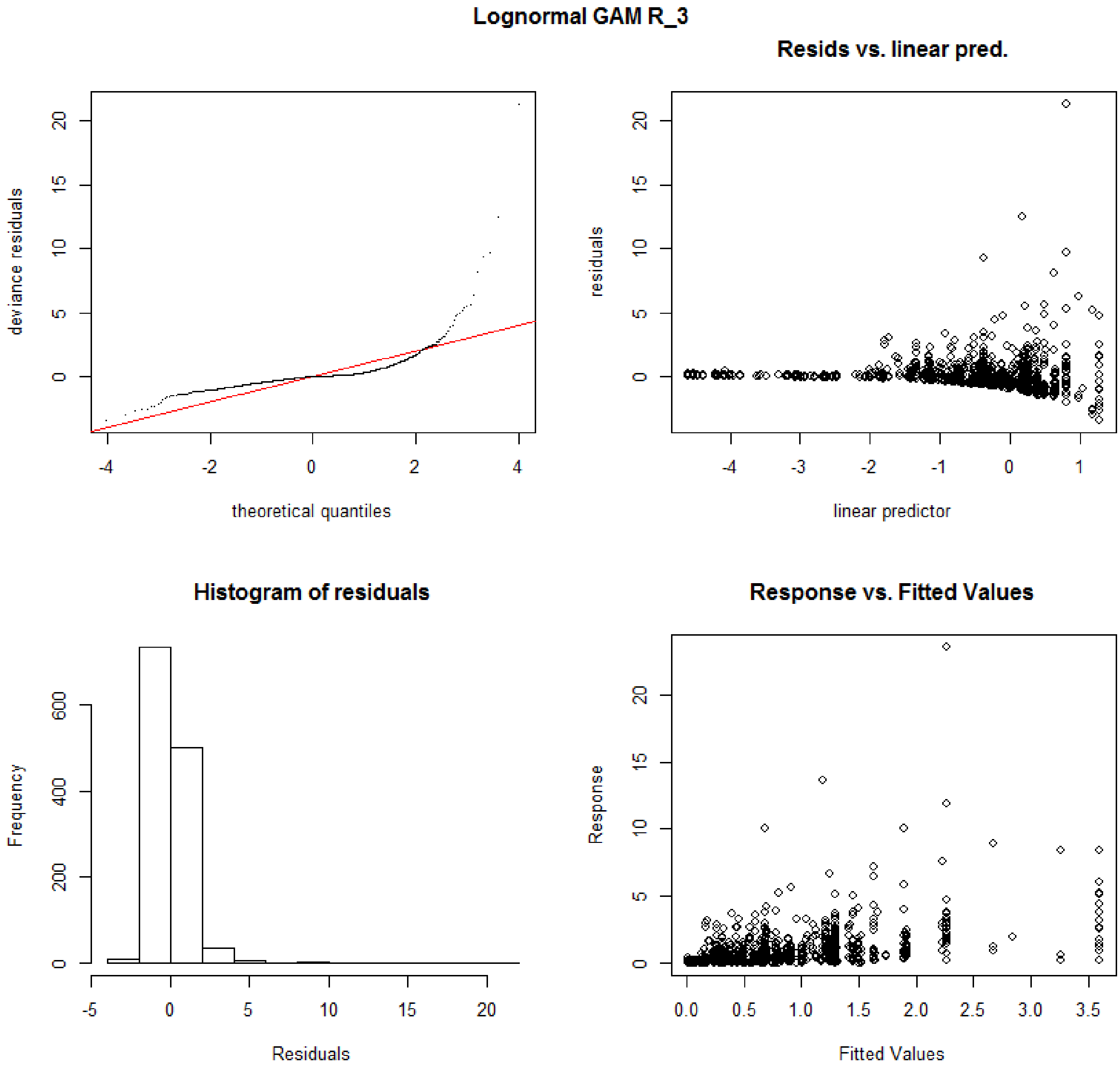
Binomial GAM R2
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values


Lognormal GAM R_2
Resids vs. linear pred.
deviance residuals
-0.10
0.00
0.10
-0.15
-0.05
0.05
0.15
theoretical quantiles
residuals
-0.10
0.00
0.10
-3.2
-3.0
-2.8
-2.6
-2.4
-2.2
linear predictor
Histogram of residuals
Frequency
0
100
200
300
400
-0.10
0.00
0.05
0.10
0.15
Residuals
Response vs. Fitted Values
Response
0.00
0.05
0.10
0.15
0.20
0.04
0.06
0.08
0.10
0.12
Fitted Values

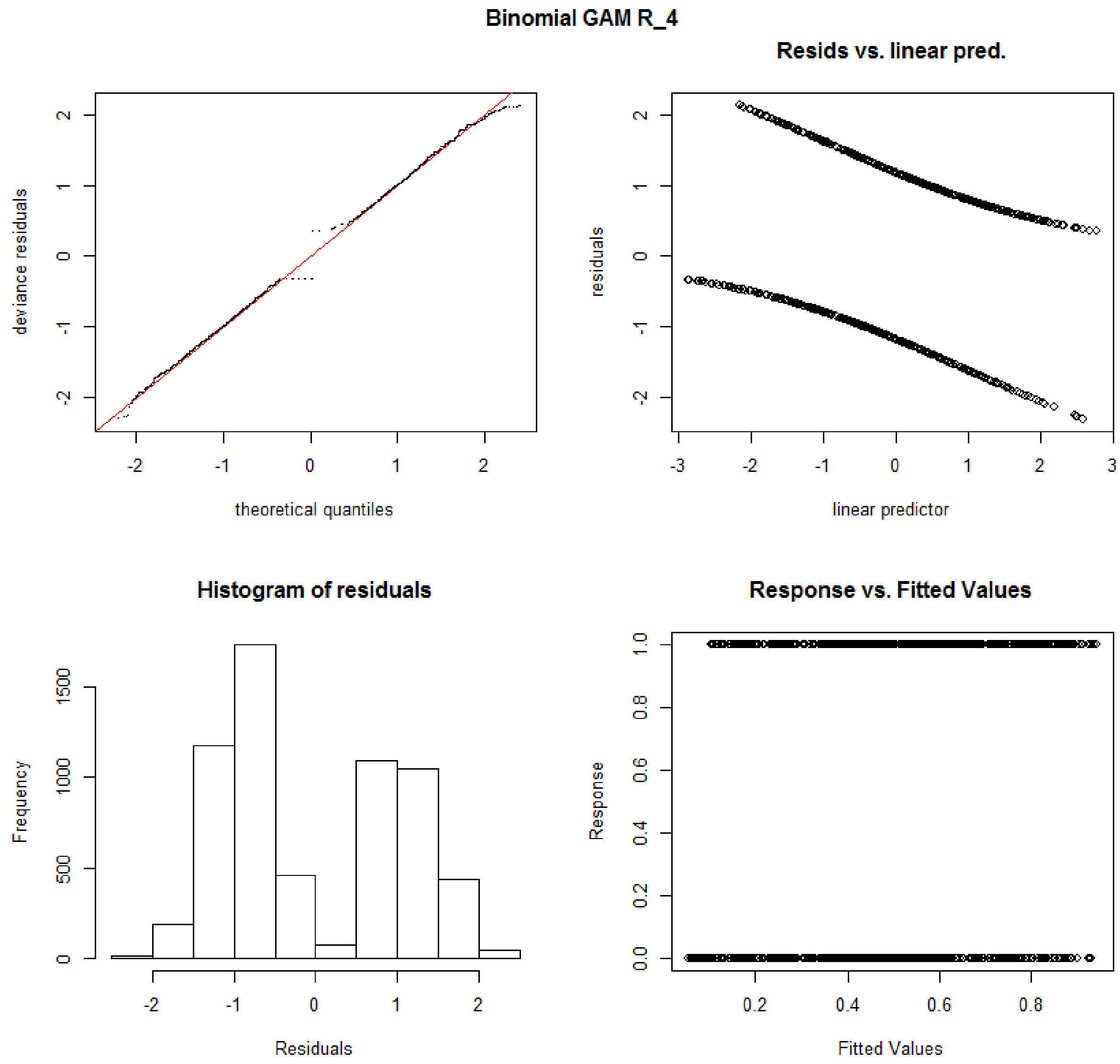
REGION 3



Binomial GAM R_3
deviance residuals
theoretical quantiles
Resids vs. linear pred.
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values


Lognormal GAM R_3
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Frequency
Residuals
Response vs. Fitted Values
Response
Fitted Values

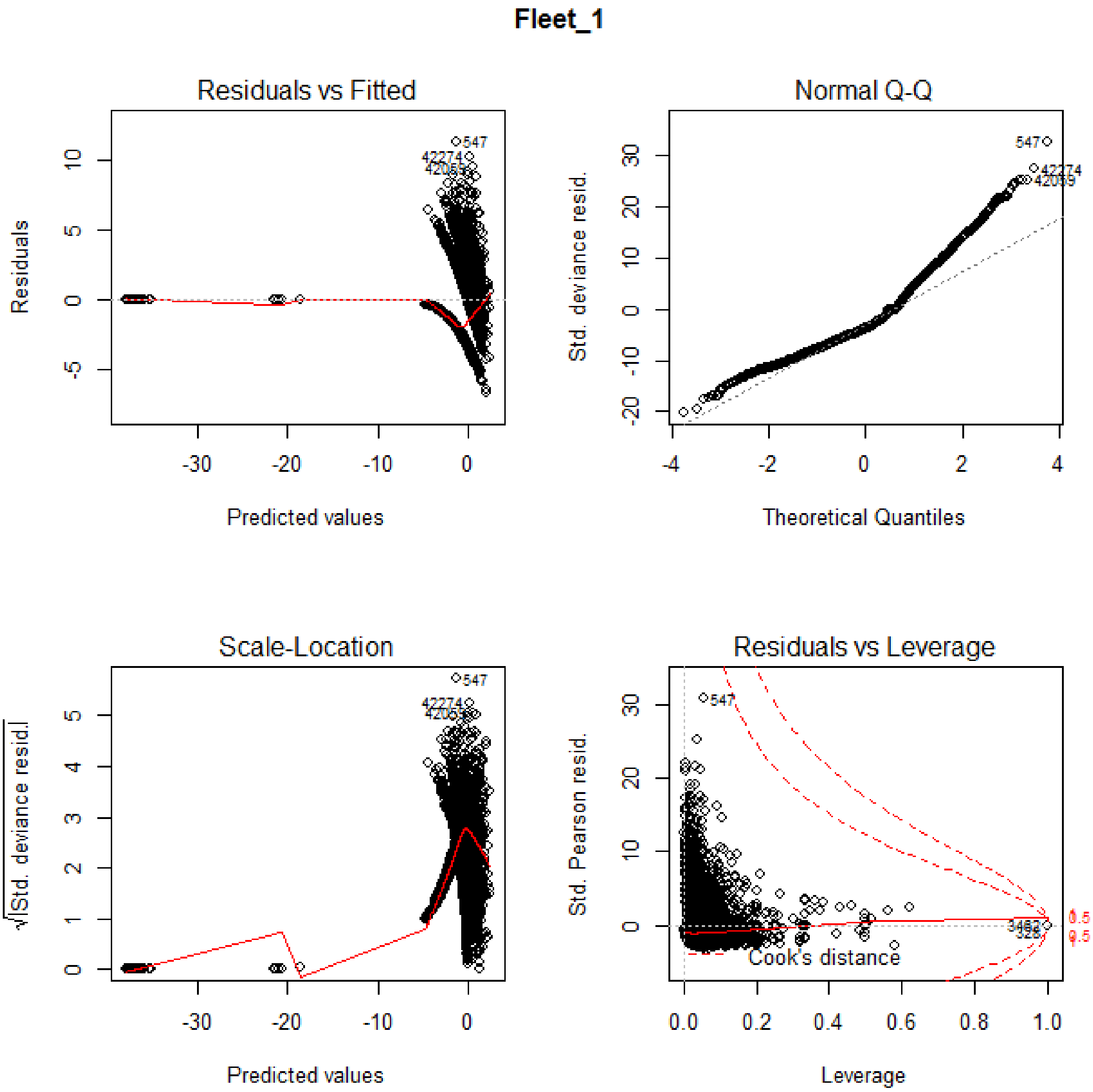
REGION 4



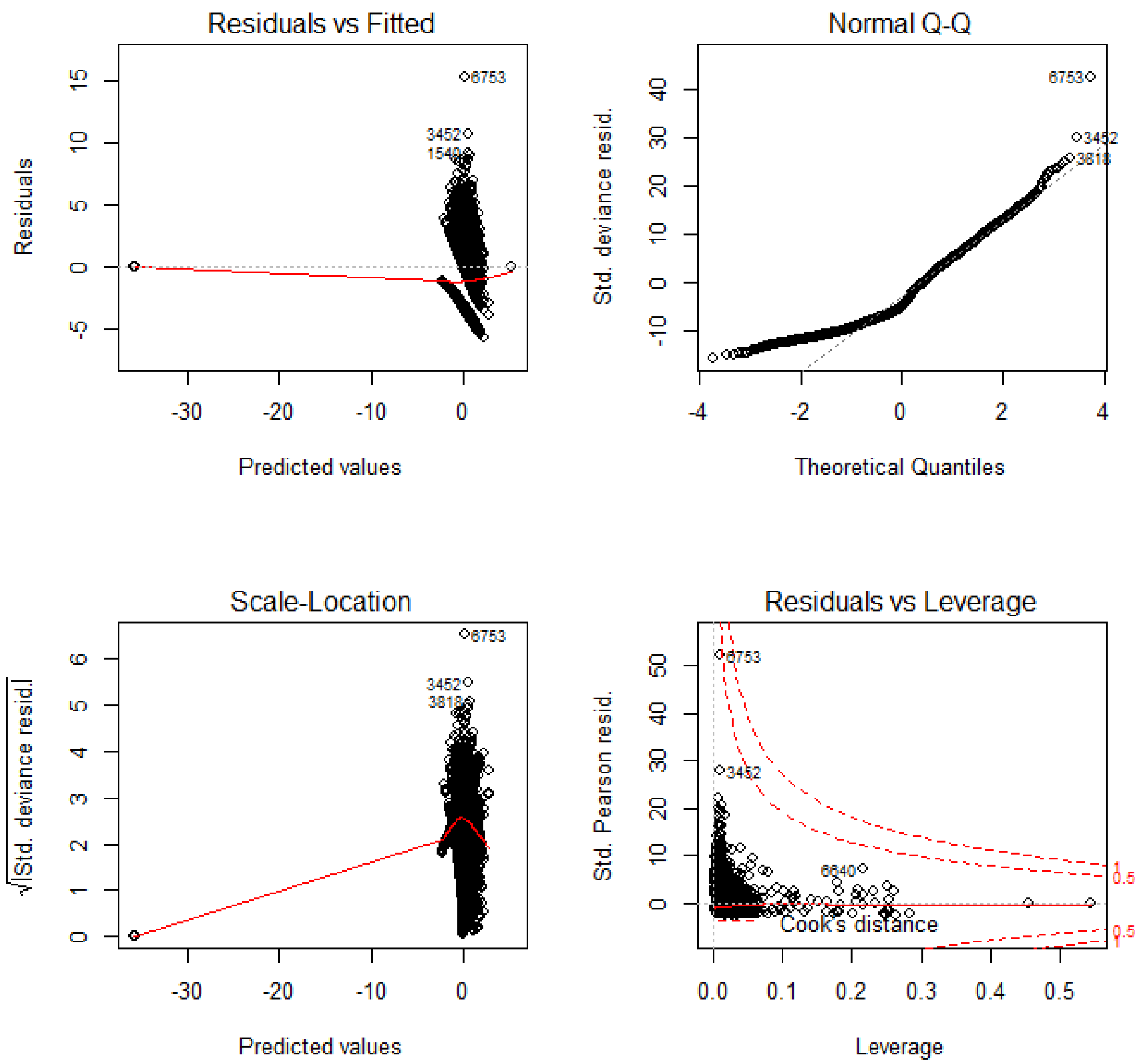
Binomial GAM R_4
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Response vs. Fitted Values
Frequency
Residuals
Response
Fitted Values

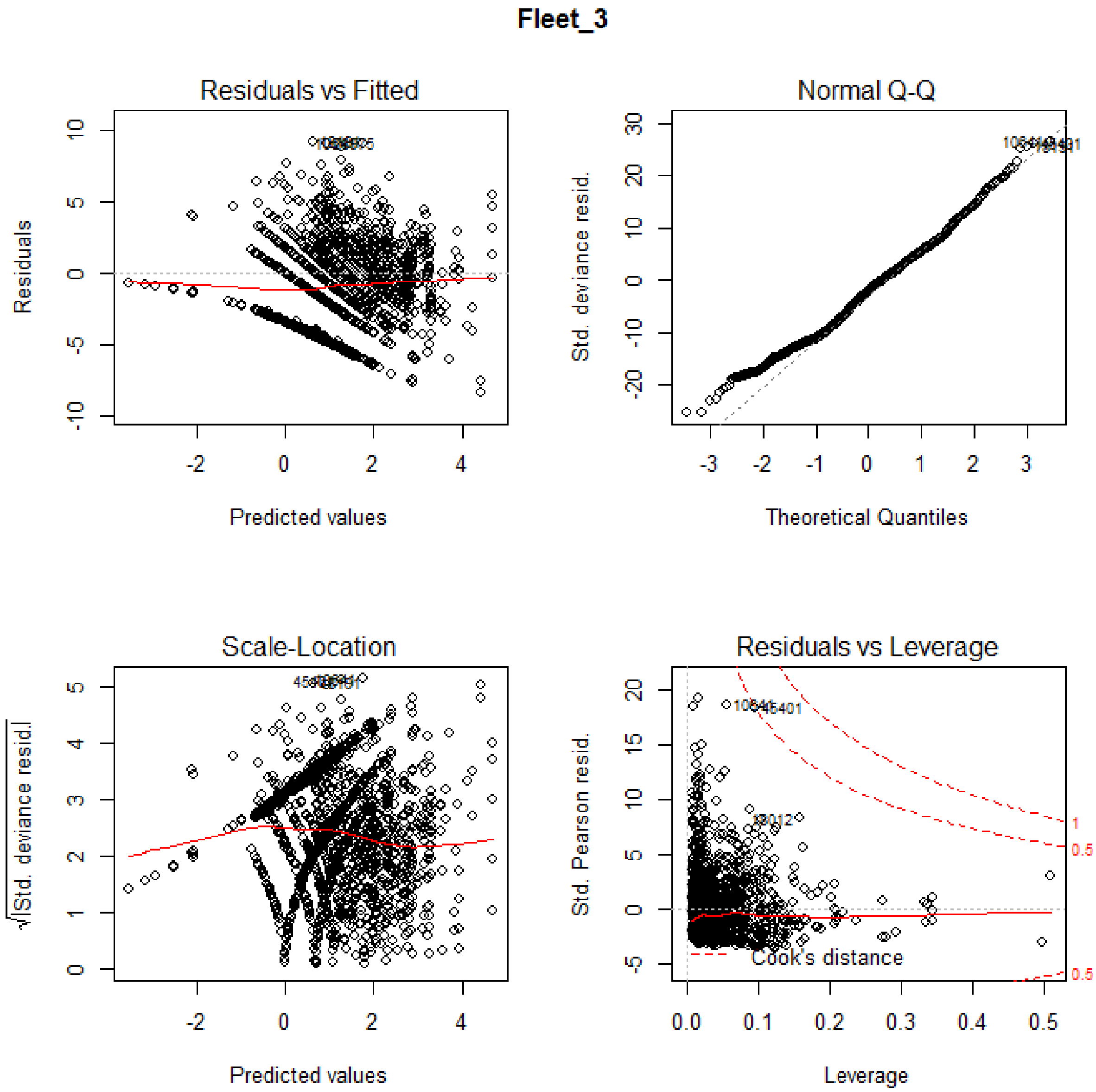
Appendix 3 Fleet S pecific Diagnostic Plots From Observer Data

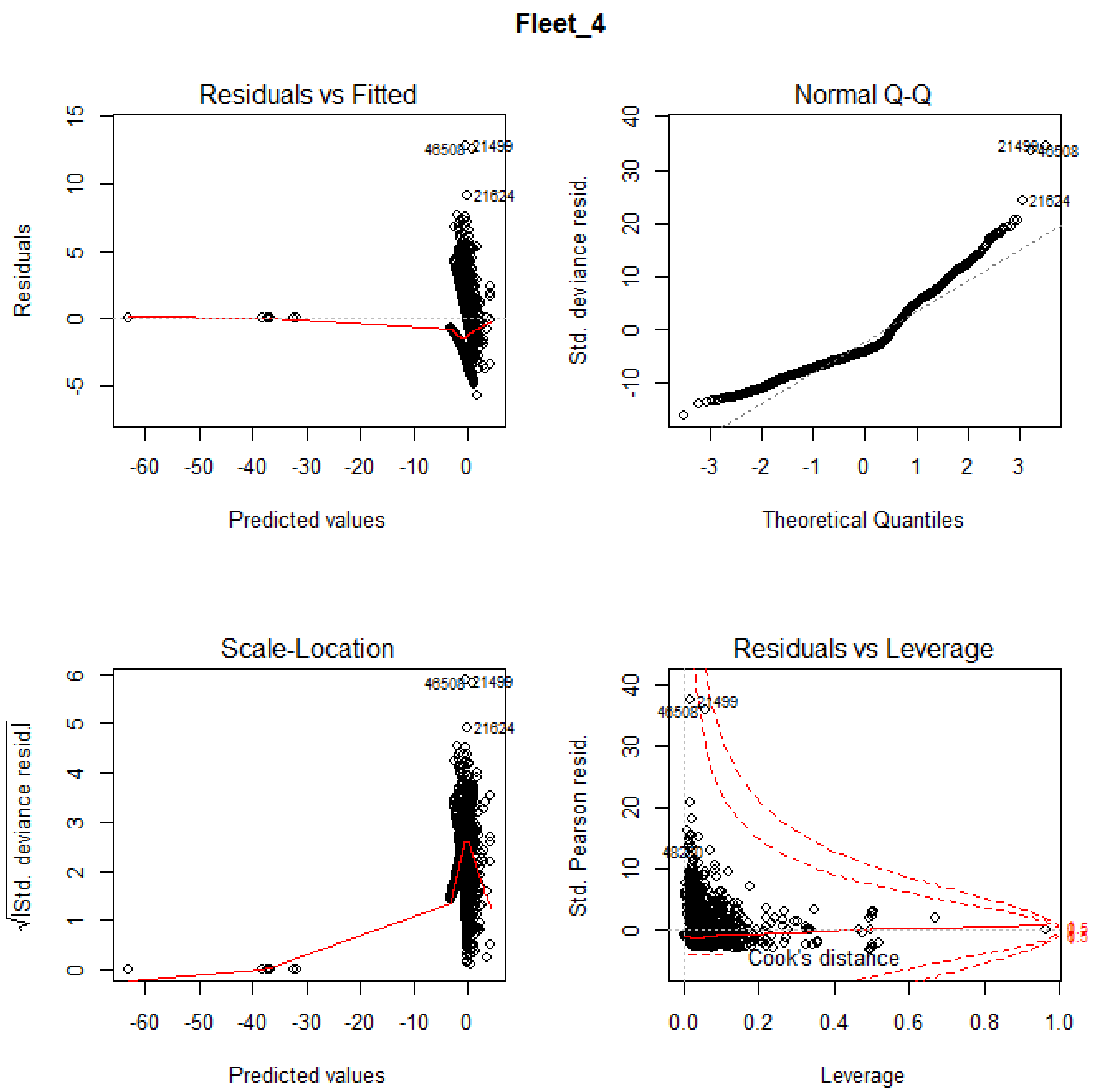
FLEET 1

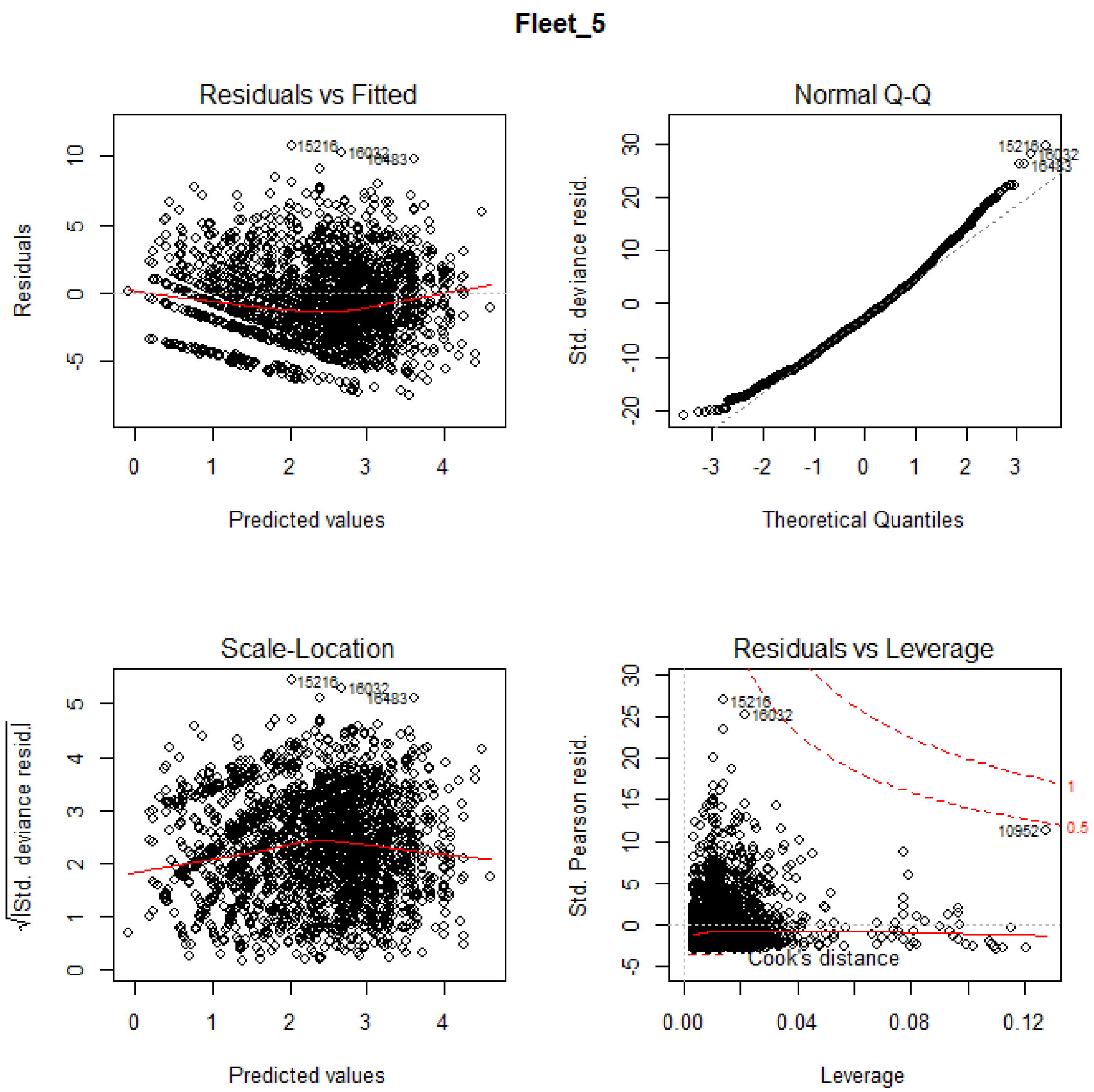


Fleet_2

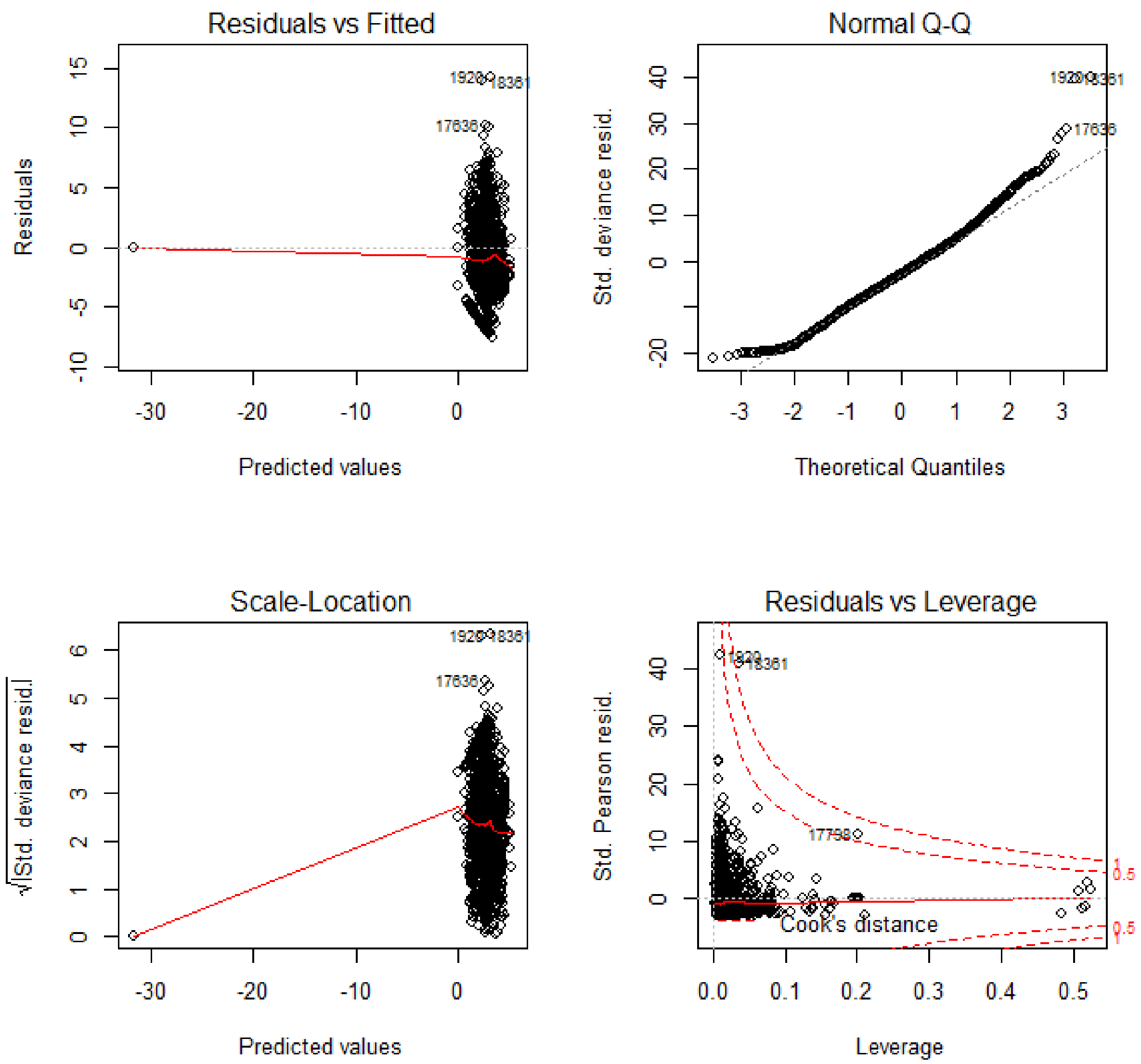

Residuals vs Fitted
Residuals
Predicted values
6753
3452
1540
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
6753
3452
3818
Scale-Location
√|Std. deviance resid.|
Predicted values
6753
3452
3818
Residuals vs Leverage
Std. Pearson resid.
Leverage
6753
3452
6640
Cook's distance
1
0.5
0.5
1


Fleet_3
Residuals vs Fitted
Residuals
Predicted values
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
Scale-Location
√|Std. deviance resid.|
Predicted values
Residuals vs Leverage
Std. Pearson resid.
Cook's distance
Leverage

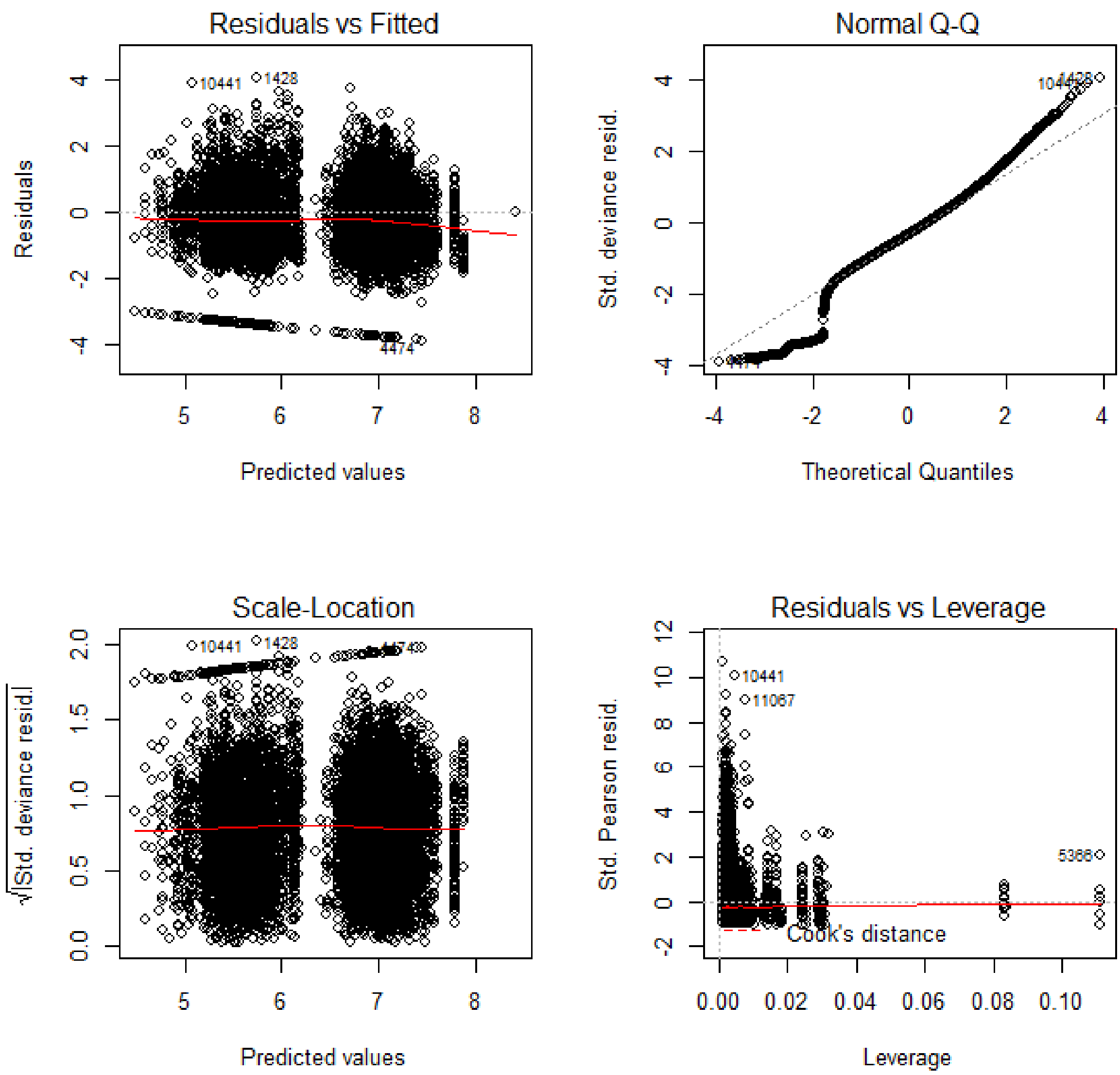

Fleet_4
Residuals vs Fitted
Residuals
Predicted values
46508
21499
21624
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
Scale-Location
√|Std. deviance resid.|
Residuals vs Leverage
Std. Pearson resid.
Leverage
Cook's distance


Fleet_5
Residuals vs Fitted
Residuals
Predicted values
15216
16032
16483
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
Scale-Location
√|Std. deviance resid.|
Predicted values
Residuals vs Leverage
Std. Pearson resid.
Leverage
Cook's distance
10952
1
0.5

Fleet_6

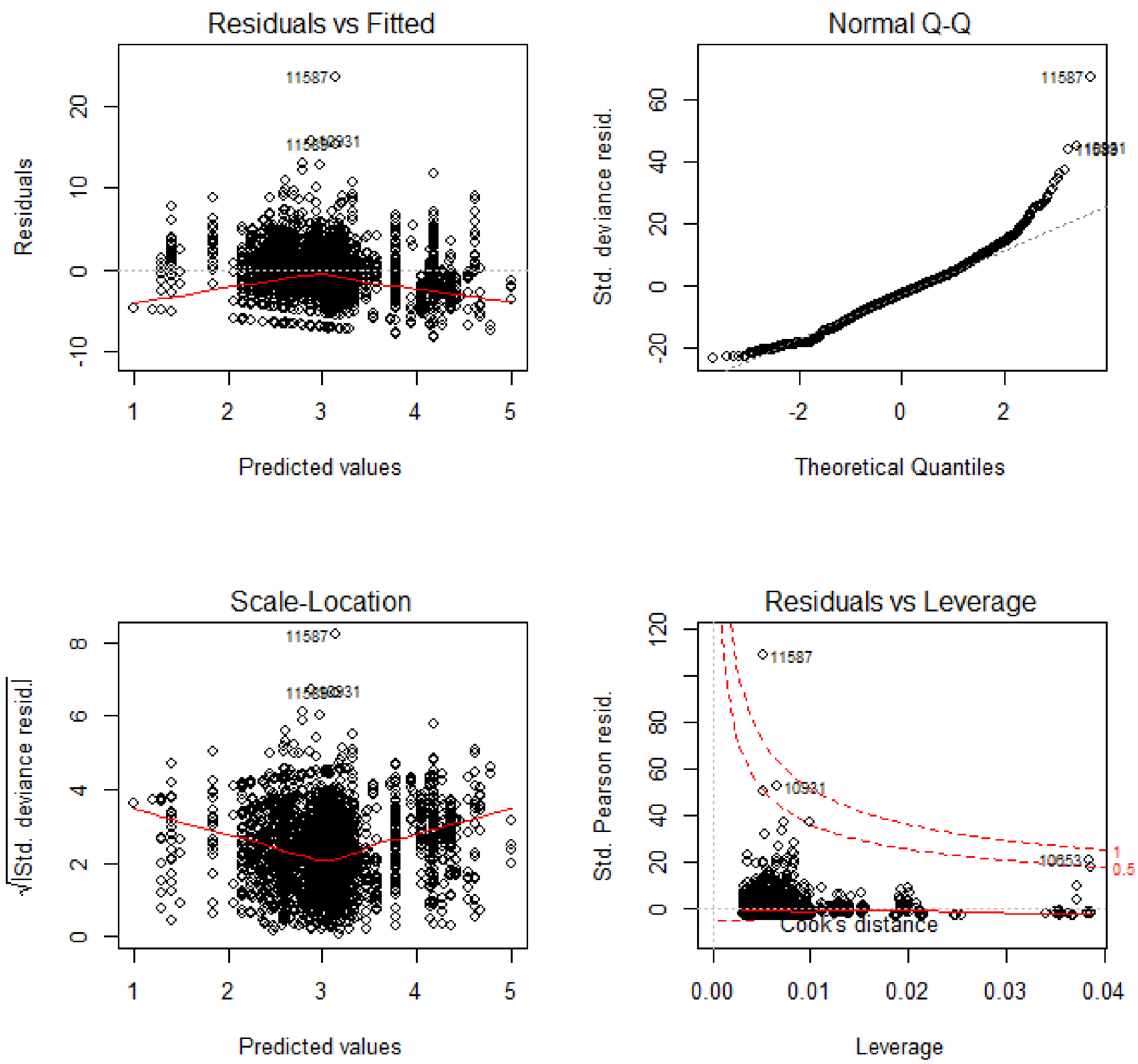

Residuals vs Fitted
Residuals
Predicted values
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
Scale-Location
√|Std. deviance resid.|
Predicted values
Residuals vs Leverage
Std. Pearson resid.
Cook's distance
Leverage

Fleet_8_NB

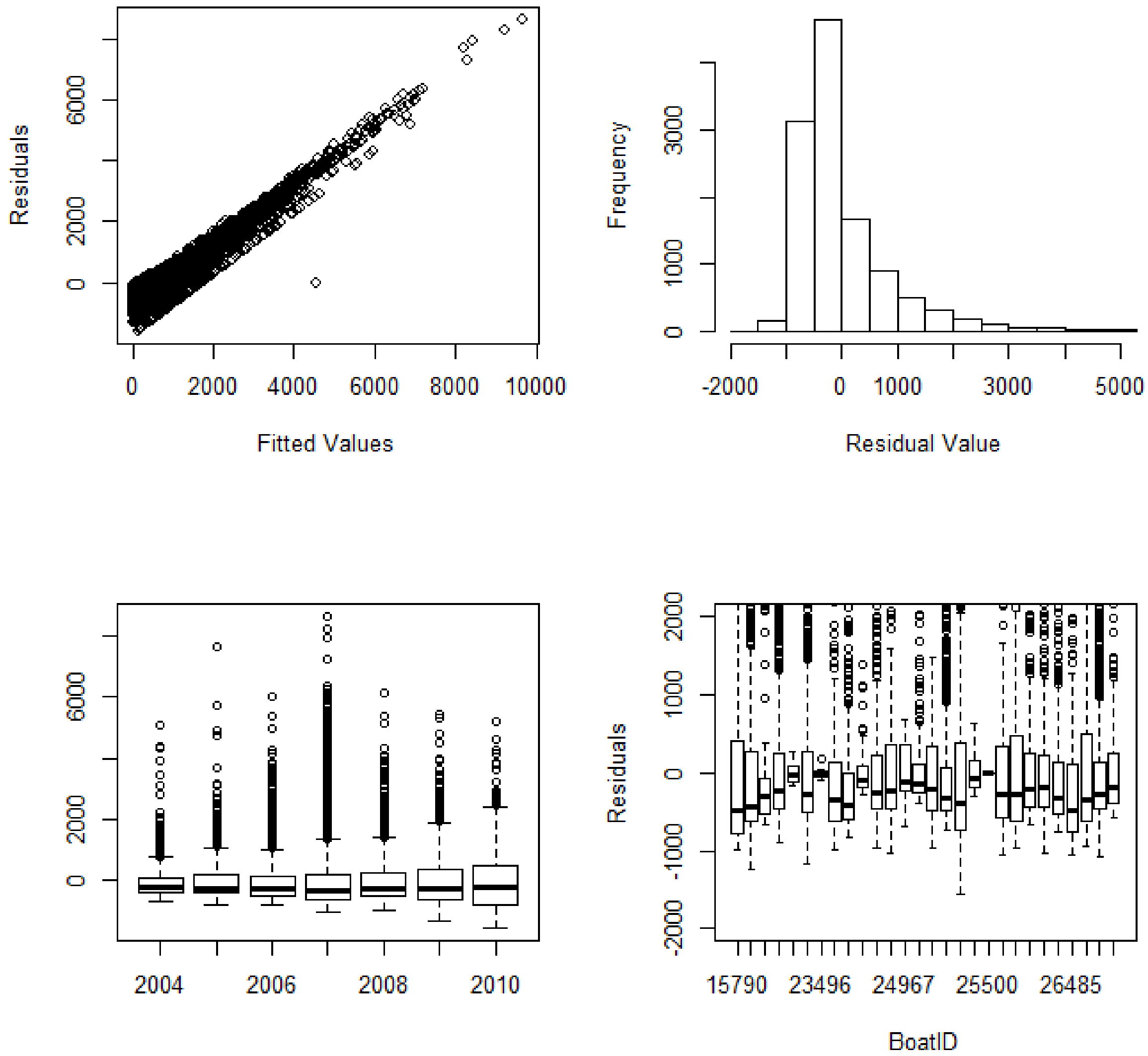


Residuals vs Fitted
Residuals
Predicted values
10441
1428
4474
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
Scale-Location
√|Std. deviance resid.|
Predicted values
Residuals vs Leverage
Std. Pearson resid.
Leverage
11067
5368
Cook's distance

Fleet_7


Residuals vs Fitted
Residuals
Predicted values
11587
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
11587
Scale-Location
√|Std. deviance resid.|
Predicted values
11587
Residuals vs Leverage
Std. Pearson resid.
Leverage
11587
10653
Cook's distance
1
0.5

FLEET 8



Residuals
Fitted Values
Frequency
Residual Value
Residuals
BoatID