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A CPUE index based on a GAMM

A proposed monitoring series

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Summary

- An updated CPUE model based on a generalised additive mixed model (GAMM) is presented.
- Random Cell by Year interactions replace a spline involving Year in the previous generalised additive model (GAM) to address 'oversmoothing'.
- The fitted GAMM performs better than alternative random effects and fixed effects CPUE models in a range of diagnostic tests and has a distinct advantage in terms of mean squared error.
- The GAMM based index is independent of the Constant Squares and Variable Squares assumptions.
- The calculated index is quite similar to the Core Vessel w0.8 Base index and is also insensitive to alternative assumptions about the relationship between effort and observation weighting.

1 Introduction

The Base CPUE indices used as a key data input into the SBT operating model are weighted averages of the Constant Squares and Variable Squares indices. The Constant Squares and Variable Squares indices are derived from fitted generalised linear models (GLMs) but represent opposite extremes in assumptions about the relationship between CPUE in fished and unfished squares. The Variable Squares index in particular lacks a firm scientific basis. Given uncertainty in the distribution of SBT beyond fished squares, it is important that additional 'monitoring' indices not dependent upon Constant Squares and Variable Squares assumptions are available to provide a regular basis for comparison.

A generalised additive mixed model (GAMM) for southern bluefin tuna CPUE is described. The model is used in conjunction with the Laslett Core Area to produce an index of abundance for the population of SBT aged four years and above harvested by the Japanese longline fleet. The work is presented here for the consideration of the SC for suitability to be used as a monitoring index for CPUE of SBT. The CCSBT currently lists a GAM index as a data requirement of the Data Exchange.

The index presented is a refinement of previous GAM based indices (Chambers 2013) described over the past two years. The work was initiated when it was felt that the previous Laslett Core Area index was becoming less reliable as effort in the Japanese longline fishery declined.

The newly proposed model uses a spline in latitude, longitude and month to estimate average spatio-temporal distribution of CPUE over the Japanese longline fishing season. A categorical Year fixed effect allows average annual CPUE to vary between years. Differences in the spatial distribution of CPUE between years are handled by a random interaction effect between 5-degree square and Year. In order to accommodate the random effects we assume that log transformed CPUE is normally distributed about its predicted value.

As with the GAM based indices presented previously (Chambers 2013), the abundance index is calculated by predicting CPUE over the Laslett Core Area grid of latitude, longitude and months. The abundance trend suggested by the new GAMM index is not very different from the w0.8 Core Vessel Base CPUE index.

The new spline appears to be more stable than the previous GAM model as evidenced by maps of predicted CPUE (Appendix A, Figures 7 and 8) which are much smoother than similar maps derived from previous models (see Chambers 2013).

Method

Notation

Notation used is defined in the table below.

Notation	Var. Type	Description
$\mathrm{Cell}_{Lo,La}$	Categorical	A unit of space (5° longitude and latitude) that is invariant of time.
$\mathrm{Cell}_{Lo,La,M}$	Categorical	A unit of space (5° longitude and latitude) limited to a particular time of year, specifically the month *M= m* (all years).
$\mathrm{Cell}_{Lo,La,M,Y}$	Categorical	A unit of space-time. The level of aggregation of the catch and effort data.
$\mathrm{logCPUE}_{Lo,La,M}$	Numeric	Defined later in the paper.
$\mathrm{SBT}_{Lo,La,M,Y}$	Integer	No. of SBT aged 4+ years captured in $\mathrm{Cell}_{Lo,La}$ in month *M* of year *Y.*
$\mathrm{HOOKS}_{Lo,La,M,Y}$	Integer	
YEAR_{Y}	Categorical	*YEAR* as a categorical variable.

Upper case subscripts are used to denote a generic index and lower case subscripts are used to refer to represent specific index values.

Data

The data used to fit the GAMM are aggregated monthly totals of Japanese longline SBT catch and effort by 5 degree square from the CPUE_INPUTS table within the CCSBT database. The observations are limited to the JAP_ADJ dataset. In addition, only observations with latitudes between 25 S and 55 S and months between March and October are considered. Observations before 1969 are also excluded due to reduced reliability of these early data. The fitted data include observed catch and effort from months and latitudes excluded from analyses of Core Vessel CPUE (Itoh and Takahashi 2014), but the abundance index calculated from the fitted model only includes predictions from areas 4-9 and months April-September.

It should be noted that in this case the modelled data include catch and effort from vessels not considered part of the core fleet of Japanese longline vessels (Itoh et al. 2013).

As distinct from other models fitted to catch and effort data, longitude, latitude and month are fitted as continuous variables. A simple transformation of the longitude values is required for continuity about the international dateline.

The quantity modelled is log transformed CPUE of SBT aged 4+ years defined as:

$$\log \mathrm{CPUE}_{lo,la,m.y} = \log\left(\frac{\mathrm{SBT}_{lo,la,m,y}}{\mathrm{Hooks}_{lo,la,m,y}} \times 1000 + 0.2\right)$$

The fitted model

The fitted model is specified as

$$\mathrm{logCPUE}_{lo,la,m,y} = s(\mathrm{LONG}_{lo}, \mathrm{LAT}_{la}, \mathrm{MONTH}_{m}) + \mathrm{YEAR}_{Y} + 1|(\mathrm{Cell}_{lo,la}: \mathrm{YEAR}) + e_{lo,la,m,y}$$

Variation in the spatio-temporal distribution of CPUE between years is modelled with the random interaction effect between categorical variablesYEAR_{Y}^{*} and $\mathrm{Cell}_{Lo,La}$.

$$1|(\mathrm{Cell}_{lo,la}: \mathrm{YEAR}_{y}) \sim N(0, \sigma_{\nu}^{2})$$

The catch and effort observations on the CCSBT database are aggregated monthly totals from fishing at 5 degree square level. The amount of effort that contributes to each aggregated observation varies markedly between 5 degree squares. Analysis of residuals from fitted models reveals aggregated observations corresponding to greater numbers of hooks tend to be more precise (Figure 1).

The observations can be weighted to address non-constant variance. Observation weighting of $w_{lo,la,m,y}$ assumes that:

$$e_{lo,la,m,y} \sim N\left(0, \frac{\sigma^{2}}{w_{lo,la,m,y}}\right)$$

The GAM index submitted to the CCSBT data exchange assumed

$$w_{lo,la,m,y} = \min(\mathrm{sqrt}(\mathrm{HOOKS}_{lo,la,m,y}), \mathrm{sqrt}(500\,000))$$

This assumption is fairly arbitrary.

In this paper a procedure is used to calculate less arbitrary observation weights recognising that the absolute residual is an estimator of error standard deviation (Kutner et al. 2005). Initially the GAMM was fitted with unit weights assumed for all observations. A local smoothed fit of absolute residuals against the square root of hooks set was fitted using the loess function (R Core Team, 2012) with default settings. The loess fit is illustrated in Figure 1. Observation weights were then based on the fitted values from the loess smoothed fit according to

$$w_{lo,la,m,y} = \frac{1}{(\hat{s}_{lo,la,m,y})^{2}}$$

The model was then refitted with the loess estimated weights. The use of loess re-weighted observations makes negligible difference to the resulting GAMM index compared with the more arbitrary observation weighting assumed for the index submitted to the 2014 Data Exchange (Figure 2).

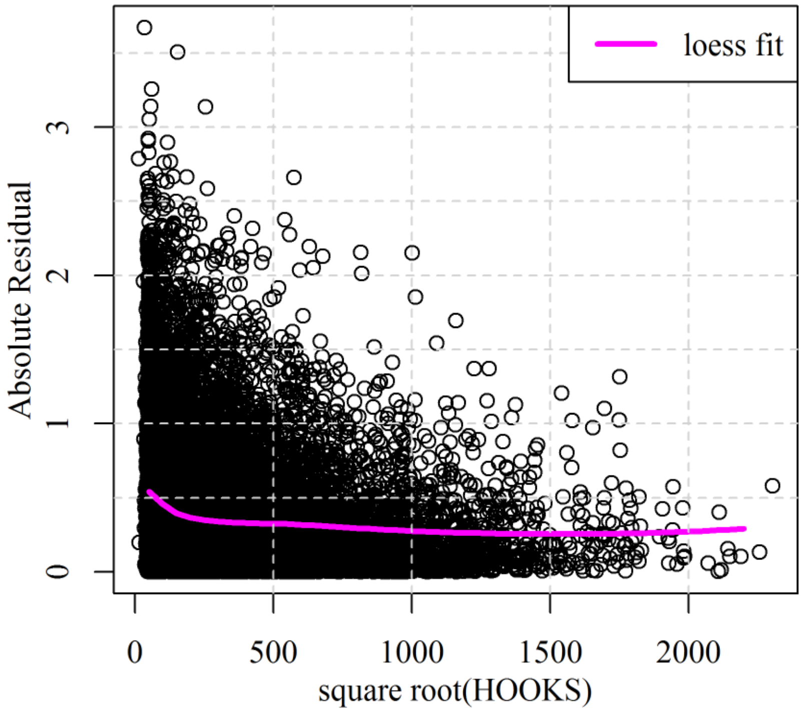

Figure 1 Plot of absolute residuals versus the square root of hooks set. Solid line is a loess local smooth fit

All models were fitted in R using the gamm4 package (Wood, 2011). The use of 64 bit version of R to fit the model is recommended. Even so it took several hours to fit the model.

The weighted model has residual standard deviation of 0.583 whilst the estimated standard deviation of the random YEAR-CELL interaction was 0.22.

Spatial effects on CPUE are mapped in the Appendix (Figures 8 and 9).

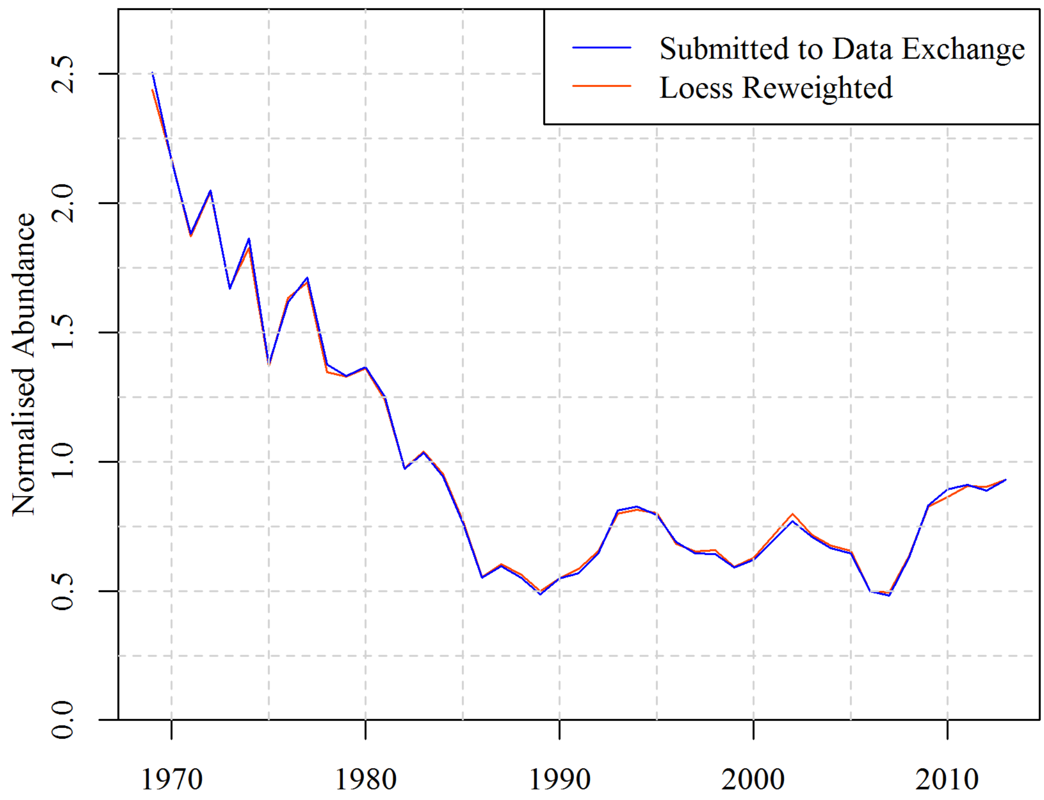

Figure 2 Comparison of loess reweighted GAMM presented with the GAM index submitted to the 2014 CCSBT Data Exchange

Calculation of the index

The fitted model with revised loess observation weights was used to predict log CPUE in the Laslett Core Area (Laslett, 2001) each year. The annual index value is proportional to the average of the 272 annual predictions over the Laslett Core Area.

As the model is fitted using gamm4 which calls the lmer function, the predict function is unavailable. Unbiased prediction of CPUE from the random effects variance requires consideration of the MSE as well as the random effects variance. However, unlike the Variable Squares index, the Laslett Core Area comprises the same number of cells each year. Since these are multiplicative and constant between years they can be excluded from the calculation without changing the normalised index.

Full R code is given in Appendix C.

2 Results

The GAMM index of abundance

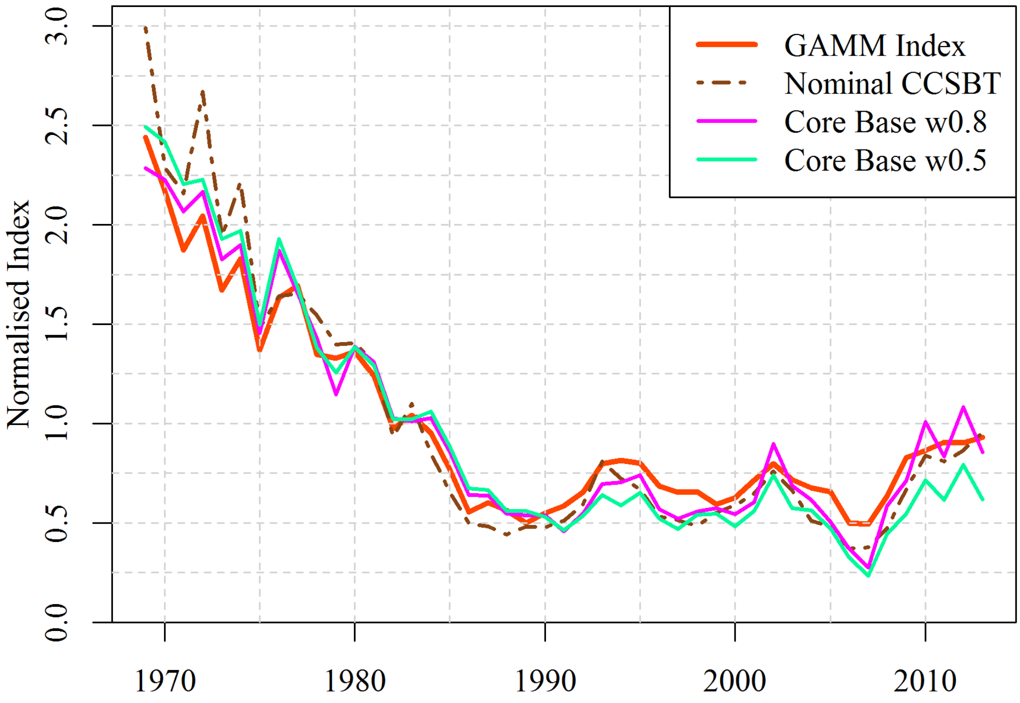

Figure 3 SBT CPUE indices 1969–2013

The four indices compared are in fairly close general agreement (Figure 3). The w0.5 index has tended to be a little lower than the others over the last four years. The deviation of the w0.5 Core Vessel index from the others is driven by the continuing departure of the Variable Squares index from the Constant Squares index which must be beginning to become a concern.

The fitted spline term is summarised by maps of CPUE effects shown in the Appendix (Figures 8 and 9). These are considerably smoother than maps derived from previous GAMs (Chambers 2013). The maps also suggest that in a given month, on a given latitude CPUE does not vary much which provides some support for the structure of the Base CPUE models (Itoh and Takahashi 2014).

Distribution of random effects

The random effects appear to be approximately normally distributed and centred about zero each year (see Figures 11 and 12 in the Appendix). The distribution of random effects within years is of particular interest. This matter is discussed in greater detail in the Discussion.

Comparison with other SBT CPUE indices

Since 2008, the Core CPUE indices do not average to one (Itoh and Takahashi, 2014), it is not immediately obvious how a similar adjustment should be made for an alternative index for comparison. Historic CPUE is fixed for the Base Indices up to 1985. However, it should be reasonable to compare indices normalised to have mean from 1986.

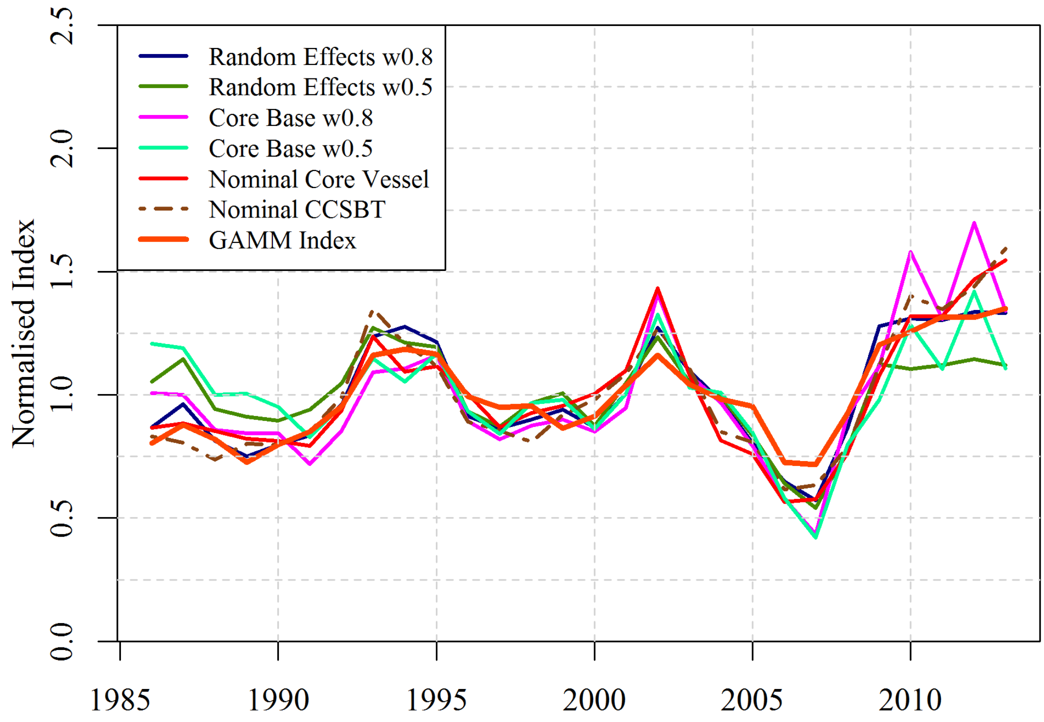

Figure 4 All indices scaled to have a mean of 1.0 over the interval 1986 to 2013

The overall trends in these re-normalised CPUE indices over the last thirty years are similar, particularly prior to about 2009, and more or less flat (Figure 4). Increasing departure occurs between the indices after 2009. The GAMM index appears to show less extreme fluctuation. The weighted Core Base indices (Core Base w0.8 and Core Base w0.5) appear more variable than the other indices in recent years.

A plot of residuals versus fitted values is shown in Figure 5. To allow comparison with diagnostics from other models, Figure 5 excludes observations not fitted to other models.

As is observed with the random effects and fixed effects models (Chambers 2014), the cloud of residuals comprises two components. The diagonal lines along the bottom left hand corner are aggregated observations where fishing has occurred, but no catch of SBT has been reported. The zero catch observations dominate one of two separate components of residuals. The main component, in the top right corner, is quite separate from the zero catch observations. The two separate groups only become apparent when both the horizontal and vertical scales of the plots are large. 'The two-component' aspect of the pattern of residuals suggests the zero inflated nature of observed CPUE has not been fully captured by the data. The zero inflation of the CPUE data might be related to variation in the targeting of SBT relative to bigeye and yellowfin.

The pattern of residuals from the GAMM are better in some respects from those realised from alternative GLMM and GLM models described in Chambers (2014). The residuals are concentrated more tightly around zero as evidenced by horizontal lines indicating 95 percent confidence intervals (Figure 5). The residuals are also clearly better centred than the random effects or fixed effects model residuals. Weighting observations according to hooks set results in fewer large positive residuals of observations with large effort. The GAMM also does a better job of predicting zero CPUE than the random effects or fixed effects models.

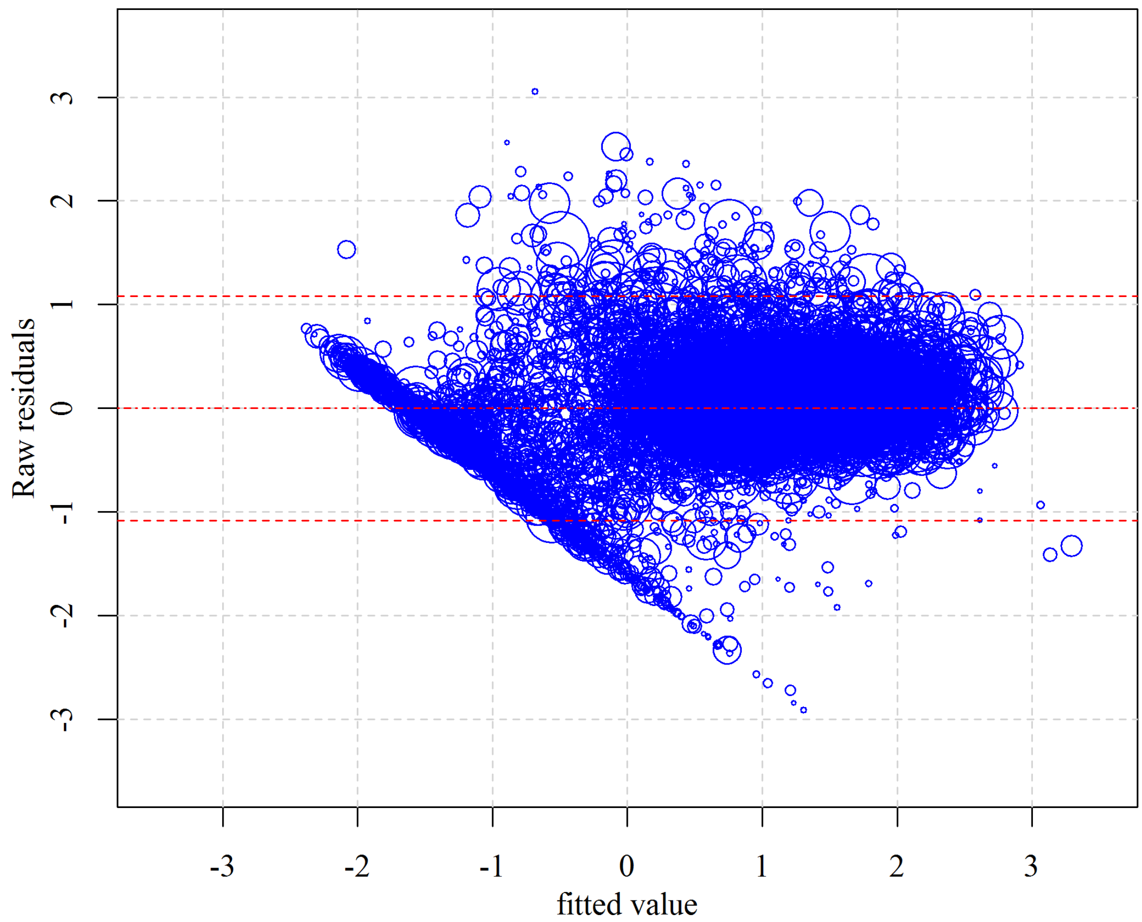

Figure 5 Residuals versus fitted values for observations from CCSBT Statistical Areas 4-9 and months April to September. Plot area is proportional to number of hooks set. Horizontal lines at 0.0 and +/- 1.96 standard deviations asymptotic 95 percent confidence intervals

A direct comparison of residuals from the GAMM to those realised from the Random Effects model is shown in Figure 6. The boxplots reveal a smaller interquartile range for the GAMM residuals compared with the random effects model residuals. A regression coefficient that is clearly less than unity also reveals that the magnitude of the GAMM residuals tends to be smaller than the random effects model. A plot of residuals versus fitted values by year is provided in the Appendix (Figure 10).

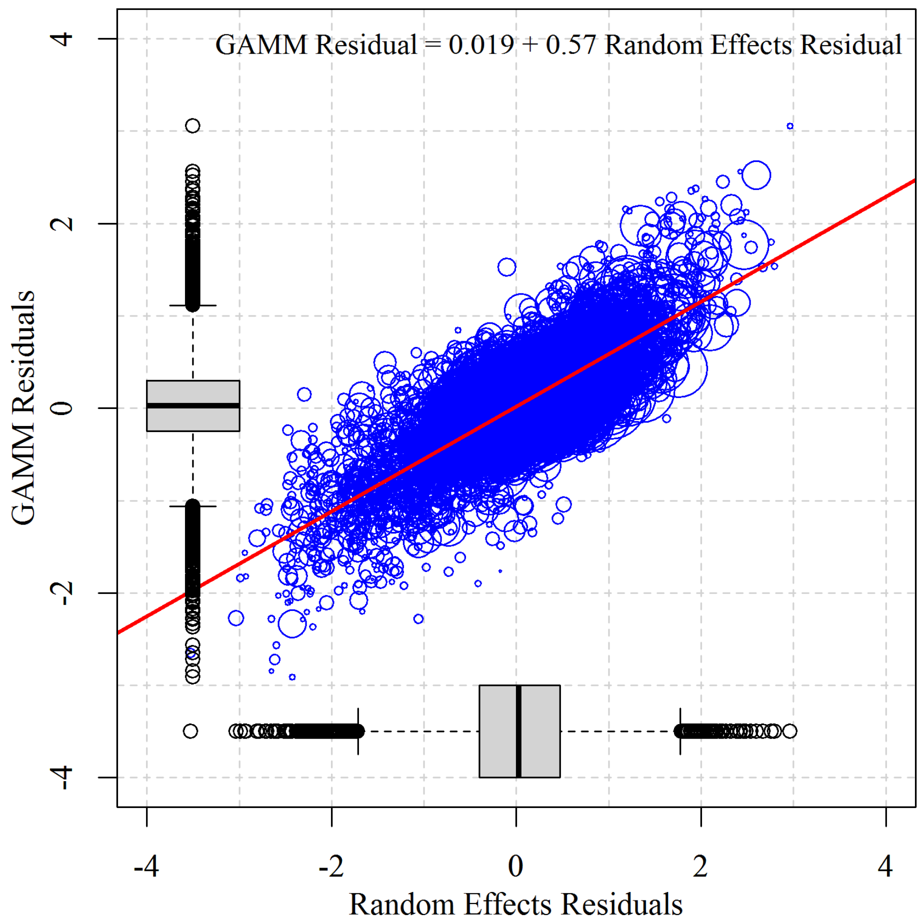

Figure 6 GAMM residuals versus Random Effects residuals. Plot size proportional to number of hooks set

Since the weighted regression model does not assume errors are identically distributed there is not much sense in looking at QQ plots. Nevertheless QQ plots of residuals by year are provided in the Appendix (Figure 11).

The fitted GAMM explains considerably more variance in log CPUE than either the random effects or fixed effects models described in Chambers (2014). The MSE for the GAMM is 0.340 whilst for the random effects model. This compares with 0.619 for the random effects model and 0.616 for the fixed effects model (Figure 7).

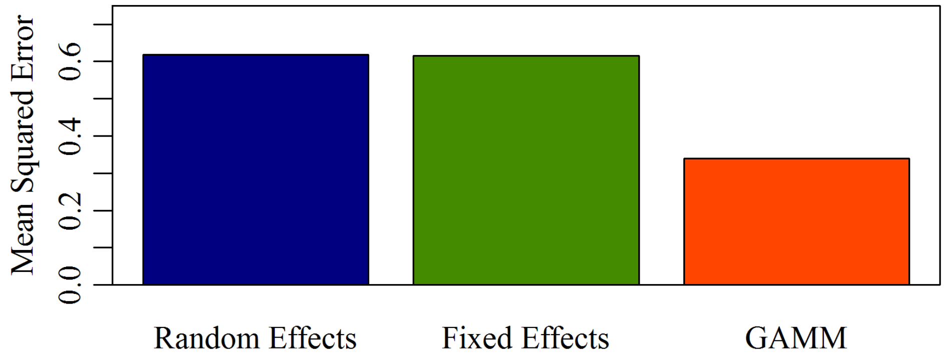

Figure 7 Barplot showing Mean Squared Error of 3 alternative CPUE models for SBT.

3 Discussion

Replacing the spline term involving year from the previous GAM (Chambers 2013) with Cell by Year random effects results in more stable estimation as evidenced by smoother isopleths of predicted CPUE. More detailed information on the distribution of SBT could be inferred by fitting the same model to restricted age classes.

The Core Base CPUE indices make explicit assumptions about the relationship between the spatial distribution of CPUE relative to the spatial distribution of fished cells. The index proposed here does not make assumptions of this type. The implications of this given the large contraction in the spatial distribution of fishing warrants some consideration. Decisions made by fishers about where to fish are invariably strongly influenced by their expectations about catch rates and their decisions then determine the spatial distribution of observed data. Predicted CPUE in $Cell_{lo,la}$ locations that are not fished during a calendar year are based solely on the fitted spatiotemporal spline and a Year effect. It might be expected that this would result in positive bias in predicted CPUE in unfished cells. However, the assumption of normally distributed random effects limits the extent to which this can happen. Approximately half of the predicted random effects need to be negative. The negative (and positive) random effects can only come from fished cells. Although the random effects have not been nested within year, so the fitted model does not explicitly assume random effects sum to zero each year, model diagnostics provided in the Appendix (Figures 12 and 13) suggest this is approximately the case.

The change in observation weighting using loess smoothed re-weighting makes very little difference to the series, although it does reduce the value of the index in 1969 slightly.

It is reassuring that the GAMM index and the nominal CPUE index are not too different from the Core CPUE indices. The GAMM index also appears quite insensitive to alternative weighting schemes for the observations.

Appendix A: Spatial Effects

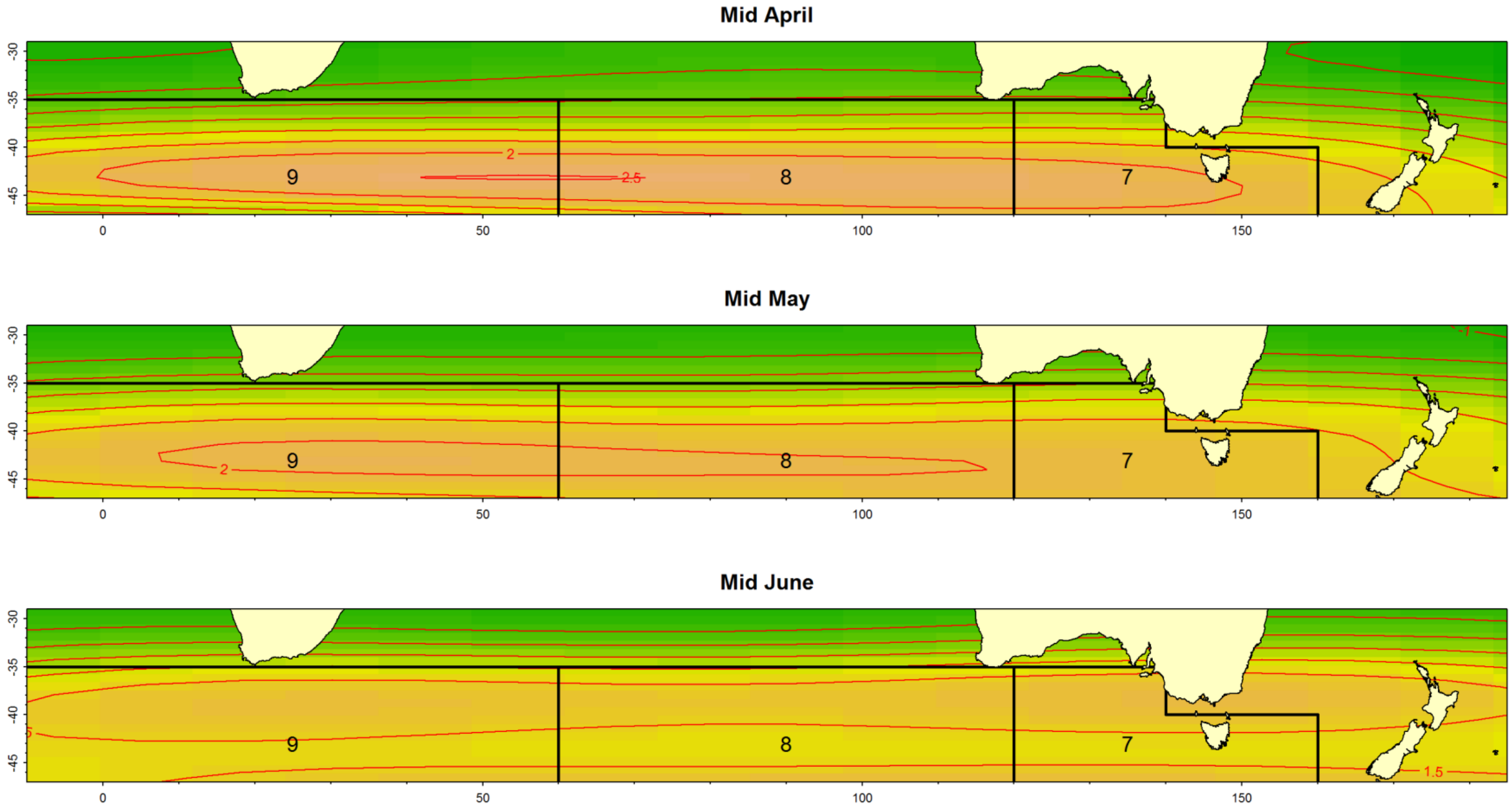

Figure 8 Spatial effects on log CPUE in Mid-April, Mid-May and Mid-June

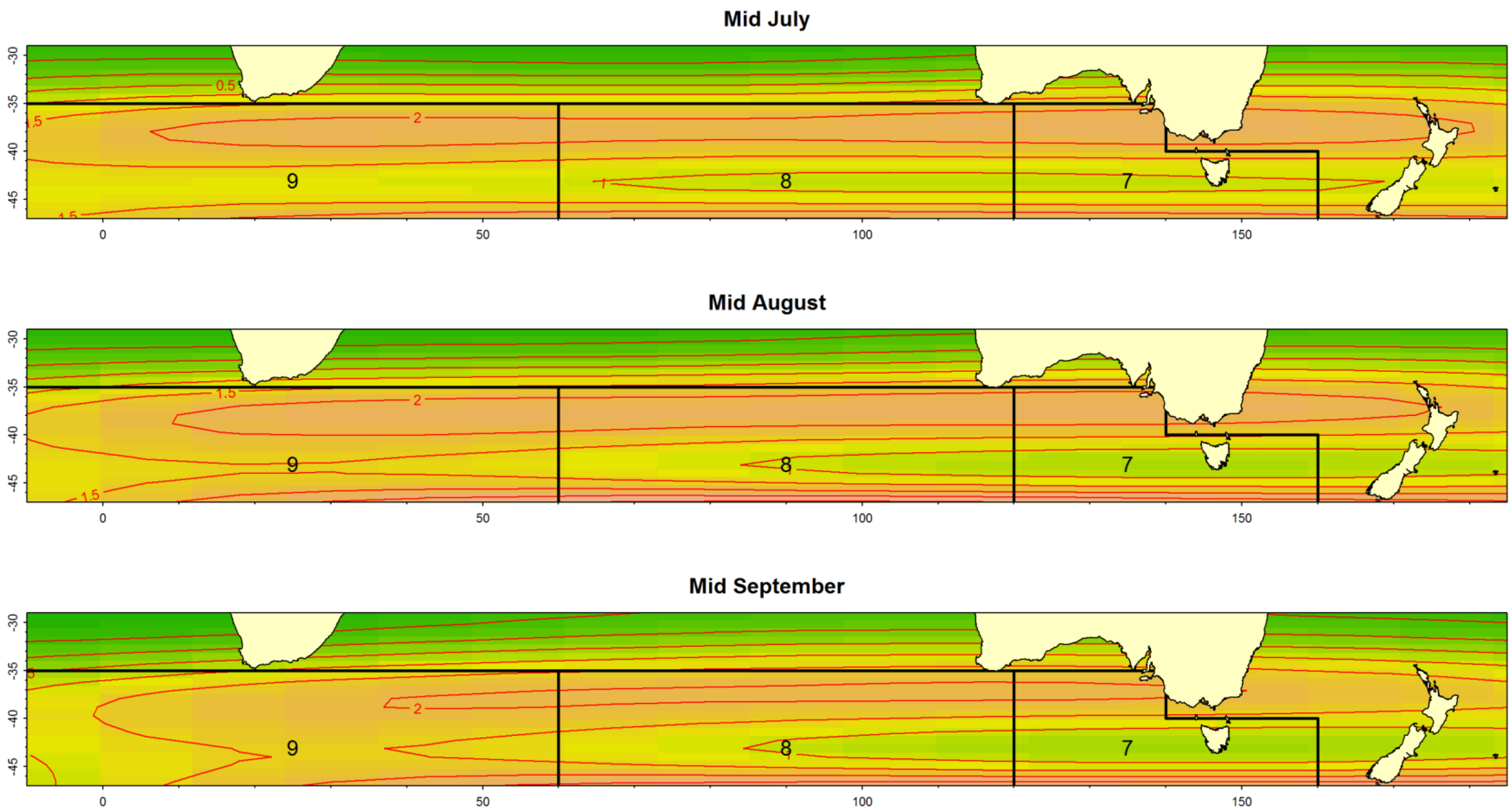

Figure 9 Spatial effects on log CPUE in Mid-July, Mid-August and Mid-September

Appendix B: Additional diagnostics

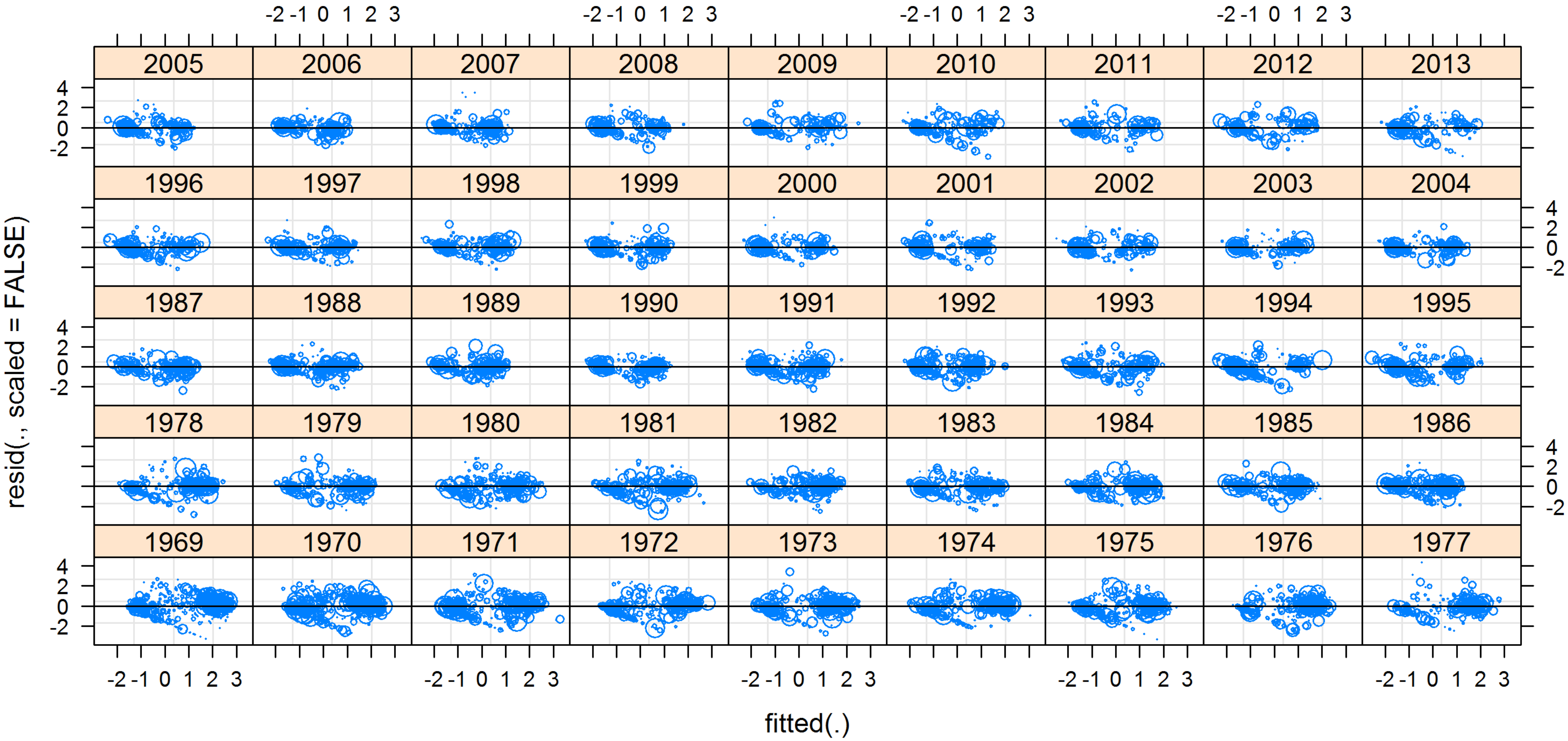

Figure 10 Unscaled residuals versus fitted values by year. Area of plot character proportional to number of hooks set

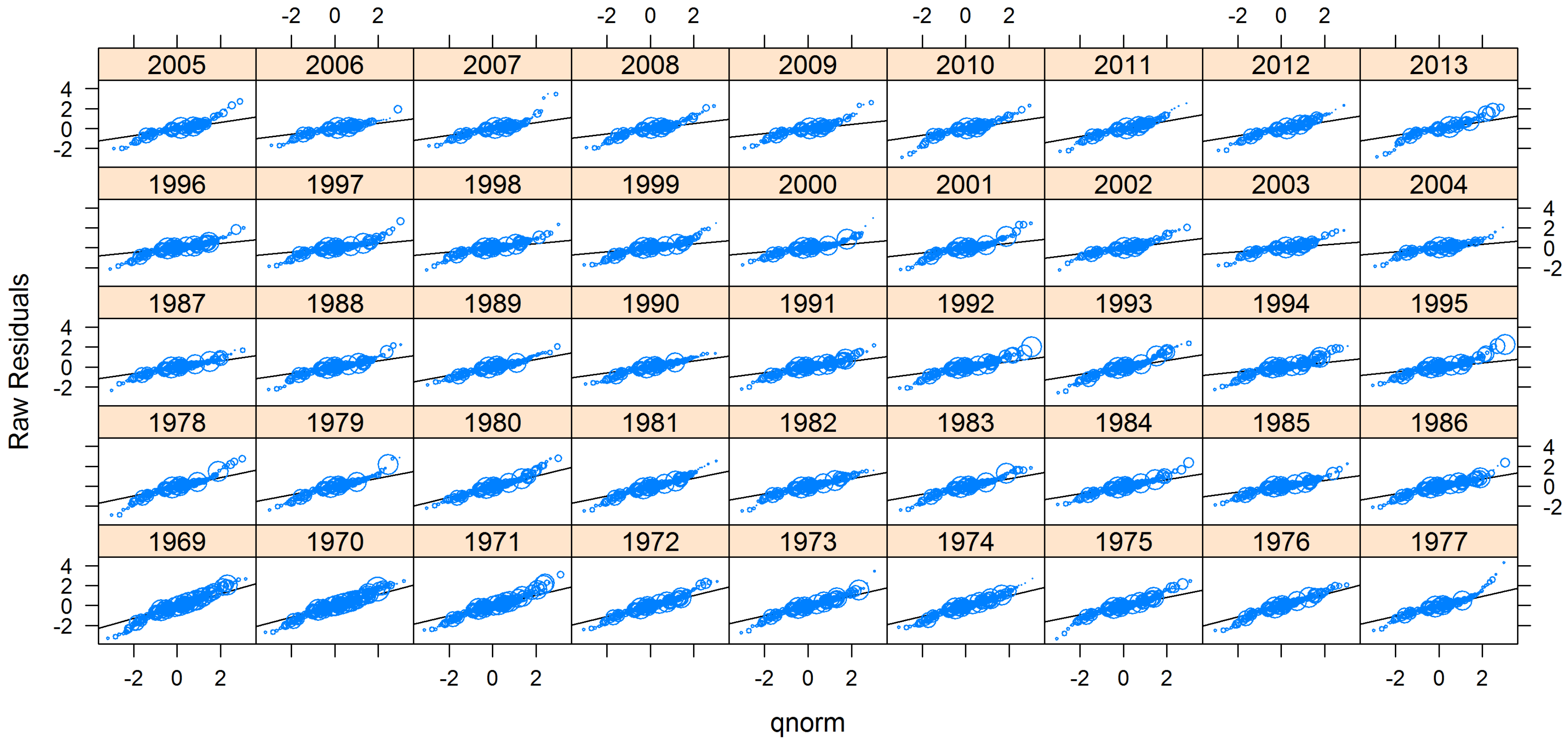

Figure 11 QQ-normal plots of residuals by year. Area of plot characters proportional to number of hooks set. Lines are through first and third quartiles

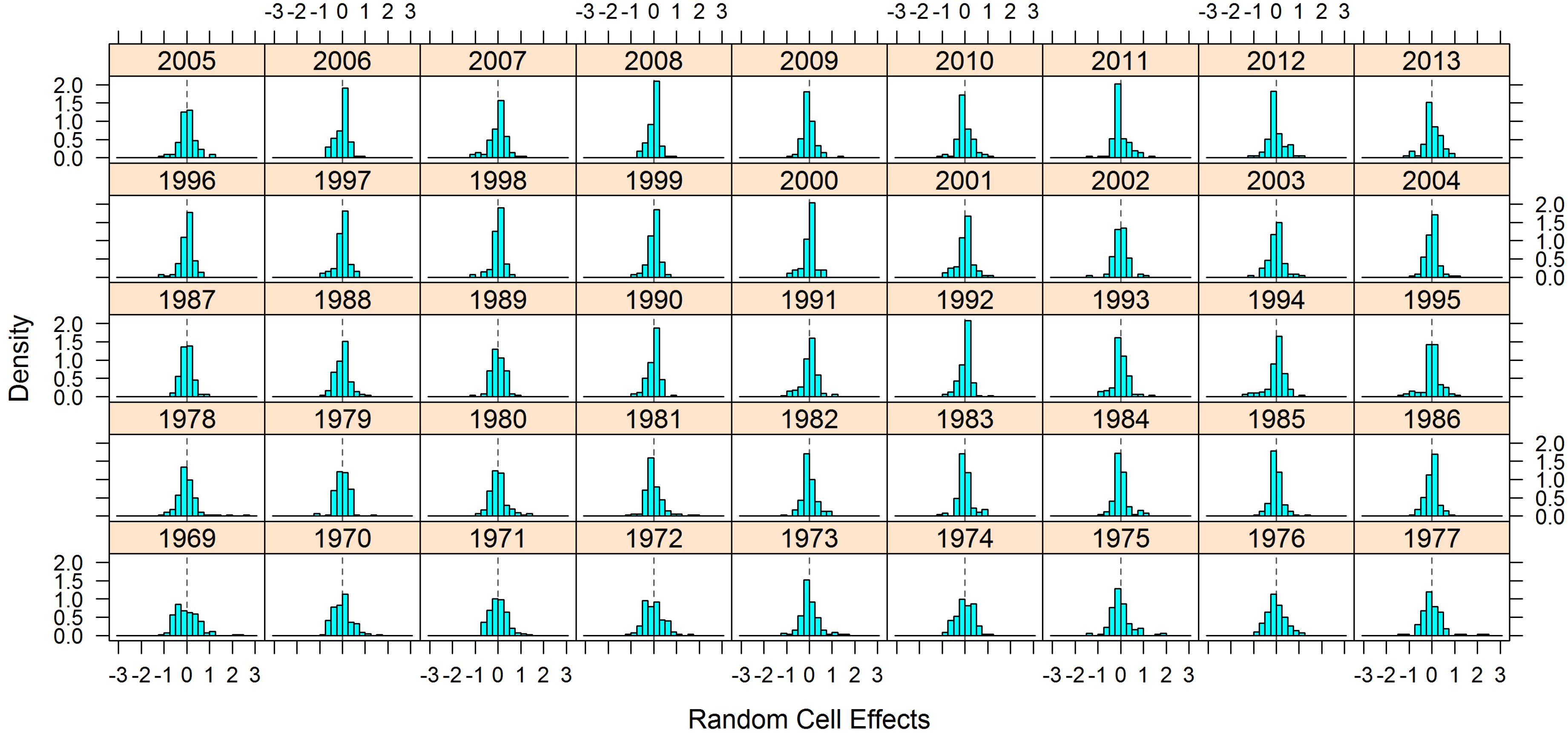

Figure 12 Histograms of BLUPS for random Cell:Year interaction effects plotted by year. Vertical dashed line at effect size of 0.0.

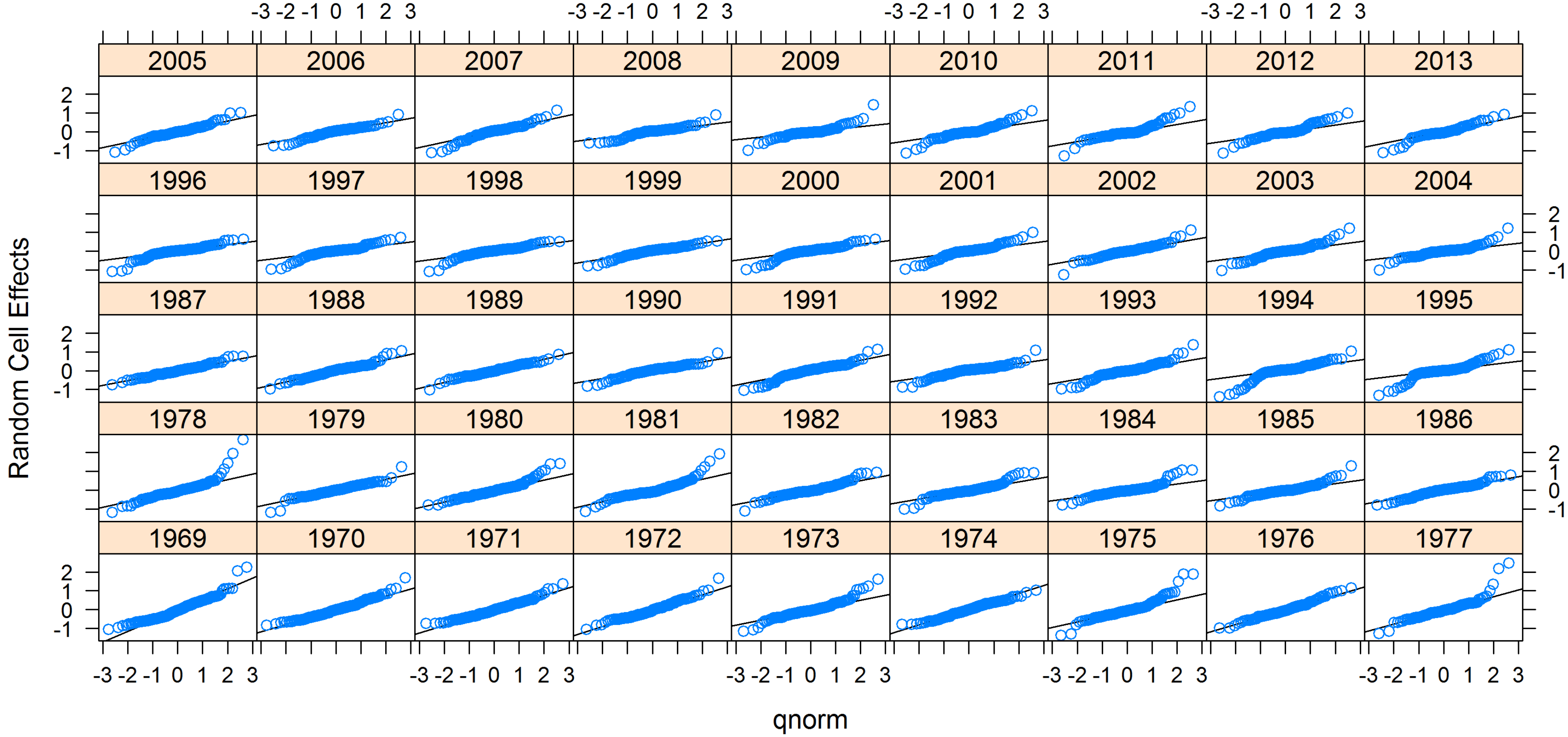

Figure 13 QQ-normal plots of random effects by year. Lines plotted through first and third quartiles.

Appendix C: R Code

```
########################
### Updated GAMM for 2014 ###
########################
library(mgcv);library(RODBC)
SBT.2014 <- odbcConnectAccess("C:\\CPUEInputs_6513_Revised.mdb")
CPUE.2014 <- sqlFetch(SBT.2014, "CPUE_INPUTS")
CPUE.2014 <- CPUE.2014[CPUE.2014$DATA_CODE == "JP_ADJ",]
CPUE.2014$LONG[CPUE.2014$LONG < -80] <- CPUE.2014$LONG[CPUE.2014$LONG < -80] +
360
CPUE.2014$YEAR.F <- as.factor(CPUE.2014$YEAR)
Sum.4plus <- function(X)
{
Four.Plus <- as.numeric(X[16:32])
SBT.4plus <- round(sum(Four.Plus),digits = 1)
return(SBT.4plus)
}
CPUE.2014$SBT_4Plus <- apply(CPUE.2014,1,Sum.4plus)
CPUE.2014 <- CPUE.df[CPUE.2014$HOOKS > 0,]
CPUE.2014 <- CPUE.2014[!(CPUE.2014$YEAR %in% c("1965","1966","1967","1968")),]
CPUE.2014$CELL <- as.factor(paste(CPUE.2014$LONG,CPUE.2014$LAT,sep = '|'))
CPUE.2014$MONTH <- CPUE.2014$MONTH + 0.5
CPUE.2014 <- CPUE.2014[CPUE.2014$MONTH >= 3.5 & CPUE.2014$MONTH <= 10.5,]
GAMM4.Unweighted <- gamm4(log.CPUE ~ t2(LONG,LAT,MONTH) + YEAR.F - 1, data = CPUE.df,
random =~ (1|CELL:YEAR.F))
CPUE.df$Abs.Resids <-residuals(GAMM4.Unweighted$mer)
CPUE.df$SQRT_HOOKS <- sqrt(CPUE.df$HOOKS)
Resid.Lo <- loess(Abs.Resids ~ SQRT_HOOKS,data = CPUE.df)
CPUE.df$fitted.st.dev <- predict(Resid.Lo,CPUE.df)
CPUE.df$Weight <- 1/CPUE.df$fitted.st.dev^2
GAMM4.2014 <- gamm4(log.CPUE ~ t2(LONG,LAT,MONTH) + YEAR.F - 1, data = CPUE.df,
random =~ (1|CELL:YEAR.F),weights = Weight)
GAMM4.2014.Ranefs <- as.data.frame(ranef(GAMM4.2014$mer)[1])
RanEf.LONG.LAT <- character(nrow(GAMM4.2014.Ranefs))
RanEf.YEARS <- character(nrow(GAMM4.2014.Ranefs))
for (i in 1:nrow(GAMM4.2014.Ranefs))
{
RanEf.LONG.LAT[i] <- strsplit(rownames(GAMM4.2014.Ranefs),":")[[i]][1]
RanEf.YEARS[i] <- strsplit(rownames(GAMM4.2014.Ranefs),":")[[i]][2]
}
Laslett.Months <-
c(4,4,4,4,4,4,4,4,4,4,4,4,4,4,4,4,4,4,4,4,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,6,6,6,6,6,6,6,6,6,6,6,6,6,
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9,9,9)
Laslett.Longs <-
```

```
c(-10,5,0,5,10,15,20,25,30,35,40,45,10,15,20,25,30,35,40,45,10,5,0,5,10,15,20,25,30,35,40,45,-
10,15,20,25,30,35,40,45,-10,-5,0,5,10,15,20,25,30,35,40,45,-10,15,20,25,30,35,40,45,-10,-
5,0,5,10,15,20,25,30,35,40,45,-10,15,20,25,30,35,40,45,15,20,25,30,35,40,15,20,25,30,35,40,
15,20,25,30,35,40,15,20,25,30,35,40,90,95,100,75,80,85,90,95,100,105,90,95,100,105,75,80,85,
90,95,100,105,90,95,100,105,90,95,100,105,110,115,120,90,95,100,105,110,115,150,155,160,1
65,170,175,150,155,160,165,170,175,130,135,140,145,150,155,160,165,170,175,130,135,140,1
45,150,155,160,165,170,175,150,155,160,165,170,175,150,155,160,165,170,175,130,135,140,1
45,150,155,160,165,170,175,130,135,140,145,150,155,160,165,170,175,150,155,160,165,170,1
75,150,155,160,165,170,175,130,135,140,145,150,155,160,165,170,175,130,135,140,145,150,1
55,160,165,170,175,150,155,160,165,170,175,140,145,140,145,150,155,160,165,170,175,150,1
55,160,165,170,175,140,145,140,145,150,155,160,165,170,175,150,155)
Laslett.Lats <- c(-40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-35,-35,-35,-35,-35,-35,-35,-35,-
40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-35,-35,-35,-35,-35,-35,-35,-35,-40,-40,-40,-40,-40,-
40,-40,-40,-40,-40,-40,-40,-35,-35,-35,-35,-35,-35,-35,-35,-40,-40,-40,-40,-40,-40,-40,-40,-40,-
40,-40,-35,-35,-35,-35,-35,-35,-35,-35,-40,-40,-40,-40,-40,-40,-35,-35,-35,-35,-35,-35,-40,-40,-40,-
40,-40,-40,-35,-35,-35,-35,-35,-35,-40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-35,-35,-35,-35,-40,-40,-
40,-40,-40,-40,-40,-35,-35,-35,-35,-40,-40,-40,-40,-40,-40,-40,-35,-35,-35,-35,-35,-35,-30,-30,-30,-
30,-30,-30,-35,-35,-35,-35,-35,-35,-40,-40,-40,-40,-40,-40,-40,-40,-40,-40,-45,-45,-45,-45,-45,-45,-
45,-45,-45,-45,-30,-30,-30,-30,-30,-30,-35,-35,-35,-35,-35,-35,-40,-40,-40,-40,-40,-40,-40,-40,-40,-
40,-45,-45,-45,-45,-45,-45,-45,-45,-45,-45,-30,-30,-30,-30,-30,-30,-35,-35,-35,-35,-35,-35,-40,-40,-
40,-40,-40,-40,-40,-40,-40,-40,-45,-45,-45,-45,-30,-30,-30,-30,-30,-30,-35,-35,-35,-35,-35,-35,-40,
-40,-45,-45,-30,-30,-30,-30,-30,-30,-35,-35,-35,-35,-35,-35,-40,-40,-45,-45,-30,-30,-30,-30,-30,-
30,-35,-35)
RanEfs <- data.frame(YEAR.F = as.factor(RanEf.YEARS),
CELL = as.factor(RanEf.LONG.LAT),RanEf = GAMM4.2014.Ranefs[,1])
CPUE.grid <- data.frame(YEAR.F = as.factor(SBT.Years),LONG =
rep(Laslett.Longs,length(1969:2013)),
LAT = rep(Laslett.Lats,length(1969:2013)),MONTH = rep(Laslett.Months,length(1969:2013)))
CPUE.grid$MONTH <- CPUE.grid$MONTH + 0.5
CPUE.grid$CELL <- as.factor(paste(CPUE.grid$LONG,CPUE.grid$LAT,sep = '|'))
CPUE.grid$pred <- predict(GAMM4.2014$gam,CPUE.grid)
CPUE.grid <- merge(CPUE.grid,RanEfs,by = c("YEAR.F","CELL"),all.x = TRUE)
CPUE.grid$RanEf <- ifelse(is.na(CPUE.grid$RanEf),0,CPUE.grid$RanEf)
CPUE.grid$MSE <- summary(GAMM4.2014$mer)$sigma^2
CPUE.grid$Overall.Pred <- exp(CPUE.grid$pred + CPUE.grid$MSE/2 + CPUE.grid$RanEf - 0.2)
GAMM4.Index <- tapply(CPUE.grid$Overall.Pred,CPUE.grid$YEAR.F,mean)
GAMM4.Index <- GAMM4.Index/mean(GAMM4.Index)
```

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