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A CPUE model with interactions as random effects

Model diagnostics

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Summary

- This paper presents a CPUE index for SBT based on a linear mixed model with interaction terms fitted as random effects, rather than fixed effects as assumed to date.

- The assumption of the random effects model that the interaction effects should follow a normal distribution should provide more robust estimation of interaction effects where effort is low.

- Model diagnostics reveal that the variance of residuals of the CPUE observations is inversely related to the number of hooks set.

- It is also evident from the pattern of residuals that the 'zero inflated' nature of observed CPUE is not fully explained by the fitted random effects model.

- Comparison of diagnostics from the random effects and a corresponding fixed effects model reveal similar departures from model assumptions.

- The w0.8 and w0.5 type indices derived from the fitted random effects model are not very different from the corresponding Base w0.8 and w0.5 CPUE indices used in the operating model. There is perhaps some suggestion that the random effects indices have been less variable over the last five years or so.

- Comparison of Constant Squares and Variable Squares type indices based on the random effects model reveal that these indices have diverged in recent years. It is suggested that the future suitability of the Variable Squares and Constant Squares indices be given some consideration.

1 Introduction

The CPUE working group has previously identified a CPUE model with interactions modelled as random effects to be a useful monitoring series for SBT (see e.g. Anonymous 2013, Attachment 6). An initial index derived from a random effects model fitted to the CPUE_INPUTS database table was presented at the CPUE Webinar in April 2014 (see Chambers 2014a).

This paper provides model diagnostics for the random effects model that was presented at the 2014 CPUE working group webinar. The random effects model has been refitted to updated catch and effort data and the associated indices re-calculated up to 2013. The indices presented are intended as far as possible to be comparable with the Base CPUE indices fitted to the Core Vessel data provided by Japanese scientists and to incorporate the same Constant Squares and Variable Squares area index weightings.

The data fitted to the model are not identical to those fitted to the Core CPUE model because of data subsetting used to define a core Japanese fleet. It is not possible to identially replicate the core fleet data using information on the CCSBT database. Similarly it was not possible to consider the effects of bycatch of yellowfin and bigeye tuna in the model because these data were not available on the CCSBT database for Japanese catch and effort data fitted to the model.

The potential benefit of fitting the interaction terms as random effects is that the estimates of individual interaction effects are likely to be more robust to outliers in CPUE when effort data is low.

The paper defines the fitted random effects model and provides a range of diagnostic plots to allow the reliability and utility of the model to be assessed.

2 Methods

The fitted data

The fitted data were sourced from the aggregated catch and effort data on the CPUE_INPUTS table within CCSBT database. From these data observations with DATA_CODE "COMBINED"; YEAR between 1969 and 2013; MONTH between 4 and 9 and STAT_AREA_CODE between 4 and 9 were selected. Observations from Statistical Areas 5 and 6 were combined. Aggregated observations within these strata with fewer than 10 thousand hooks were excluded. This processing of data was intended to ensure as far as possible the data fitted to the random effects model was similar to the data fitted to the Base models. However, data on catch of yellowfin and bigeye tuna, which are used as covariates in the Base CPUE model, were not available. The fitted data also differ to some extent from those fitted to the Base models in that catch and effort from non-Core vessels are included in the aggregated 5 degree square observations. These differences could only be removed with access to the raw data.

The linear model used for the Core CPUE indices

The structure of the fitted model is also intended to be as similar as possible to the linear model used in the calculation of the Core CPUE indices used in the SBT assessment model and management procedure.

The CPUE indices used in the SBT operating model and management procedure are based on the generalised linear model described in Itoh et al. (2013).

$$\log(CPUE + 0.2) = Intercept + Year + Month + Area + Lat5 + BET\_CPUE + YFT\_CPUE + Month * Area + Year * Lat5 + Year * Area + Error$$

Linear mixed model with interactions as random effects

The random effects model is intended to be as similar as possible to the Base model aside from the change to the interaction terms to be examined. The bycatch terms are not included because these data were not available for Japanese fleets on the CCSBT database. The random effects linear model was therefore specified as:

$$\log(CPUE + 0.2) = Intercept + Year + Month + Area + Lat5 + 1 | Month : Area + 1 | Year : Lat5 + 1 | Year : Area + Error$$

$$1|\mathrm{Year{:}\ Area} \sim \mathrm{Normal}(0, \sigma^2_{ya})$$

$$1|\mathrm{Year{:}\ Lat5} \sim \mathrm{Normal}(0, \sigma^2_{yl})$$

$$1|\mathrm{Month{:}\ Area} \sim \mathrm{Normal}(0, \sigma^2_{ma})$$

$$\mathrm{Error} \sim \mathrm{Normal}(0, \sigma^2)$$

The model is easily fitted in the R package lme4 (Bates et al. 2011). However, at the time of writing, the standard version of lme4 lacks a predict function because the most appropriate approach to predictions using this package has not yet been resolved.

Results

The variance components of the random effect model are summarised in Table 1. The Area by Month interaction explains more variance than the interactions involving Year. The standard deviation of the random interaction effects provides a measure of the strength of the shrinkage of the corresponding interactions. Lower standard deviation indicates relatively stronger shrinkage. The residual variance can be compared with the mean squared error of fixed effects models.

Table 1 Variance components of random effects CPUE model

Groups	Variance	Std. Dev.
Area:Year	0.0566	0.238
Latitude:Year	0.0500	0.224
Area:Month	0.115	0.339
Residual	0.619	0.787

The area-month interactions are probably most naturally modelled as fixed effects, as these are largely driven by inherent biological characteristics of the stock in response to seasonal signals. The number of observations available to estimate these effects is also so great that there is unlikely to be any difference between fixed effects estimates and random effects predictions. Evidently there is greater seasonal variation in CPUE in areas 4 and 7 than in the others (Figure 1).

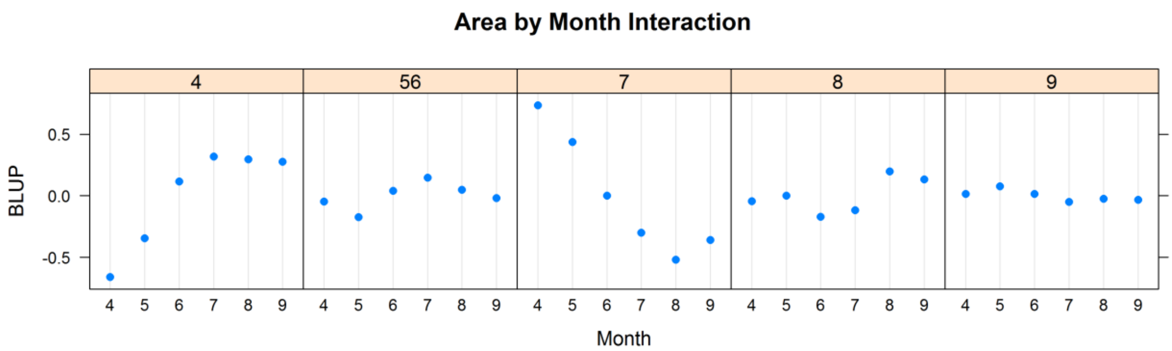


Figure 1: Predicted Area-Month interaction random effects grouped by CCSBT statistical area.

Plots of Area by Year and Latitude by Year interactions are provided in Appendix A (Figures 14 and 15).

Basic model diagnostics

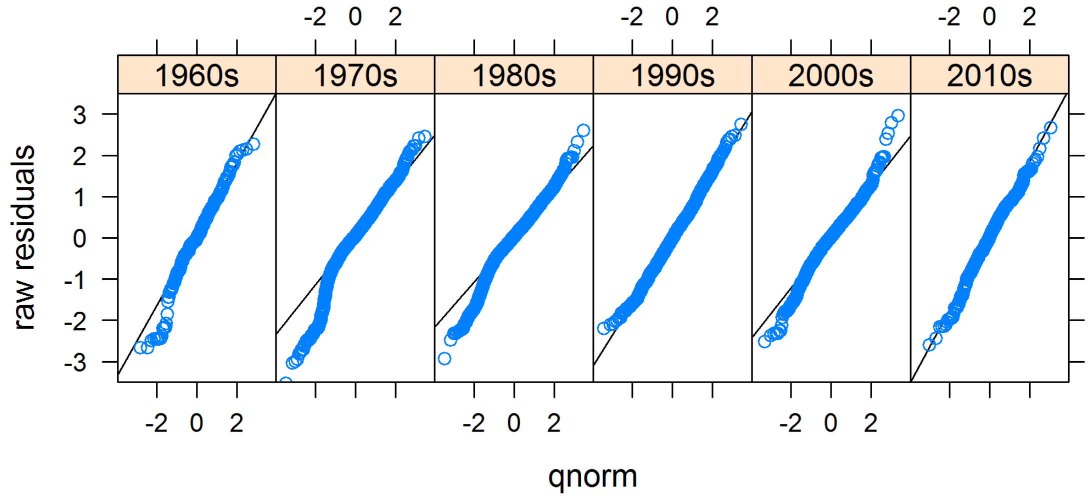


Figure 2 Normal quantile-quantile plots of residuals grouped by decade. Lines are through first and third quartiles.

Some departure from normality of residuals is to be expected because the modelled variable is truncated at log(0.2). However, the quantile-quantile plots (Figure 2) suggest a different problem. The residuals, particularly in the 1970s (and to a lesser extent the 1980s), reveal negatively skewed residuals as well as possibly the effect of truncated CPUE. Plots of residuals versus fitted values are provided later in Figure 5 and also by year in Appendix A (Figure 11).

The random effects are assumed to be normally distributed with means of zero. This assumption provides the mechanism for 'shrinkage' of outlying interaction estimates based on few observations. Quantile-quantile plots suggest the Area-by-Year and Latitude-by-Year effects are normally distributed, but the Area-by-Month interactions are over-dispersed (Figure 3). As mentioned above, the Area-by-Month interactions are more naturally considered as fixed effects as they model consistent dynamics in the movement of CPUE between the Statistical Areas each year. The departure from normality of the Area-by-Month interactions is not a cause for concern, but highlights their suitability to be modelled as fixed effects.

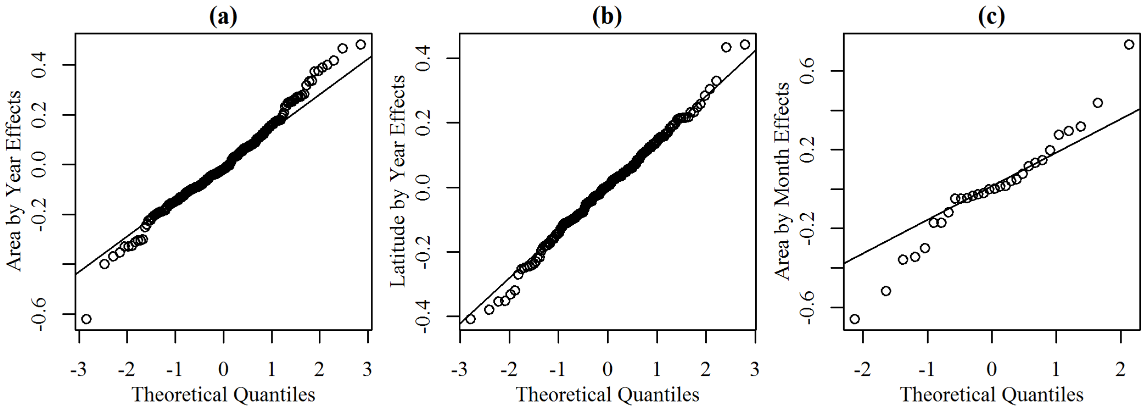


Figure 3 Normal quantile-quantile plots of estimated (a) Area by Year, (b) Latitude by Year and (c) Area by Month random effects. Lines are through first and third quantiles.

A complication related to modelling the aggregated data is that the catch and effort observations fitted to the model result from different amounts of effort and therefore contain different amounts of information. The relationship between residuals from the random effects model and hooks set is illustrated in Figure 4. As would be expected, the variance of residuals declines with increasing effort. The observed residual pattern provides an argument for weighting the observations according to the number of hooks set. An approach that can be used to estimate appropriate observation weights is described in Chambers (2014b).

The Base w0.8 and w0.5 CPUE indices used in the stock assessment are derived from a GLM fitted to unweighted observations. The fitted values from the Base model are then weighted according to effort to calculate the Variable Squares and Constant Squares indices. For comparability with the Core Base indices this approach has also been used to produce the random effects model indices presented in this paper.

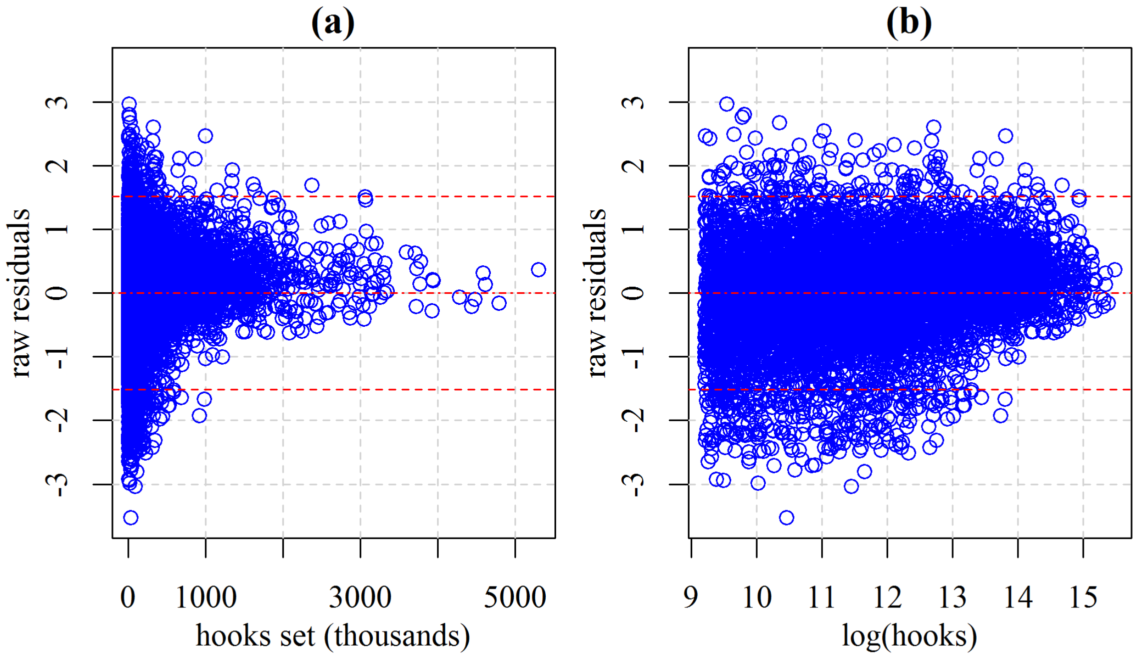


Figure 4 Raw residuals versus (a) hooks and (b) log hooks. Horizontal lines are at 0.0 and ± 1.96 standard deviations.

Corresponding fixed effects model

The random effects model is not directly comparable with the Base model because it is fitted to different data and does not include bycatch terms. A directly comparable fixed effects model was therefore defined that is equivalent to the random effects model except that the interactions are fitted as fixed effects as opposed to random effects. The fixed effects model was specified as

$$\log(CPUE + 0.2) = Intercept + Year + Month + Area + Lat5 + Month * Area + Year * Lat5 + Year * Area + Error$$

The fixed effects model explains slightly more variance in the response variable than the random effects model. This occurs because the interaction effects are not constrained by distributional assumptions. The cost of the increased robustness and potentially lower bias of the random effects is slightly higher variance. The difference is very small, however, as the mean squared error of the fixed effects model is 0.616 compared with 0.619 for the random effects model.

Plots of residuals versus fitted values for the random effects and fixed effects models are shown in Figure 5. The observed pattern of residuals that result from the two models is similar. The diagonal lines along the bottom left hand corner are aggregated observations where fishing has occurred, but no catch of SBT has been reported. It is notable that zero catch observations are observed over a wide range of fitted values as estimated by both models.

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 model.

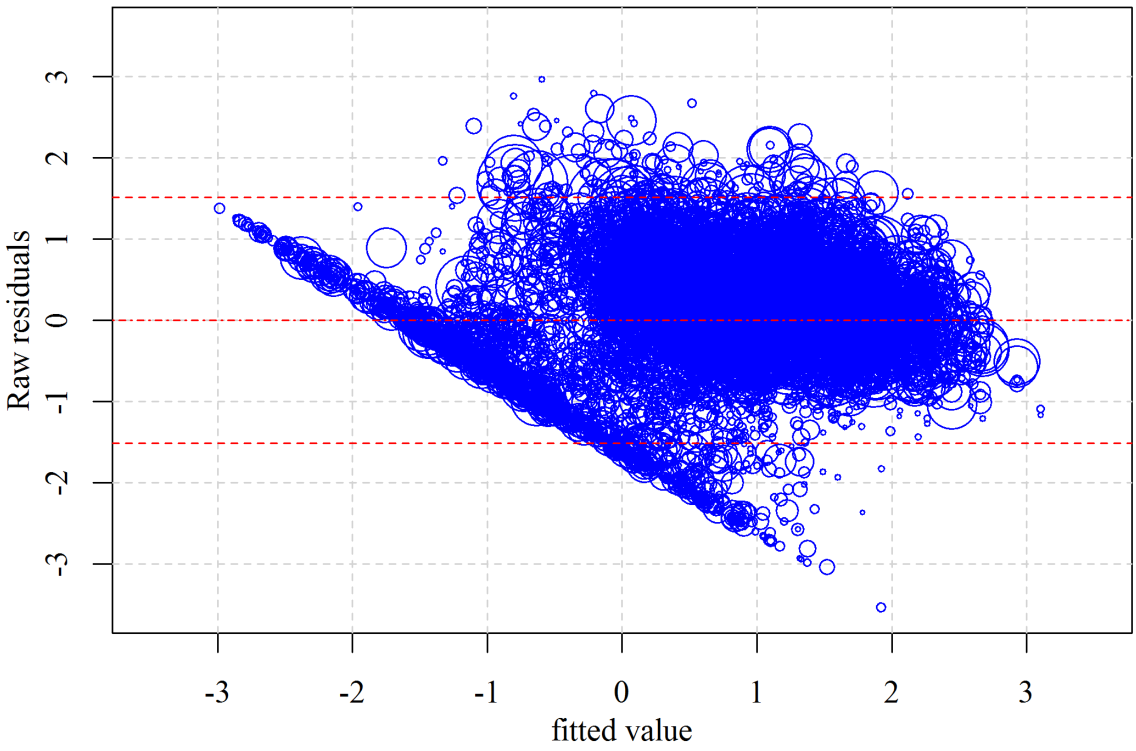
Differences in the relative targeting of yellowfin and bigeye probably contribute to some observations where SBT catch is lower than expected. The inclusion of these terms might reduce the two component characteristic of the residual plot shown in Figure 5. The true Core Vessel data might also be less prone to zero inflation and species targeting issues.

Another feature of the residuals worth noting is the positive skew of the main component in the top right hand corner. There is a lack of large negative residuals for fitted values greater than about zero. This suggests that the assumption of normally distributed residuals is questionable for this model.

Differences between the residual pattern of the random effects and fixed effects models that can be observed from Figure 5 are subtle. The most obvious difference is seen in the top left hand distribution of the two plots showing large positive residuals with low fitted values. These observations often coincide with high effort. The random effects model tends to be better at predicting the catch rates of these observations with fitted values being slightly higher and consequently residuals slightly smaller.

Residuals against fitted values by Year are shown for the random effects model in Appendix A (Figure 11).

(a)



(b)

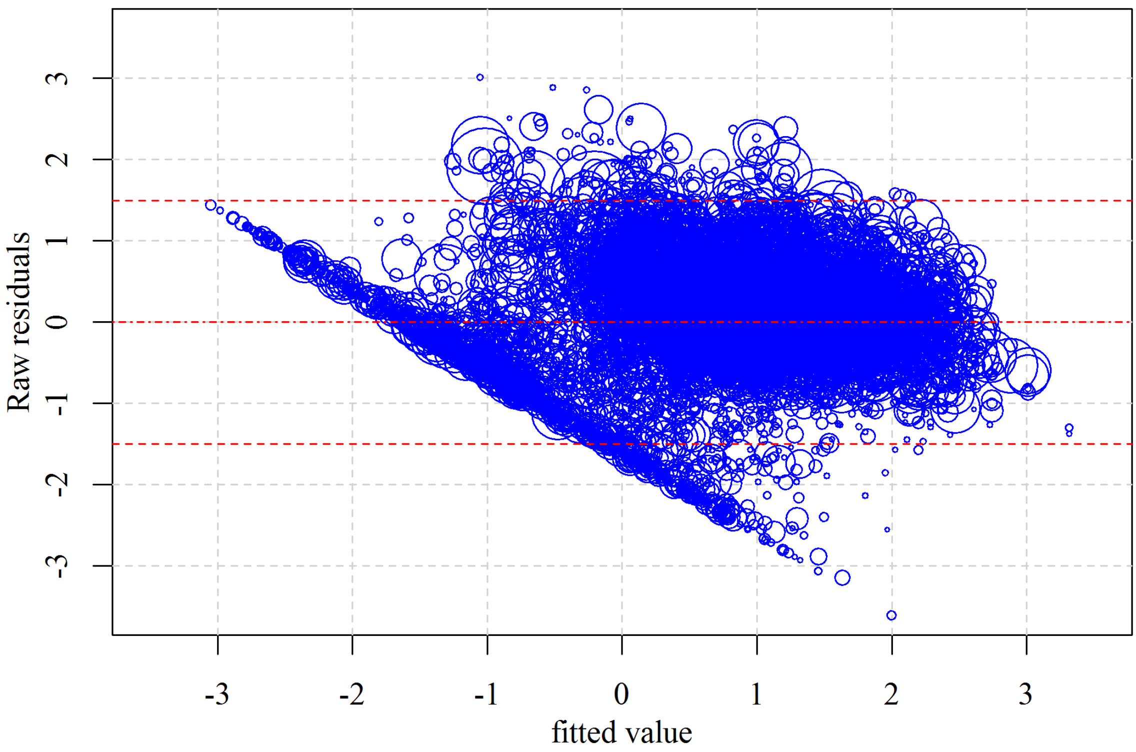


Figure 5 Raw residuals versus fitted values for the (a) random effects and (b) fixed effects models. Areas of plot characters are proportional to number of hooks set. Red horizontal lines are zero and +/- 1.96 standard deviations.

Calculation of area weighted abundance indices

Constant Squares and Variable Squares type indices

Given the fitted random effects model and area weighted indices, indices corresponding to the Variable Squares and Constant Squares assumptions can be calculated by adapting the approach described in Itoh et al. (2014).

$$\mathrm{CS}_{4+,y} = \sum_{m}\sum_{a}\sum_{l}(\mathrm{AI}_{\mathrm{CS}})_{(1969-2013)mal}\left[\exp\left(\mathrm{Intercept} + \mathrm{Year}_y + \mathrm{Month}_m + \mathrm{Area}_a + \mathrm{Lat5}_l + 1|\mathrm{Month}_m{:}\,\mathrm{Area}_a + 1\middle|\mathrm{Year}_y{:}\,\mathrm{Lat5}_l + 1\middle|\mathrm{Year}_y{:}\,\mathrm{Area}_a + {}^{\sigma^2}\!/_2\right) - 0.2\right]$$

$$\mathrm{VS}_{4+,y} = \sum_{m}\sum_{a}\sum_{l}(\mathrm{AI}_{\mathrm{VS}})_{ymal}\left[\exp\left(\mathrm{Intercept} + \mathrm{Year}_y + \mathrm{Month}_m + \mathrm{Area}_a + \mathrm{Lat5}_l + 1|\mathrm{Month}_m{:}\,\mathrm{Area}_a + 1\middle|\mathrm{Year}_y{:}\,\mathrm{Lat5}_l + 1\middle|\mathrm{Year}_y{:}\,\mathrm{Area}_a + {}^{\sigma^2}\!/_2\right) - 0.2\right]$$

Prediction with random effects

Fitting a lognormal model with random effects introduces further complexity in order to account for the random effects variance when the predictions of log CPUE are exponentiated. This might not matter too much in the calculation of the Constant Squares index, but does for the Variable Squares index. In the present paper this matter is addressed by simulating multiple replicates of predicted log CPUE from the fitted model, exponentiating the replicates and calculating the indices based on the mean of the exponentiated replicates.

Replicates of predicted log CPUE based on the variance-covariance matrix of fitted model were performed using the sim function (Gelman et al.) in R. Once the Constant Squares and Variable Squares indices have been calculated, the calculation of the weighted indices is straight forward. However, it is important to note that the Constant Squares and Variable Squares indices should be each rescaled to have the same average (e.g. an average of one).

$$(\mathrm{w}0.8)_y = 0.8\mathrm{CS}_y^* + 0.2\mathrm{VS}_y^*$$

$$(\mathrm{w}0.5)_y = 0.5\mathrm{CS}_y^* + 0.5\mathrm{VS}_y^*$$

Where CS_y^* and VS_y^* denote Constant Squares and Variable Squares index values where each index has been scaled to have a mean of 1.0. Full R code to calculate the indices is provided in Appendix C.

3 Results and Discussion

The calculated Constant Squares and Variable Squares series are shown in Figure 6. The indicated estimates of uncertainty are based on 500 replications generated by the sim function. The Constant Squares and Variable Squares indices have clearly diverged since 2007. The Variable Squares index in particular seems difficult to reconcile with recent trends in nominal CPUE. Alternative approaches for handling possible historic changes in the spatial distribution of SBT with regards to the CPUE inputs should be considered in the near future.

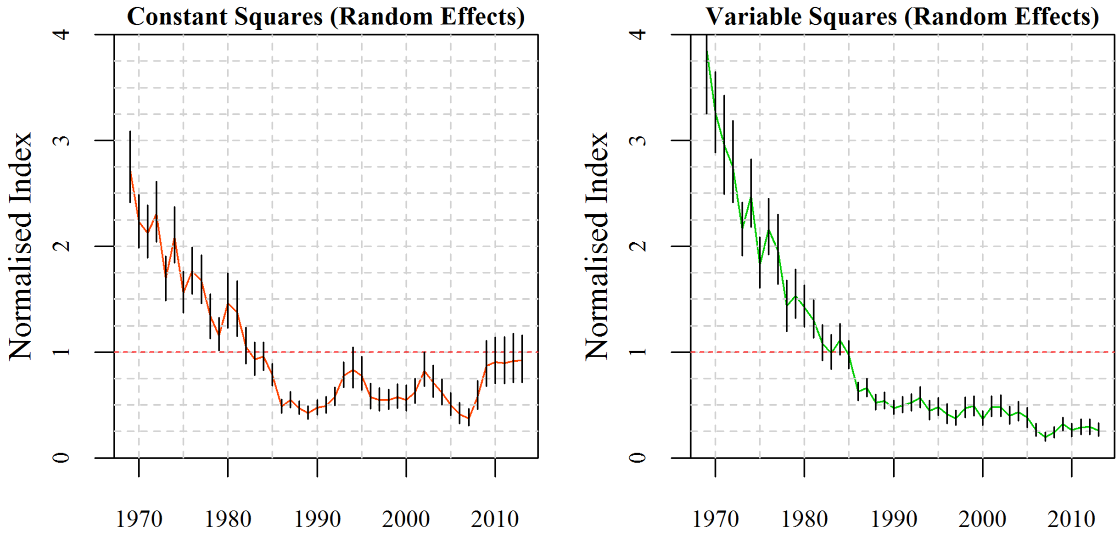


Figure 6 Constant Squares and Variable Squares indices based on the fitted random effects model scaled to average 1.0 over the interval 1969–2013.

Time series of annual summaries of the Variable Squares area weightings are given in Figure 7. The continuing low level of the Variable Squares index is driven by an overall decline in the Variable Squares index weightings. A restrictive TAC is likely to have contributed to this decline.

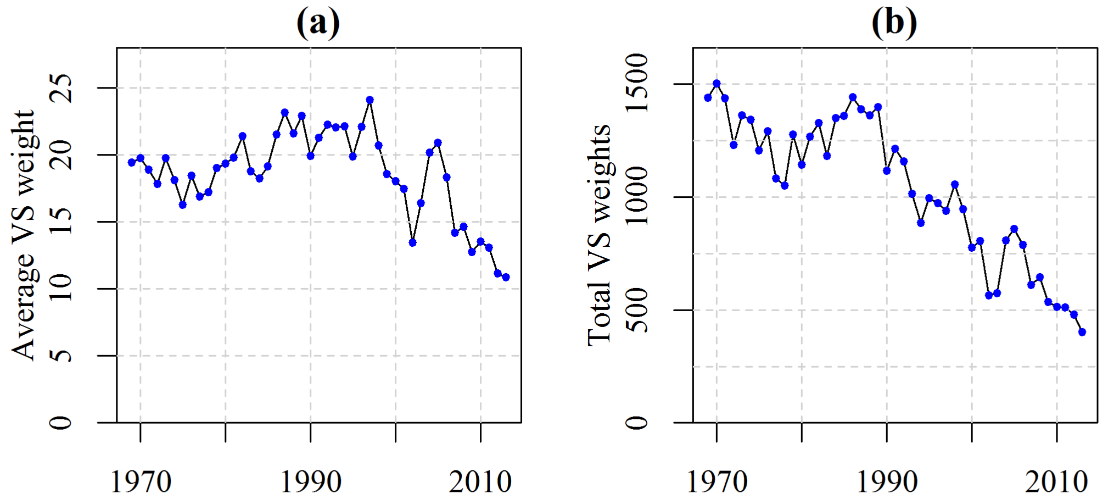


Figure 7 Average (a) and sum (b) of Variable Squares weights by year, 1969–2013.

Comparison of random effects based indices with other CPUE indices

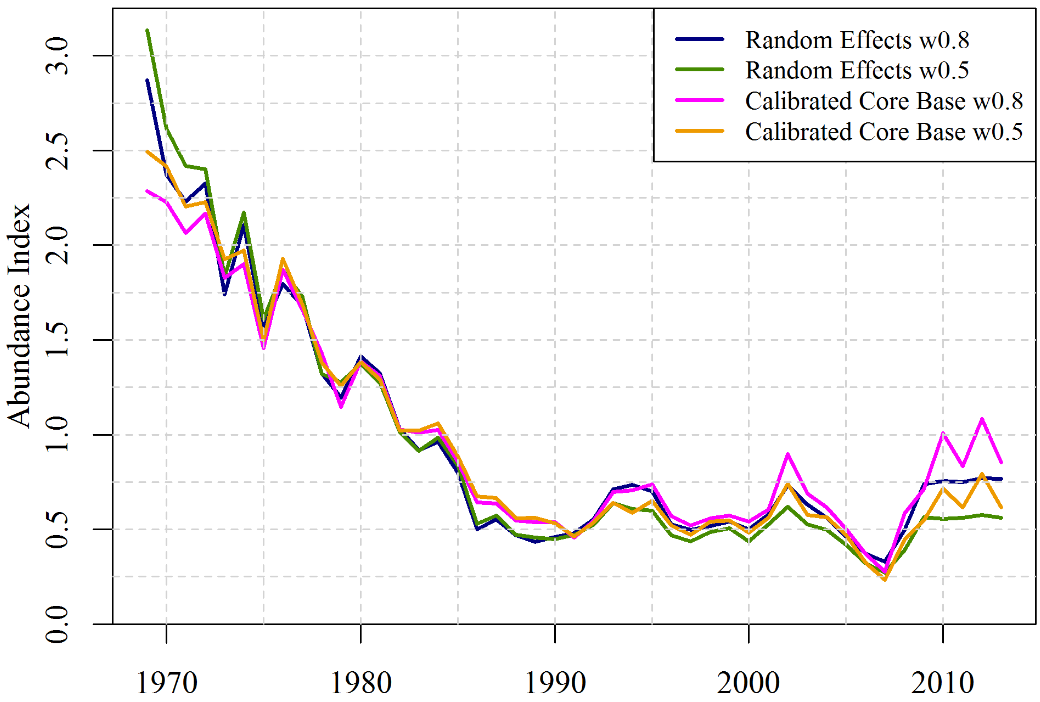


Figure 8 Weighted indices incorporating the Constant Squares and Variable Squares Area weightings. All indices have been scaled to have a mean of 1.0 over the interval 1969-2008.

The calibration of the Core vessel Base indices makes comparisons a little complicated. The calibrated indices each have a mean of 1 over the interval 1969 to 2008. Therefore we scale the random effects indices to also have this characteristic. For most of the interval 1969-2013, the four indices are in good agreement (Figure 8). However, variability between the indices has been greater over the last five or six years, partly due to the divergence of the Variable Squares and Constant Squares indices.

The historic values of the Core Base indices for the years 1969 to 1985 means that comparison with indices derived from the Base CPUE model is easier to interpret from1986 onwards. Overall the seven indices are similar over the period 1986 to 2013 (Figure 9). The random effects indices are a little smoother in recent years which might be due in part to more robust random effects estimation of interactions based on strata with few observations.

It is notable that the nominal CPUEs of the core fleet and the overall nominal CPUE are very similar (Figure 9). The trajectory of the nominal indices has continued to be positive over the last four years whereas the modelled indices are flatter over this period. At least in the case of the random effects indices this flatness is not entirely due to the effect of the Variable Squares weightings since the constant squares index is also flat over this interval, albeit at a higher level (Figure 6).

The set of area weighted indices are compared in Figure 10. The w0.8 indices are clearly higher than the corresponding w0.5 indices since about 2009. The variability of the indices based on the fixed effects model described in this paper over the last four years is intermediate between the random effects indices and the Base indices. It is possible that some of the difference between the random effects and Core Base indices is due to the bycatch terms which are included in the Base model but not the random effects model. The core vessel data might also be a little more variable than the overall data when effort is low. Nevertheless there is some suggestion that fitting the interactions as random effects produces an index that has been more stable in recent years.

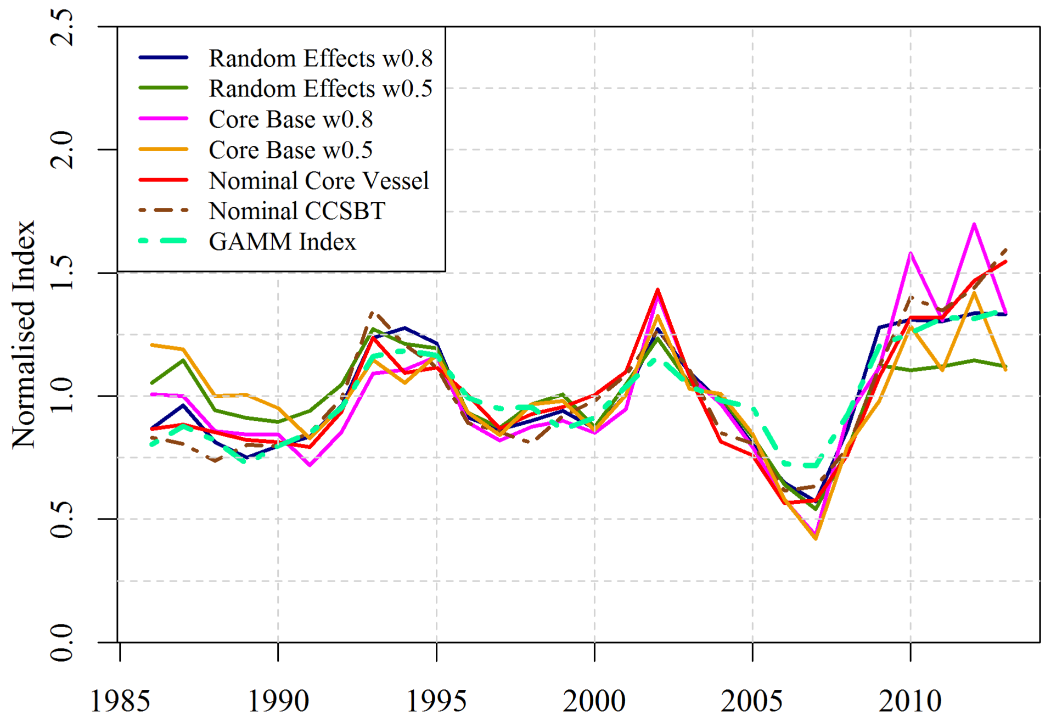


Figure 9 Alternative CPUE indices for SBT each scaled to have an average of 1.0 over the interval 1986–2013.

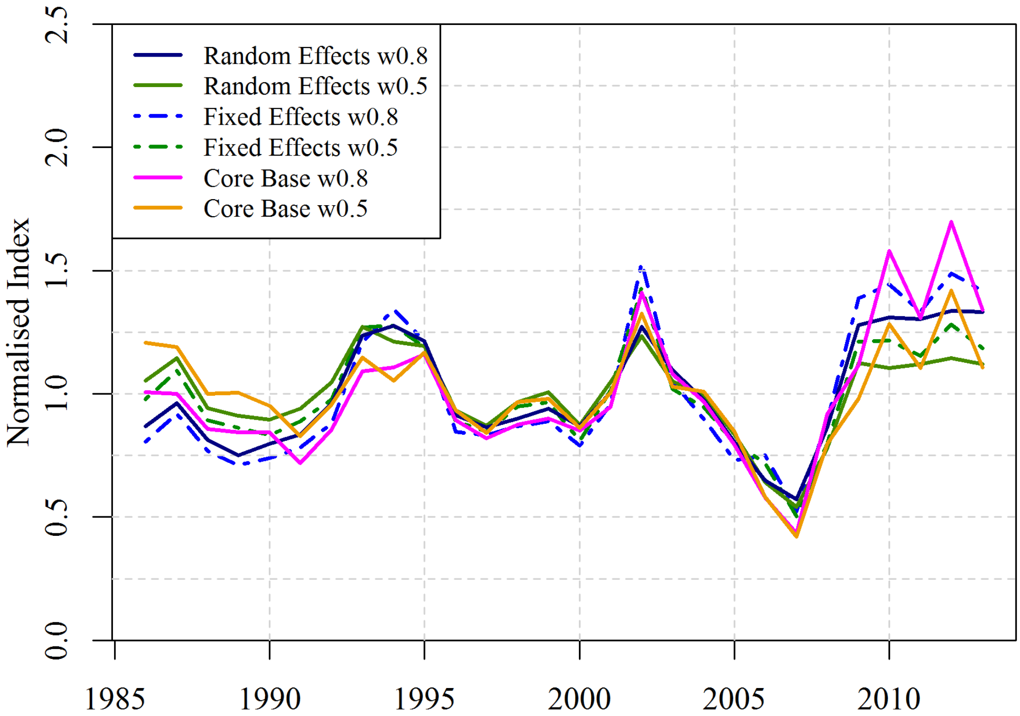


Figure 10 Area weighted model based CPUE indices for SBT. Each index is scaled to have an average of 1.0 over the interval 1986–2013.

Appendix A: Additional Diagnostics

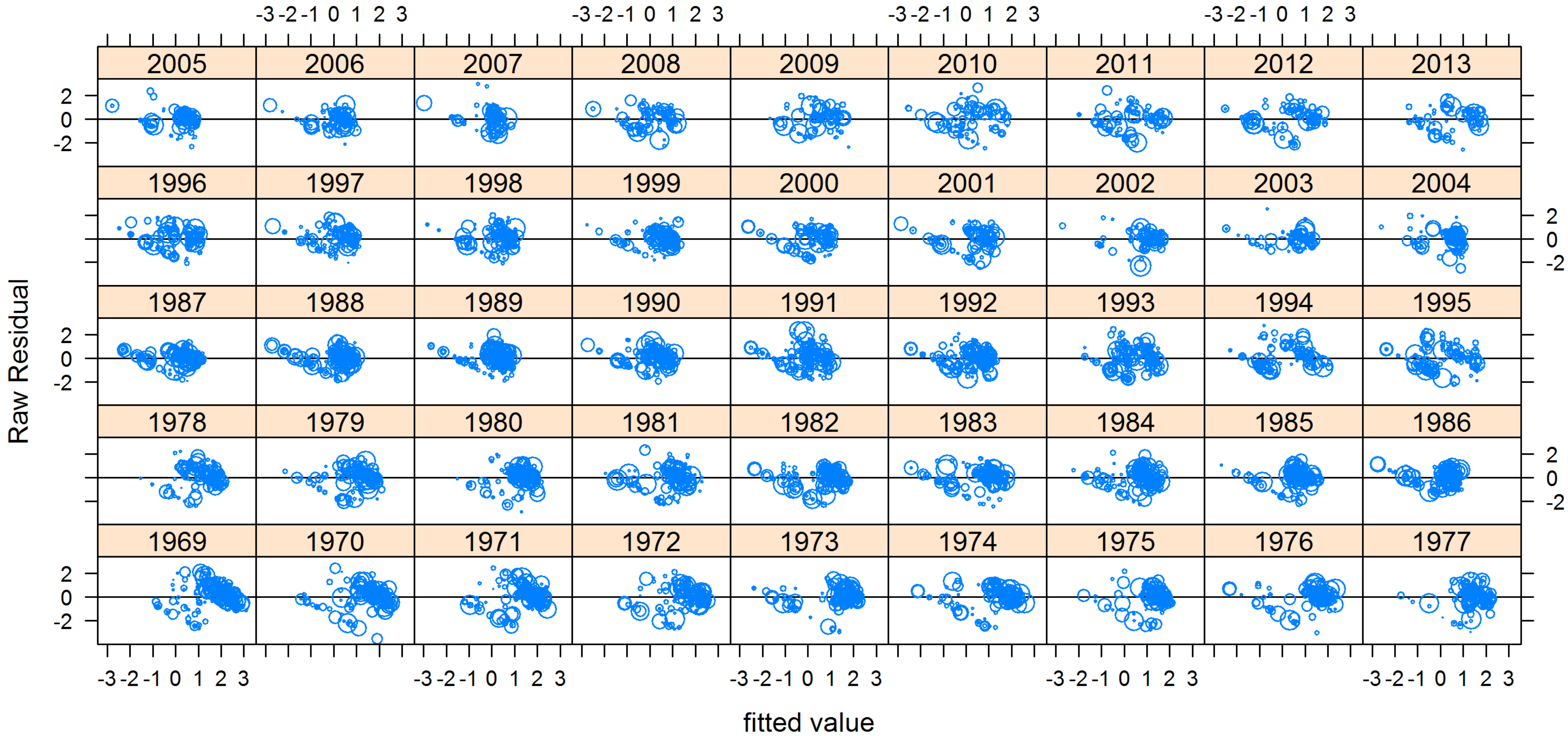


Figure 11 Residuals versus fitted values plotted by year. Plot character size proportional to number of hooks set.

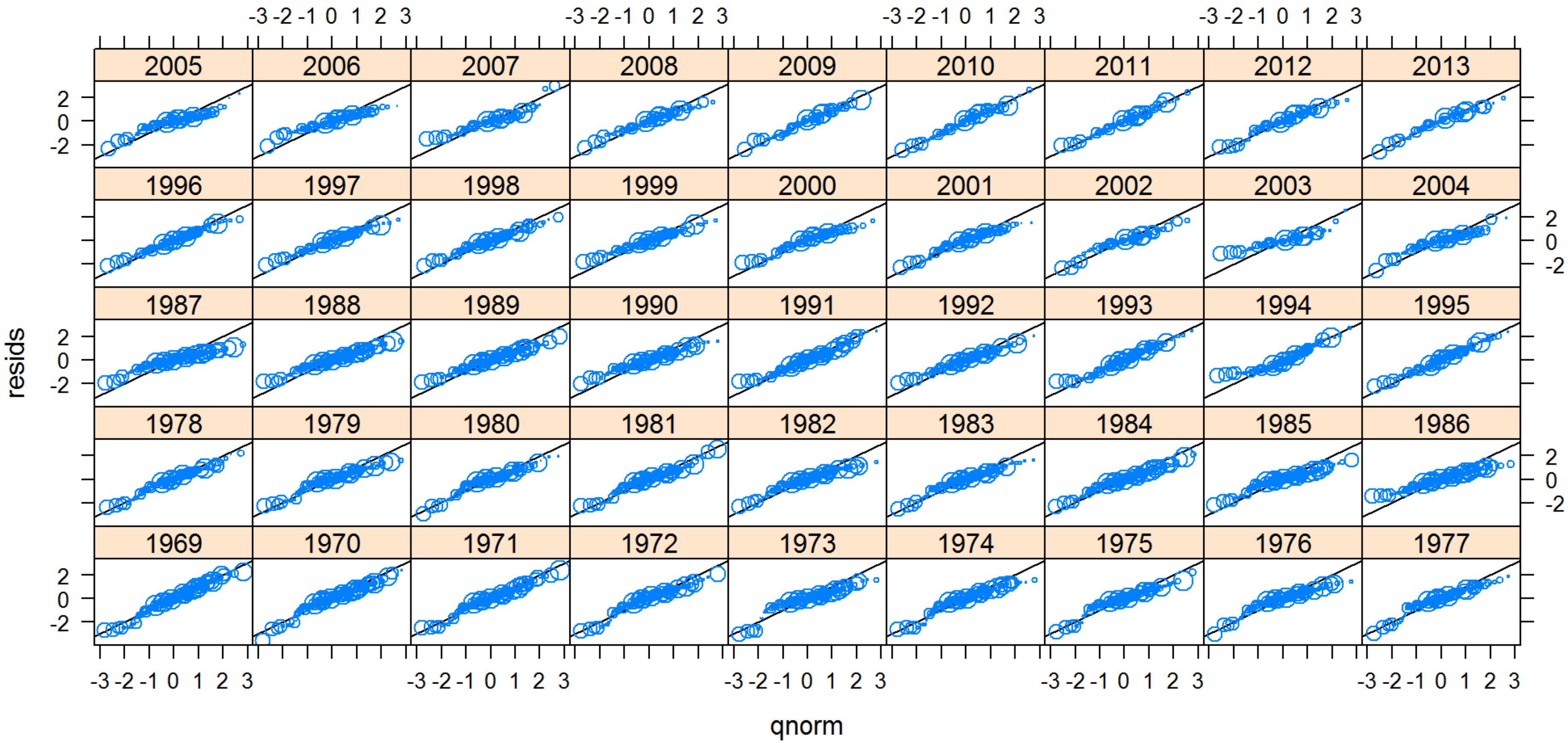


Figure 12 Quantile-quantile plots of residuals by year. Plot character size proportional to number of hooks set.

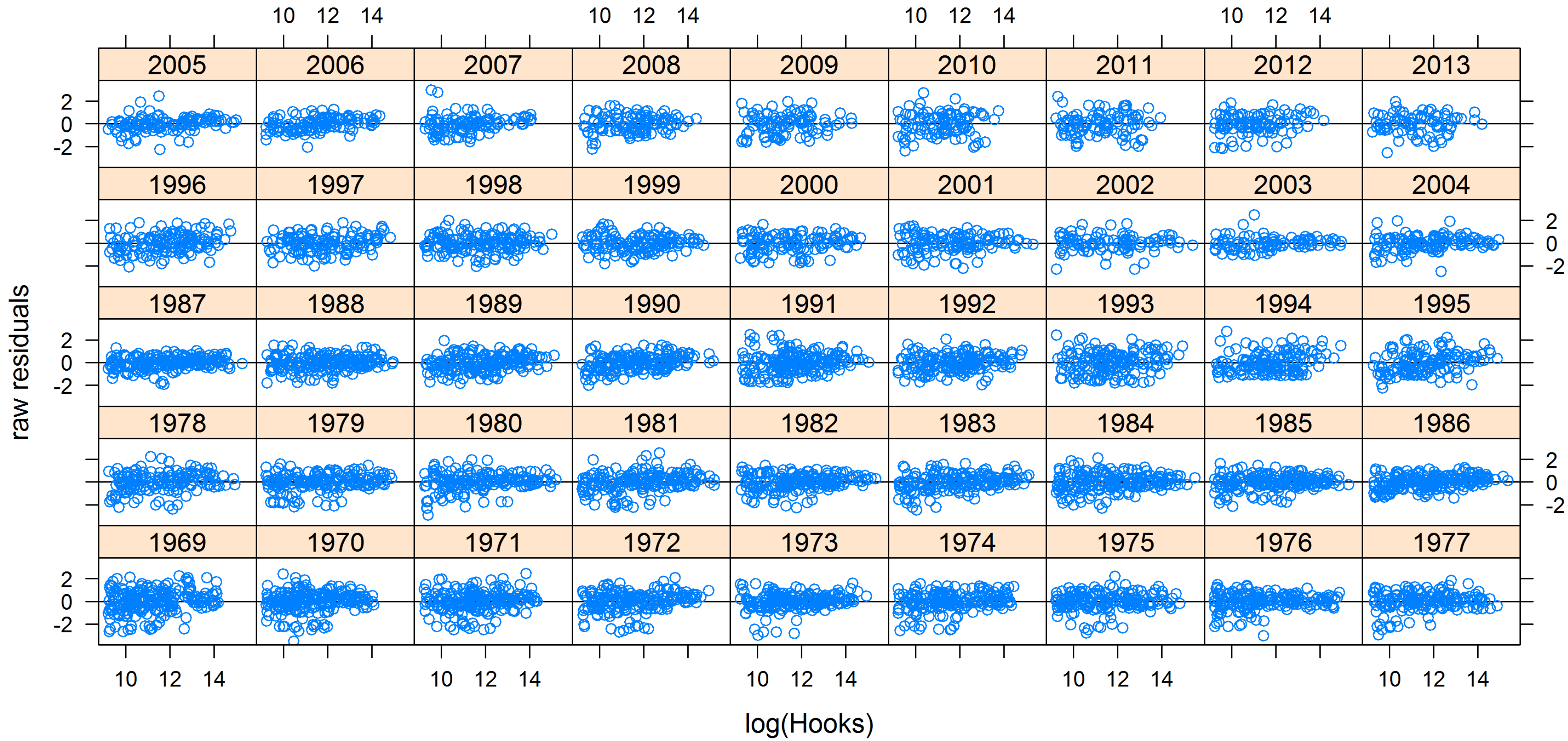


Figure 13 Observation residuals versus log transformed hooks set by year.

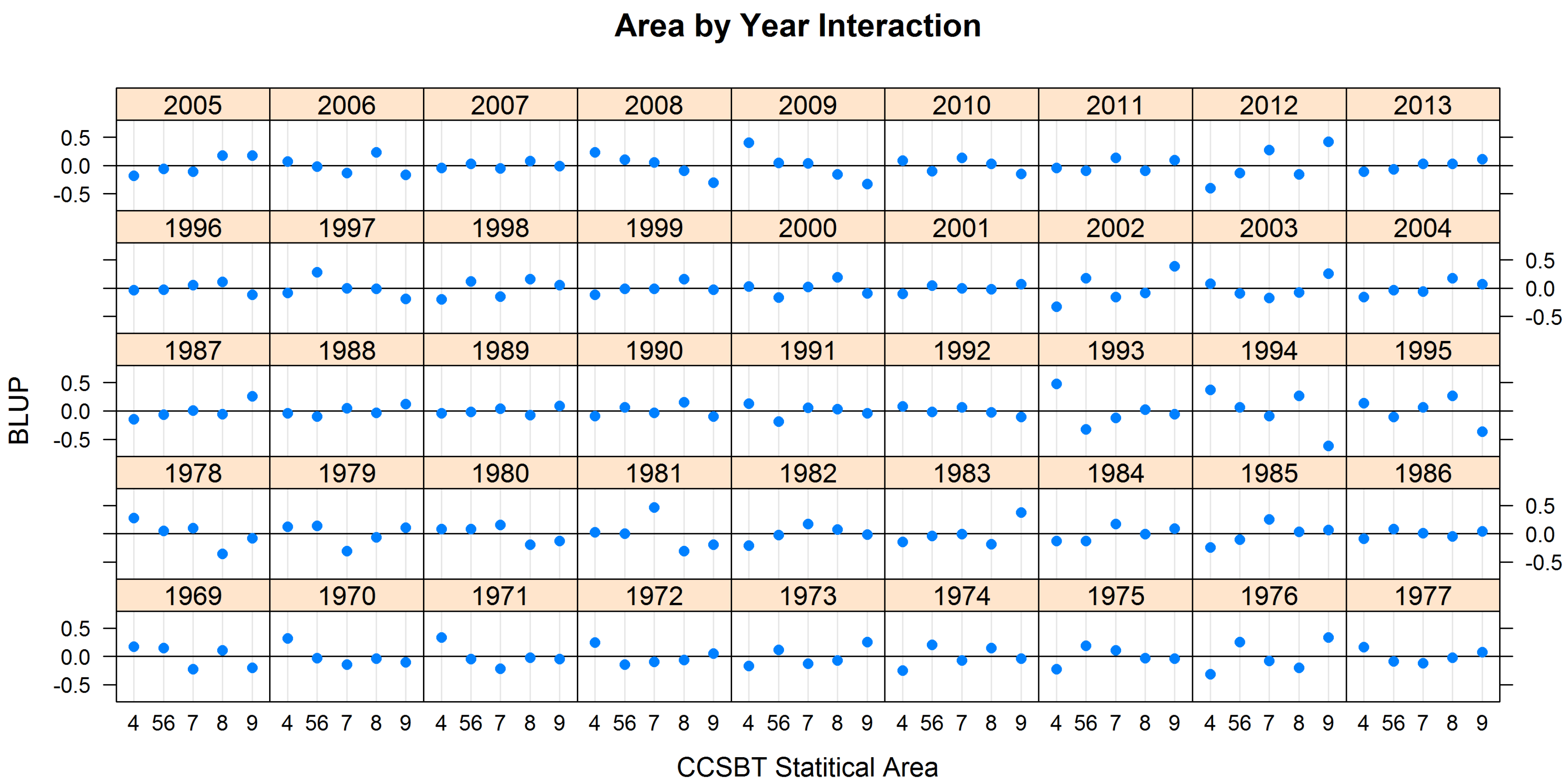


Figure 14 Predicted random Area-by-Year interaction effects plotted by year.

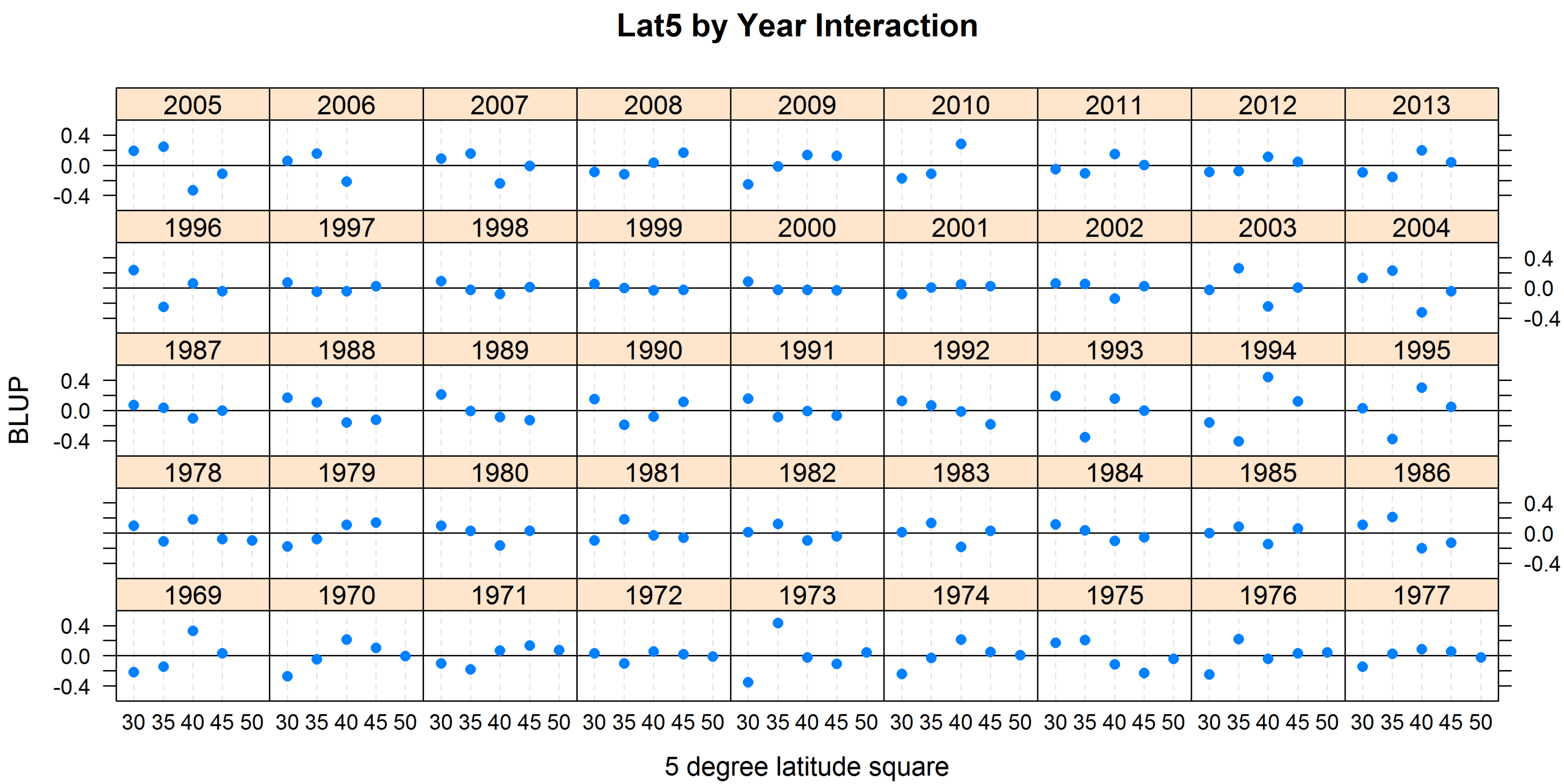


Figure 15 Predicted random Latitude-by-Year interaction effects plotted by year.

Appendix B: R Code

```
library(lme4);library(RODBC);library(arm)
### Load the Catch and Effort Data ###
setwd("C:\\SEC_CPUEInputs_6513_Revised") # folder with CCSBT CPUE database
SBT.2014 <- odbcConnectAccess("CPUEInputs_6513_Revised.mdb")
CPUE.2014 <- sqlFetch(SBT.2014, "CPUE_INPUTS")
CPUE.2014 <- CPUE.2014[CPUE.2014$DATA_CODE == "COMBINED",] # avoid double counting
CPUE.2014$YEAR.F <- as.factor(CPUE.2014$YEAR)
Sum.4plus <- function(X)
{
Four.Plus <- as.numeric(X[16:32])
SBT.4plus <- round(sum(Four.Plus),digits = 3)
return(SBT.4plus)
}
CPUE.2014$SBT.4plus <- apply(CPUE.2014,1,Sum.4plus)
CPUE.2014$CPUE <- 1000*CPUE.2014$SBT.4plus/CPUE.2014$N_HOOKS
###----- Exclude records from Areas 1,2,3,10,11,12 and 13 ----###
CPUE.2014 <- CPUE.2014[CPUE.2014$STAT_AREA_CODE %in% c(4,5,6,7,8,9) &
CPUE.2014$N_HOOKS >= 10000,]
CPUE.2014$SBT_AREA <- ifelse(CPUE.2014$STAT_AREA_CODE %in%
c(5,6),"56",CPUE.2014$STAT_AREA_CODE)
CPUE.2014$SBT_AREA <- as.factor(CPUE.2014$SBT_AREA)
CPUE.2014$log.CPUE <- log(CPUE.2014$CPUE + 0.2)
CPUE.2014 <- CPUE.2014[CPUE.2014$YEAR >= 1969 & CPUE.2014$YEAR <= 2013,]
CPUE.2014$YEAR.F <- as.factor(CPUE.2014$YEAR)[,drop = TRUE]
CPUE.2014 <- CPUE.2014[CPUE.2014$MONTH %in% c(4,5,6,7,8,9),]
CPUE.2014$MONTH.F <- as.factor(CPUE.2014$MONTH)[,drop = TRUE]
CPUE.2014 <- CPUE.2014[CPUE.2014$LAT > -50,]
CPUE.2014$LAT.5 <- as.factor(abs(CPUE.2014$LAT))[,drop = TRUE]
###-------------------------------------------- Fit GLMM ---------------------------------------------###
BASE.GLMM <- lmer(log.CPUE ~ YEAR.F + MONTH.F + SBT_AREA + LAT.5 +
(1|SBT_AREA:YEAR.F) + (1|SBT_AREA:MONTH.F) + (1|LAT.5:YEAR.F),data = CPUE.2014)
BASE.MSE <- attr(summary(BASE.GLMM),"sigma")^2
BASE.GLMM.sim <- sim(BASE.GLMM,500) # simulate 500 model fits
###--------------- Load Area Weights  and Make Data Frames for Prediction-----------------###
CS <- read.table("aridx_cs_2014SC.prn",header = TRUE)
VS <- read.table("aridx_vs_2014SC.prn",header = TRUE)
names(VS) <- c("YR","Q","MO","A","LAT","AI")
names(CS) <- c("Q","MO","A","LAT","AI")
CS <- CS[CS$LAT <50,]
VS <- VS[VS$LAT < 50,]
Years.Covered <- rownames(table(VS$YR))

CS.Preds <- data.frame(YEAR.F = sort(rep(Years.Covered,nrow(CS))),MONTH.F =
as.factor(rep(CS$MO,length(Years.Covered))),
SBT_AREA = factor(rep(CS$A,length(Years.Covered)),levels = c("4","56","7","8","9")),
LAT.5 = as.factor(rep(CS$LAT,length(Years.Covered))),Area.Index =
rep(CS$AI,length(Years.Covered)))
```

```
CS.Preds$log.CPUE <- 0
RanEfs <- ranef(BASE.GLMM)
Area.Year <- expand.grid(levels(CS.Preds$SBT_AREA),levels(CS.Preds$YEAR.F))
names(Area.Year) <- c("SBT_AREA","YEAR.F")
Area.Year <- Area.Year[order(Area.Year$SBT_AREA),]
Area.Month <- expand.grid(levels(CS.Preds$SBT_AREA),levels(CS.Preds$MONTH.F))
names(Area.Month) <- c("SBT_AREA","MONTH.F")
Area.Month <- Area.Month[order(Area.Month$SBT_AREA),]
Lat.Year <- expand.grid(levels(CS.Preds$LAT.5),levels(CS.Preds$YEAR.F))
names(Lat.Year) <- c("LAT.5","YEAR.F")
Lat.Year <- Lat.Year[order(Lat.Year$LAT.5),]
CS.Norm.Matrix <- matrix(0,nrow = 500,ncol = 45)
CS.MM <- model.matrix(terms(BASE.GLMM),CS.Preds)
VS.Preds <- data.frame(YEAR.F = as.factor(VS$YR),MONTH.F = as.factor(VS$MO),SBT_AREA =
as.factor(VS$A),LAT.5 = as.factor(VS$LAT),Area.Index = VS$AI)
VS.Preds$log.CPUE <- 0
VS.MM <- model.matrix(terms(BASE.GLMM),VS.Preds)
VS.Norm.Matrix <- matrix(0,nrow = 500,ncol = 45)

for (i in 1:nrow(CS.Norm.Matrix))
{
CS.Preds$log.CPUE <- CS.MM %*% BASE.GLMM.sim@fixef[i,]
Area.Year$AY <- BASE.GLMM.sim@ranef[[1]][i,,]
Lat.Year$LY <- BASE.GLMM.sim@ranef[[2]][i,,]
Area.Month$AM <- BASE.GLMM.sim@ranef[[3]][i,,]
These.CS.Preds <- merge(CS.Preds,Area.Year,by = c("SBT_AREA","YEAR.F"),all = TRUE)
These.CS.Preds <- merge(These.CS.Preds,Area.Month,by = c("SBT_AREA","MONTH.F"),all =
TRUE)
These.CS.Preds <- merge(These.CS.Preds,Lat.Year,by = c("LAT.5","YEAR.F"),all = TRUE)
These.CS.Preds$CPUE.Preds <- exp(These.CS.Preds$log.CPUE + These.CS.Preds$AY +
These.CS.Preds$AM + These.CS.Preds$LY + BASE.MSE/2) - 0.2
These.CS.Preds$Weighted.Pred <- These.CS.Preds$CPUE.Preds*These.CS.Preds$Area.Index
CS.Raw.Series <- tapply(These.CS.Preds$Weighted.Pred,These.CS.Preds$YEAR.F,sum)
CS.Norm.Matrix[i,] <- CS.Raw.Series/mean(CS.Raw.Series)
VS.Preds$log.CPUE <- VS.MM %*% BASE.GLMM.sim@fixef[i,]
These.VS.Preds <- merge(VS.Preds,Area.Year,by = c("SBT_AREA","YEAR.F"),all = TRUE)
These.VS.Preds <- merge(These.VS.Preds,Area.Month,by = c("SBT_AREA","MONTH.F"),all =
TRUE)
These.VS.Preds <- merge(These.VS.Preds,Lat.Year,by = c("LAT.5","YEAR.F"),all = TRUE)
These.VS.Preds$CPUE.Preds <- exp(These.VS.Preds$log.CPUE + These.VS.Preds$AY +
These.VS.Preds$AM + These.VS.Preds$LY + BASE.MSE/2) - 0.2
These.VS.Preds$Weighted.Pred <- These.VS.Preds$CPUE.Preds*These.VS.Preds$Area.Index
VS.Raw.Series <- tapply(These.VS.Preds$Weighted.Pred,These.VS.Preds$YEAR.F,sum)
VS.Norm.Matrix[i,] <- VS.Raw.Series/mean(VS.Raw.Series)
}
CS.Norm.Mean <- apply(CS.Norm.Matrix,2,mean)
CS.Norm.Upper <- apply(CS.Norm.Matrix,2,quantile,0.975)
CS.Norm.Lower <- apply(CS.Norm.Matrix,2,quantile,0.025)
VS.Norm.Mean <- apply(VS.Norm.Matrix,2,mean)
VS.Norm.Upper <- apply(VS.Norm.Matrix,2,quantile,0.975)
```

```
VS.Norm.Lower <- apply(VS.Norm.Matrix,2,quantile,0.025)
w08.Matrix <- 0.8*CS.Norm.Matrix + 0.2*VS.Norm.Matrix
w05.Matrix <-  0.5*CS.Norm.Matrix + 0.5*VS.Norm.Matrix
w08.mean <- apply(w08.Matrix,2,mean)
w08.upper <- apply(w08.Matrix,2,quantile,0.975)
w08.lower <- apply(w08.Matrix,2,quantile,0.025)
w05.mean <- apply(w05.Matrix,2,mean)
w05.upper <- apply(w05.Matrix,2,quantile,0.975)
w05.lower <- apply(w05.Matrix,2,quantile,0.025)
```

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