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Exploration of the Laslett Core Area CPUE Index

Statistical Smoothing of CPUE

Mark Chambers

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Department of Agriculture, Fisheries and Forestry
Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES)
Postal address GPO Box 1563 Canberra ACT 2601
Switchboard +61 2 6272 2010|
Facsimile +61 2 6272 2001
Email info.abares@daff.gov.au
Web daff.gov.au/abares

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Summary

A number of CPUE indices are monitored by the Scientific Committee of the CCSBT as indicators of the relative abundance of southern bluefin tuna in age classes harvested by international longline fleets. In recent years the level of agreement between these indices has reduced, raising concerns about the reliability of the indices, particularly those used as inputs into the operating model which estimates current biomass and is used to make projections of future spawning stock biomass. A number of recommendations aimed at addressing these concerns were made at the meeting of the CPUE Modelling Working Group in Bali in September 2011. At a subsequent webinar held in April 2012 it was recommended that the Laslett Core Area (LCA) CPUE model be applied to the areas and months used to calculate the ST Windows CPUE index. This document describes the results of this analysis.

The original paper (Laslett, 2001) outlining the LCA CPUE index describes a particular regression spline fitted to annual modelled CPUE index values. In this way annual relative abundance can be estimated by the spline evaluated in the year of interest and the unsmoothed, modelled CPUE values around their fitted values provide an indication of the precision of the underlying CPUE model. The merit of smoothing annual modelled CPUE index values is explored further. A change of the CPUE index used for the management procedure is definitely not recommended, but a smoother CPUE index might have advantages for future stock assessment and for projections of future spawning stock biomass.

Generalised additive models (GAMs) are also considered as a method of deriving CPUE indices for SBT that facilitates spatial and temporal smoothing of observed CPUE. Two alternative GAM models are fitted to SBT catch and effort data and these are used to calculate a range of indices to further investigate the cause of differences between the LCA and ST-Windows CPUE indices.

Exploratory modelling described in this report suggests recently observed differences of the level of the LCA CPUE index and the ST-Window index are due to an increase in southern bluefin tuna CPUE in Statistical Area 7 relative to Statistical Area 8 and Statistical Area 9 as well as to a decrease in the number of 5-degree cells fished in Statistical Area 8 and Statistical Area 9. These two factors appear to contribute to the observed difference in roughly equal measure.

1 Introduction

Alternative CPUE indices for SBT considered by the Extended Scientific Committee have diverged in recent years (Figure 1, Figure 2). At the meeting of the CPUE Modelling Working Group at the 16th meeting of the Scientific Committee in Bali (Anon. 2011, Attachment 5) it was agreed that a better understanding of the causes of the observed differences between the CPUE indices was desirable. The usefulness of investigating the effect of using the Laslett Core Area (LCA) model to predict CPUE on the ST-Windows domain was raised at a CPUE Working Group webinar in April 2012. A range of models are fitted to CPUE to investigate the cause of differences between observed levels of CPUE suggested by the LCA index and the ST-Windows index. Model summaries are included in this report.

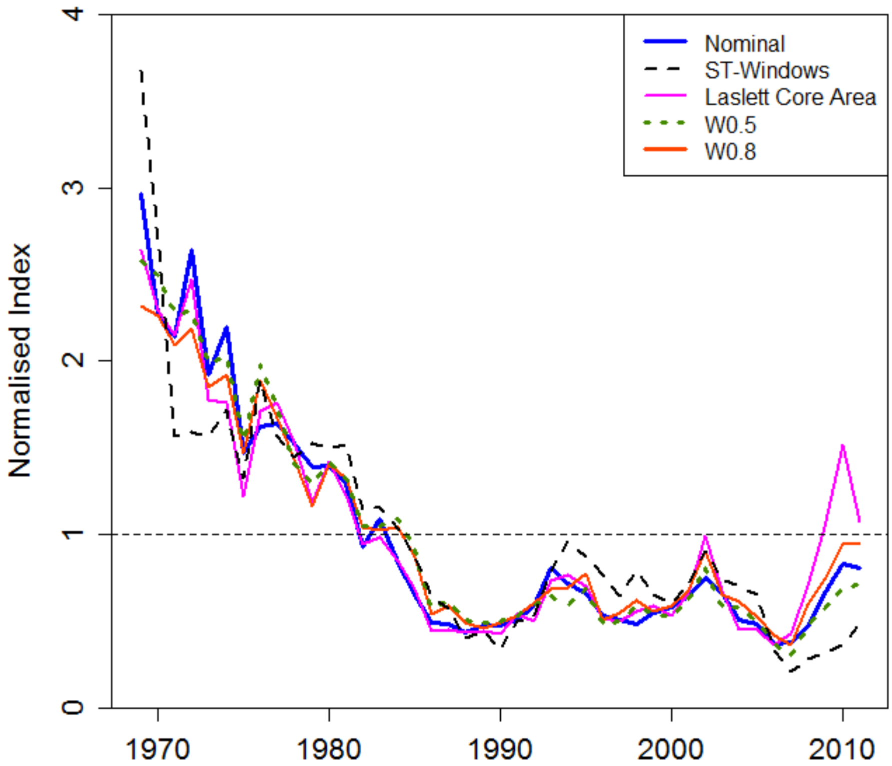


Figure 1: CPUE indices monitored by the ESC. All indices are normalised to have a mean of unity.

Data source: CCSBT

Laslett (2001) describes a procedure to smooth annual modelled index values. The effect of applying the specified smooth to CPUE indices for SBT is examined here.

The development of improved statistical methods in recent years has led to increased flexibility in methods available to model catch and effort data. Generalised Additive Models (GAMs) are similar to the model used to calculate the LCA CPUE index and have been used to model CPUE for other fish stocks. In response to inter-sessional discussion between members of the CPUE Modelling Working Group the use of generalised additive models (GAMs) to model CPUE for SBT is also investigated.

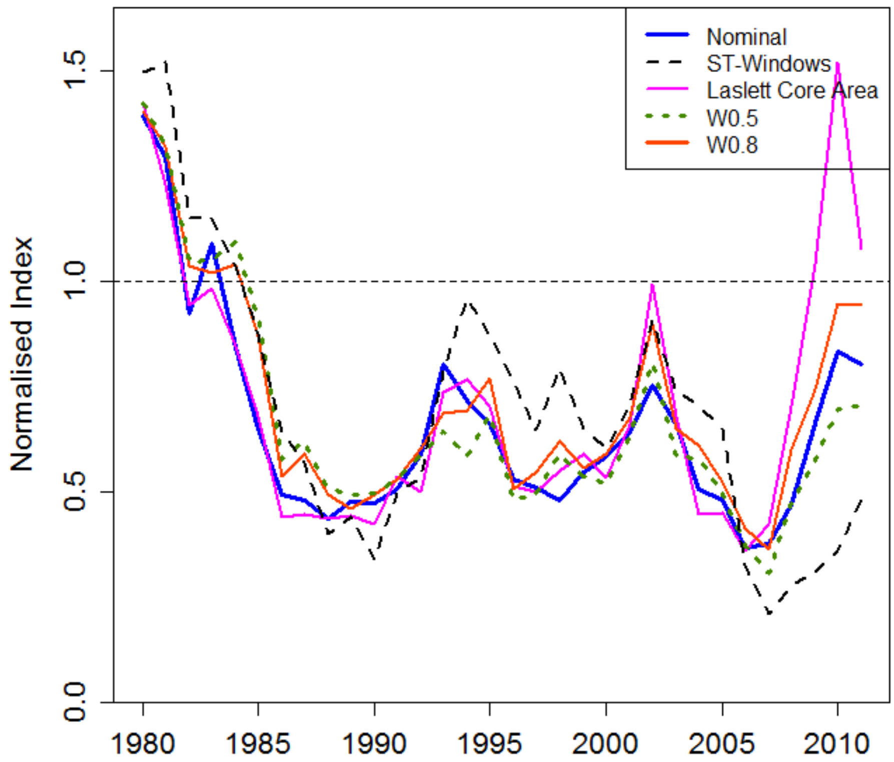


Figure 2: CPUE indices monitored by the ESC (1980-2011). All indices are normalised to have a mean of unity between 1969 and 2011.

Data source: CCSBT

2 The Laslett Core Area CPUE Index

There appear to be some misconceptions around the issue of data subsetting for the calculation of the LCA index. Laslett (2001, p. 7) intended that all available CPUE be used each year to model CPUE jointly as a smooth function of latitude, longitude and month. The 'Core Area' part of the name comes from the cells for which CPUE is predicted using the fitted model.

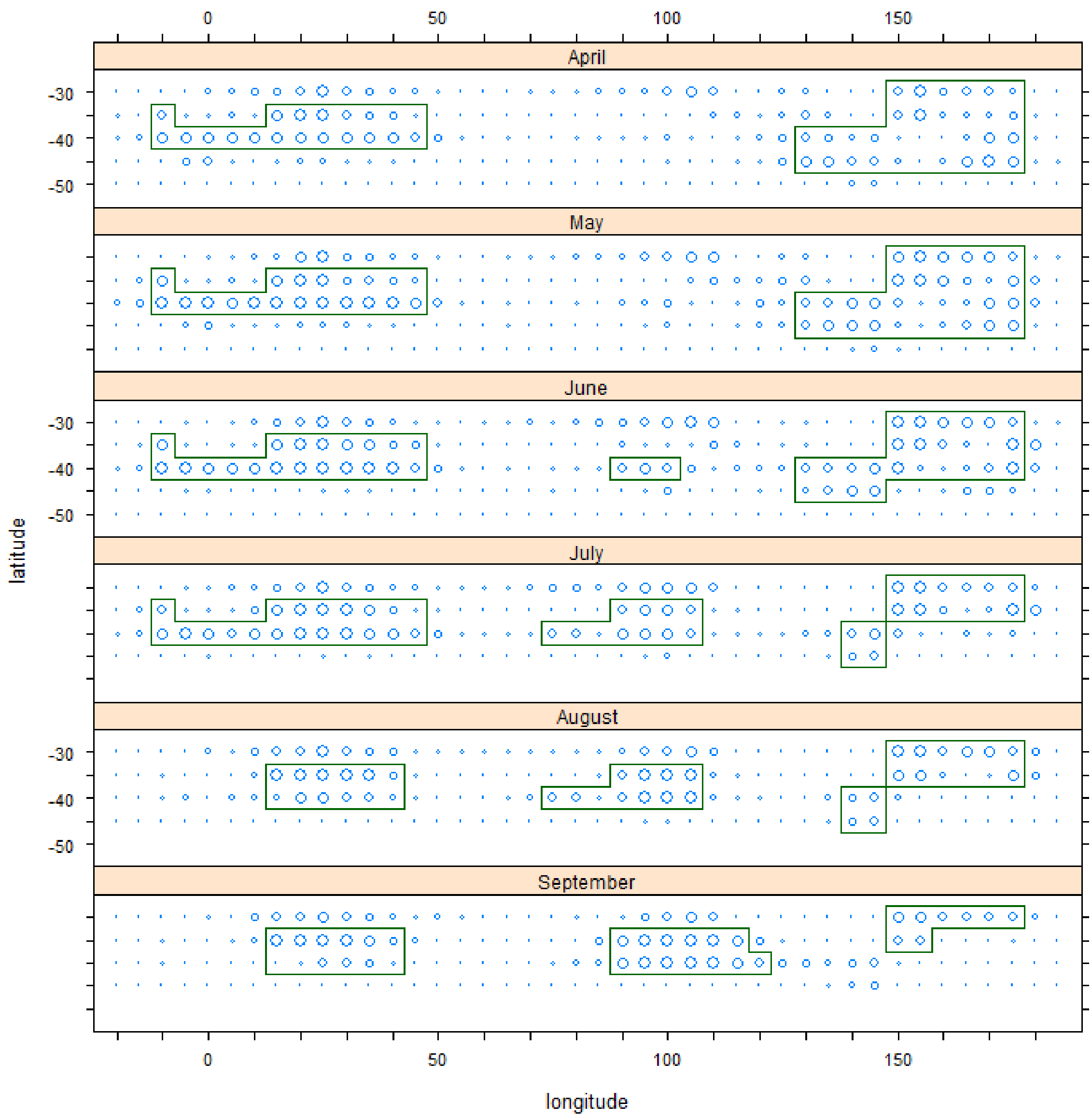


Figure 3: Plot of frequency of proportion of years fished for 5 degree × month grid squares (1969-1997). Circle area proportional to proportion of years between 1969 and 1997 with hooks > 0. Cells used to calculate the Laslett Core Area CPUE index are defined by the green polygons.

Data source: CCSBT

Laslett (2001) specified the domain for which predicted CPUE would be considered to include areas that had been reliably fished up until 1997 such that CPUE could be expected to be reasonably well estimated for each cell considered each year. The index incorporates predicted CPUE from April to September with the 5-degree cells of latitude and longitude predicted varying between months (Figure 3). In total, CPUE is predicted for 272 cells each year. It is the average of these predicted CPUE values that forms the basis of each annual index value of the LCA index. A full description of the LCA index is provided in CCSBT-SC/0103/06 (Laslett, 2001), also available on the private area of the CCSBT website (posted information paper CPUE2012_Info05 with the CPUE webinar of April 2012).

Laslett (2001) advised that if the spatial distribution of effort changed substantially such that there was little data support for parts of the core area, the reliability of the index might need to be re-examined. The coarseness of the modelled CPUE data potentially affects the reliability of the spline model used to calculate the LCA index. The small number of unique latitude values in particular is not ideal. Availability of the data at a finer spatial scale, even aggregated at a 2.5-degree grid square level, would likely lead to a considerable improvement in performance.

3 ST-Windows CPUE Index

The ST-Windows index considers catch and effort from 5×5 degree grid squares from within CCSBT Statistical Area 9 in the months of May and June and from within Statistical Area 8 in the months of September and October (See Map 1). Average CPUE in each candidate 5×5 degree cell are multiplied by the number of 1×1 degree cells fished in that 5×5 degree cell and the yearly sum of these products forms the basis of the ST-Windows index. The series is normalised by dividing each annual index value by the index mean (Takahashi, pers. comm.). The number of 5×5 degree cells fished in the ST-Win specified domain is shown in Figure 4. The number of 1×1 degree cells fished in these cells was not easily available and is not considered here.

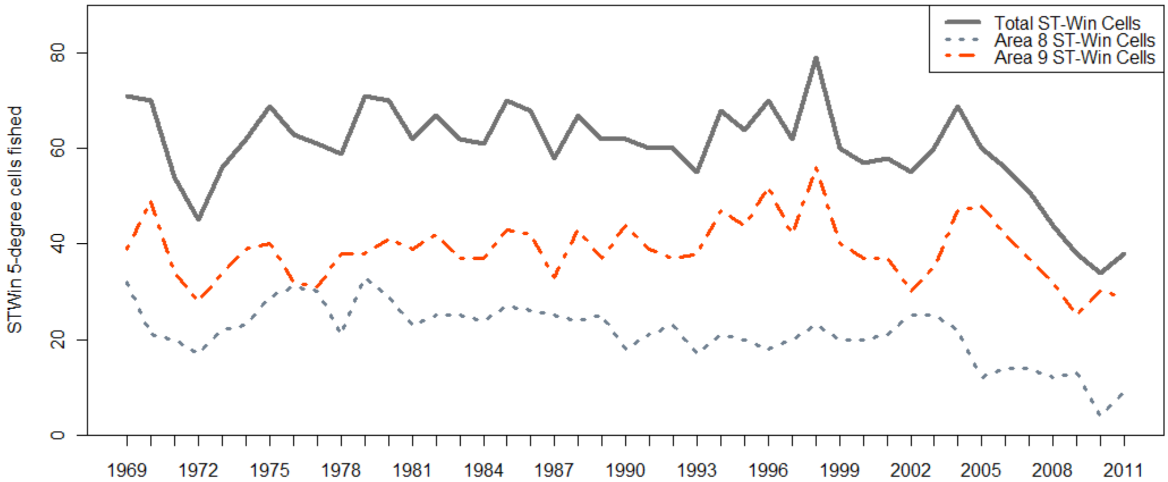


Figure 4: Number of 5-degree cells in ST-Windows domain fished annually.

Changes in the pattern of fishing of the Japanese longline fleet since 2006 have been described by Itoh (2011). The number of 5-degree cells fished that are considered for the calculation of the ST-Windows CPUE index has decreased by almost 50 percent in this time (Figure 4). If the spatial distribution of the SBT stock has not contracted to the same extent in this period, the ST-Windows index would be expected to exaggerate any decline in abundance that might have occurred at the same time, assuming CPUE is proportional to local SBT density in fished cells. The sharp dip in ST-Windows cells fished between 1971 and 1973 (Figure 4) is also seen to correlate with a period where the ST-Win index decreases much more sharply than the other indices (Figure 1).

4 Laslett Predicted ST-Windows

There is a considerable difference between the assumptions about the density of unfished cells in Statistical area 9 in April and May and Statistical Area 8 in September and October implicit in the nature of the ST-Windows and LCA CPUE indices. The ST-Win index assumes there are no SBT in these cells, whereas the LCA index assumes the density of SBT in these cells is dependent on latitude, longitude and month and this relationship can be modelled on CPUE in fished cells in the same year.

Given the differences between the LCA and the ST-Windows CPUE indices, there are a number of ways that the task of fitting the Laslett index to the ST-Windows domain could be interpreted.

1) Use the Laslett CPUE model to predict CPUE in all 5×5 degree cells in Area 9 in May and June and in Area 8 in September and October and calculate the annual index as the simple average (mean) of these predicted values.

2) Use the Laslett CPUE model to predict CPUE each year in only the 5×5 degree cells fished in that year and then calculate the annual index as the simple average (mean) of the fitted values.

It would seem that the spirit of the ST Windows index is closest to the first option. However, it is likely that predictions for grid squares that are very far from areas fished would not be well estimated. In other words, this index is likely to suffer from unreliable prediction and be affected by changes in the distribution of longline fishing effort. There seems to be little point in predicting CPUE south of 50°S given there has been almost no recorded catch from these latitudes. The second alternative has the advantage that catch rates are likely to be better estimated in the grid squares that were actually fished, but does not address the possibility that the spatial distribution of the exploitable SBT stock might have decreased over time.

The procedure used to calculate the LCA index makes changing the domain used for prediction each year inconvenient. Consequently we choose to define the ST-Windows domain to be defined to include all 5×5 degree cells within Area 9 in May and June and all in all 5×5 degree cells within Area 8 in September and October (option 1 above). No cells south of 50°S are considered. This area is held fixed each year irrespective of the cells fished.

The same model used to predict CPUE for the LCA index is used to predict CPUE on the fixed ST-Win domain described. A CPUE index is calculated as the annual mean of predicted CPUE values across this fixed domain. It is perhaps not surprising that the resulting index is usually a compromise between the LCA and ST-Windows indices (Figure 5). This new index, labelled, Laslett Predicted ST-Win Fixed, estimates CPUE to be extremely high in 1969. The fact that the ST-Windows CPUE index is more extreme in 1969 than the LCA index might suggest that catch rates were high in Statistical Areas 8 and 9 in this year, relative to other Statistical Areas.

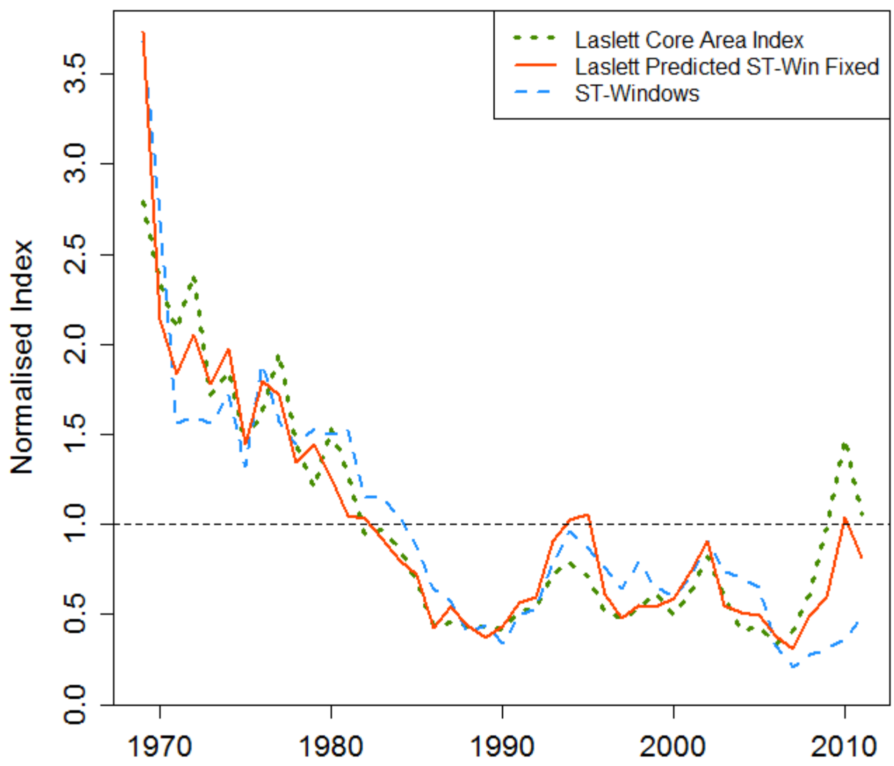


Figure 5: Comparison of Laslett Core Area CPUE index, ST-Windows index and Index based on Laslett model predicted CPUE in the ST-Windows domain.

Table 1: Explanation of CPUE indices compared in Figure 5.

Index	CPUE Model	Calculation Domain
Laslett Core Area Index	Laslett spline model	Laslett Core Area
Laslett Predicted ST-Win Fixed	Laslett spline model	All ST-Windows Cells
ST-Windows Index	Weighted Nominal	Fished ST-Windows Cells

An index derived from predicting CPUE on only fished cells in the ST-Win domain each year is not considered here. An index of this type, derived from a generalised additive model (GAM) is provided later.

5 Smoothing Modelled CPUE Indices

An aspect of Laslett's original index that seems to have been omitted from the index values presented to the ESC in recent years is the final smoothing of the individual index values. Laslett (2001, Equation 2) considered the original modelled index values to include an error component with the underlying abundance index estimated by a smooth spline fitted to the annual values.

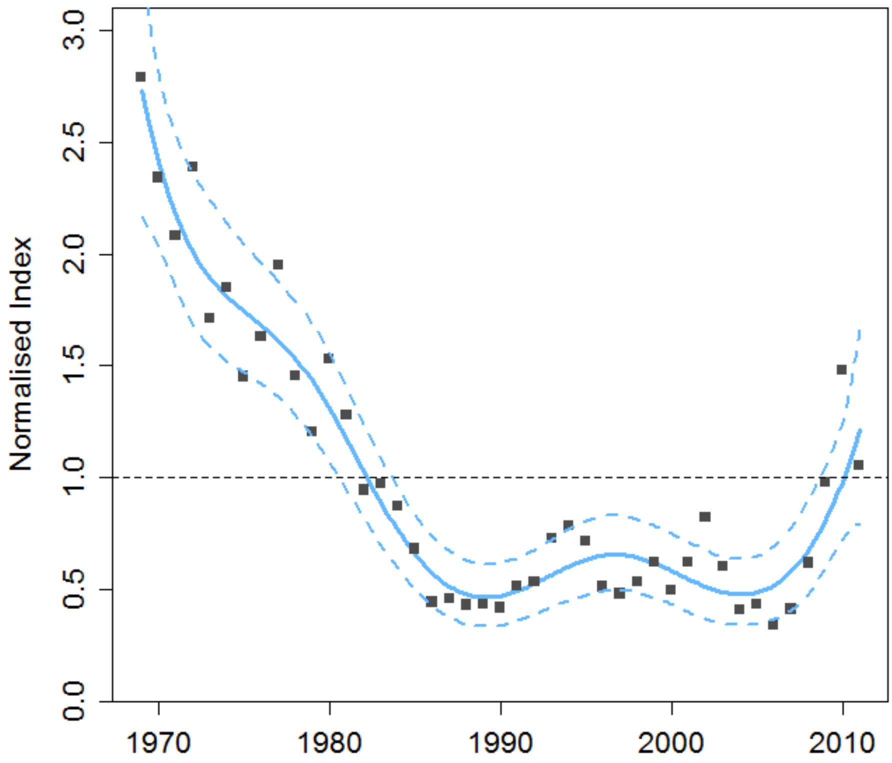


Figure 6: Normalised Laslett Core Area CPUE index with fitted hyperbolic regression spline. Black squares denote the annual averages of the model predicted values. The blue solid line is the mean of the predictive posterior of the regression spline. The blue dashed line gives the 95 percent Bayesian credible interval of the spline.

Laslett (2001) originally proposed hyperbolic regression splines of Cologne & Sposto (1994), but more common methods of smoothing such as b-splines and additive models also result in indices that deviates less from the other SBT CPUE indices than do the unsmoothed LCA index values. The smoothed LCA (Figure 7) remains consistently higher than the other indices after around 2004 although overall it's arguably not too different from the w0.8 index. After smoothing, the LCA index is less prone to sudden sharp changes in level and direction. Given the longline fishery harvests a range of year classes of SBT, a reliable index would not be expected to fluctuate too much between years. In this case it seems sensible to share information on relative abundance between years as is achieved by smoothing the index across years for instance.

Laslett suggested fitting the hyperbolic regression splines of Cologne & Sposto (1994) to the annual unsmoothed index with autocorrelation in errors modelled as an exponentially decaying function. The smooth curve shown in Figure 6 was fitted in WinBUGS and is as suggested by Laslett except that an autoregressive AR1 structure is assumed rather than the exponentially decaying autocorrelation. Estimates of the AR1 coefficient (Figure 8) suggest positive autocorrelation in the unsmoothed LCA index.

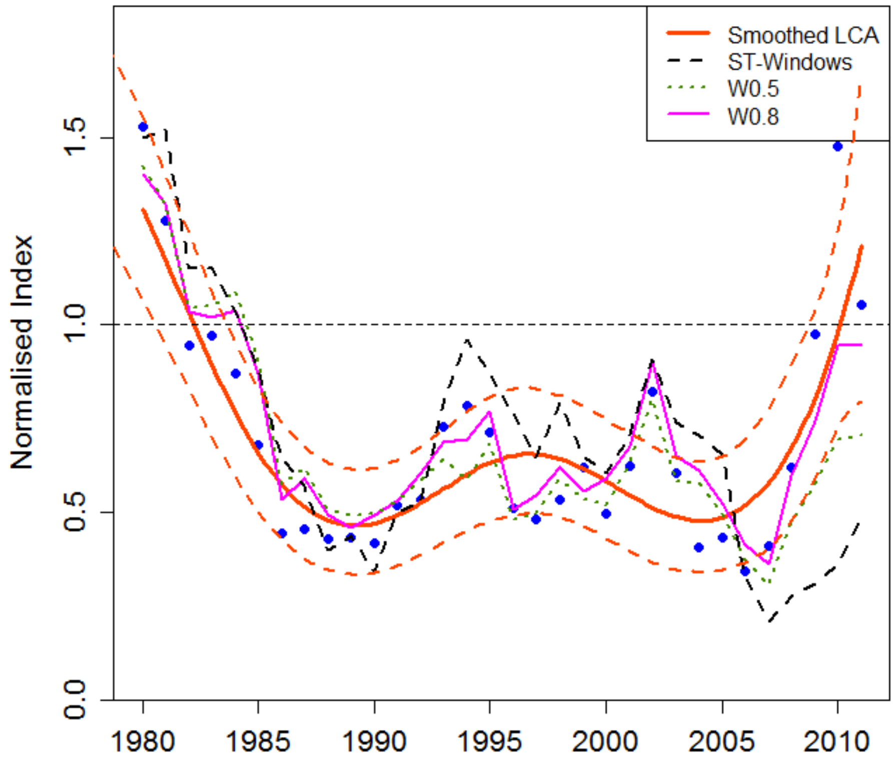


Figure 7: Comparison of smoothing spline through modelled Laslett Core Area index values with other CPUE indices monitored by the ESC (1980–2011). All indices are normalised to have a mean of unity between 1969 and 2011. Blue dots are unsmoothed Laslett Core Area index values.

The spline preserves the general abundance trend suggested by sustained increases or decreases in modelled CPUE whilst being less severely affected by noise and individual year classes. Large year-on-year fluctuations in CPUE have contributed to substantial changes in projections of future spawning stock biomass in recent years (Anon., 2010; Anon., 2011). Temporal smoothing of the annual index would be expected to moderate this undesirable behaviour and so perhaps deserves consideration for CPUE indices used as input into the SBT operating model.

Table 2: Explanation of CPUE indices compared in Figure 7

Index	CPUE Model	Calculation Domain	Smoothed?
Smoothed LCA	Laslett spline model	Laslett Core Area	Yes
ST-Windows	(Weighted) Nominal	Fished ST-Windows Cells	No
w0.5	Lognormal GLM	1:1 Constant Squares:Variable Squares	No
w0.8	Lognormal GLM	1:4 Constant Squares:Variable Squares	No

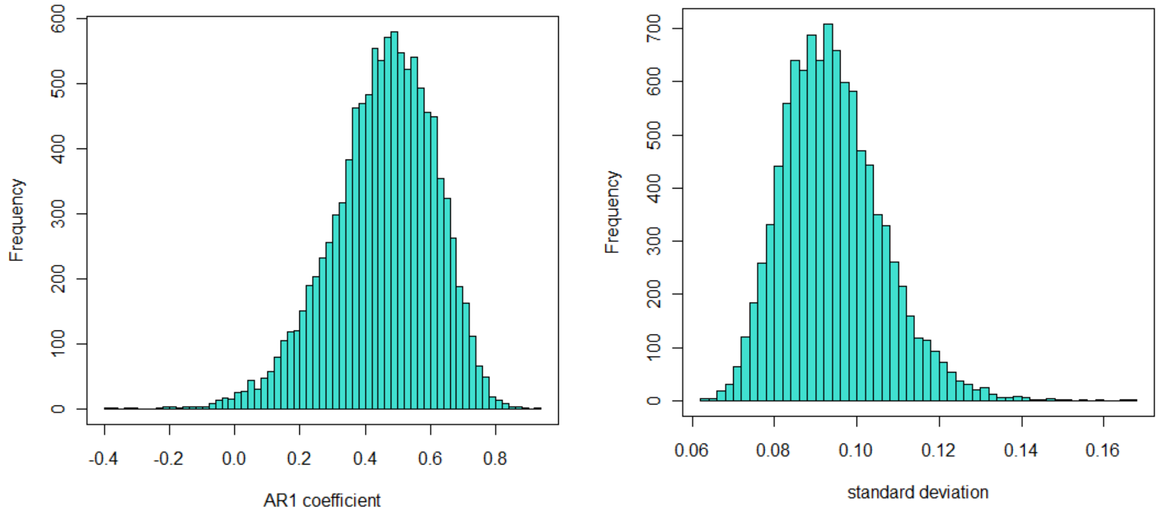


Figure 8: Histograms of posterior draws of estimated autocorrelation (left) and standard deviation (square root scale, right) in normalised unsmoothed LCA index errors assuming the hyperbolic regression spline model with AR1 error structure. The regression spline is fitted to the unsmoothed index values on the square root scale.

A further advantage of assuming a conventional, unsmoothed index comprises annual observations of underlying abundance trend observed with error is that confidence intervals for the smooth curve estimating the underlying trend can be calculated (Figures 6, 7). These confidence intervals do not incorporate model error, but provide some sense of what might be appropriate coefficients of variation for CPUE indices used in the operating model.). Since the indices are only assumed to give relative abundance, only aspects of model error that are inconsistent between years or varying levels of abundance are important. The differences between the normalised indices considered in recent years suggest that at least some of the models are affected in this way. An estimate of the coefficient of variation of CPUE could be calculated as a simple transformation of the standard deviation statistic plot in Figure 8 (right).

6 Generalised Additive Models

A generalised additive model (GAM) can be defined as a generalised linear model with a linear predictor involving a sum of smooth functions of covariates (Wood, 2006). The methodology used by Laslett (2001) can be regarded as a GAM. The development of the mgcv{} package in R has increased the flexibility of GAMs for modelling CPUE. For instance, models incorporating the non-Gaussian distribution of the quantity of interest can be entertained. Laslett (2001) mentions the application of spline models for non-Gaussian errors amongst future work.

The input data for these models are all CPUE data in STAT_AREA_CODES 4, 5, 6, 7, 8 and 9. GAMs with a log link function (quasi family) are fitted to blocks of 5 consecutive years. A tensor product spline is used to model the joint effect of latitude, longitude and month. Error variance is assumed proportional to expected value. The fitted models are then used to predict CPUE on the same domain as the LCA index giving the index plot in Figure 9.

The model described above can be fitted using the mgcv{} package in R with code such as:

```
Base.GAM <-  gam(CPUE ~ te(LONG,LAT,Month.by.Five) + as.factor(YEAR)*STAT_AREA_CODE,
family=quasi(link = log,variance = "mu"))
```

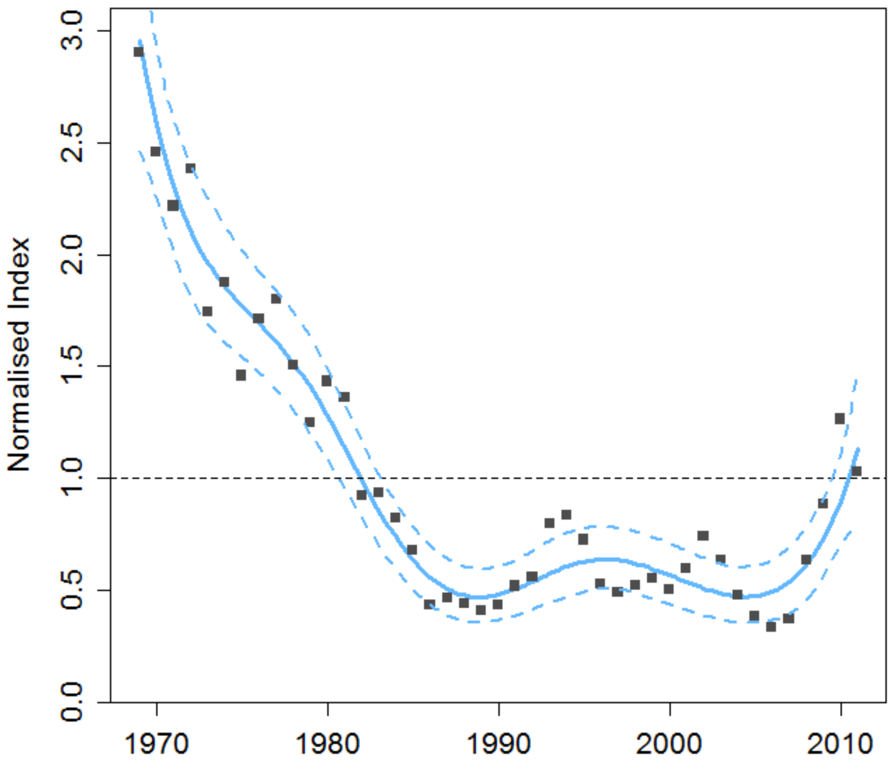


Figure 9: CPUE index derived from the Base GAM model predictions of CPUE in the Laslett Core Area with fitted hyperbolic regression spline. Black squares denote the annual averages of the model predicted values. The blue solid line is the mean of the predictive posterior of the regression spline. The blue dashed line gives the 95 percent Bayesian credible interval of the spline.

The variable Month.by.Five is simply an integer value denoting month of the year multiplied by 5 to be consistent with the treatment of month in the LCA model. STAT_AREA_CODE is converted to a factor and cells in Statistical Areas 4, 5 and 6 are grouped in the same category.

A second reduced model is also fitted which excludes the Year by Area interaction effect and Statistical Area main effect. It can be coded as shown below.

```
Fixed.Dist.GAM <-  gam(CPUE ~ te(LONG,LAT,Month.by.Five) + as.factor(YEAR),
family=quasi(link = log,variance = "mu"))
```

This second reduced model allows the spatial distribution of CPUE to change across the year, but this pattern of change is the same each year. This model is referred to as the Fixed Dist GAM in the remainder of this report. The spatial distribution of modelled CPUE by month estimated the Fixed-Dist GAM between April and September is shown in Figure 14 and Figure 15.

The inclusion of the Year by STAT-AREA_CODE interaction in the Base GAM model allows the relative mean CPUE to differ by STAT_AREA between years. This additional flexibility means that the Base GAM model is closer to the model used in the LCA index. Indices calculated by fitting the two GAM models to the LCA domain are shown in Figure 10. Whilst qualitatively the smoothed indices are very similar, the differences in their levels in recent years are important. Indices derived from models that incorporate additional flexibility in the spatio-temporal distribution of CPUE exhibit a greater increase in CPUE since 2005. This is consistent with previous analyses (See e.g. Chambers, 2011) that showed indices derived from generalised linear models with Year by STAT_AREA_CODE interactions exhibited a greater increase in CPUE than equivalent models that did not include Year by STAT_AREA_CODE interactions.

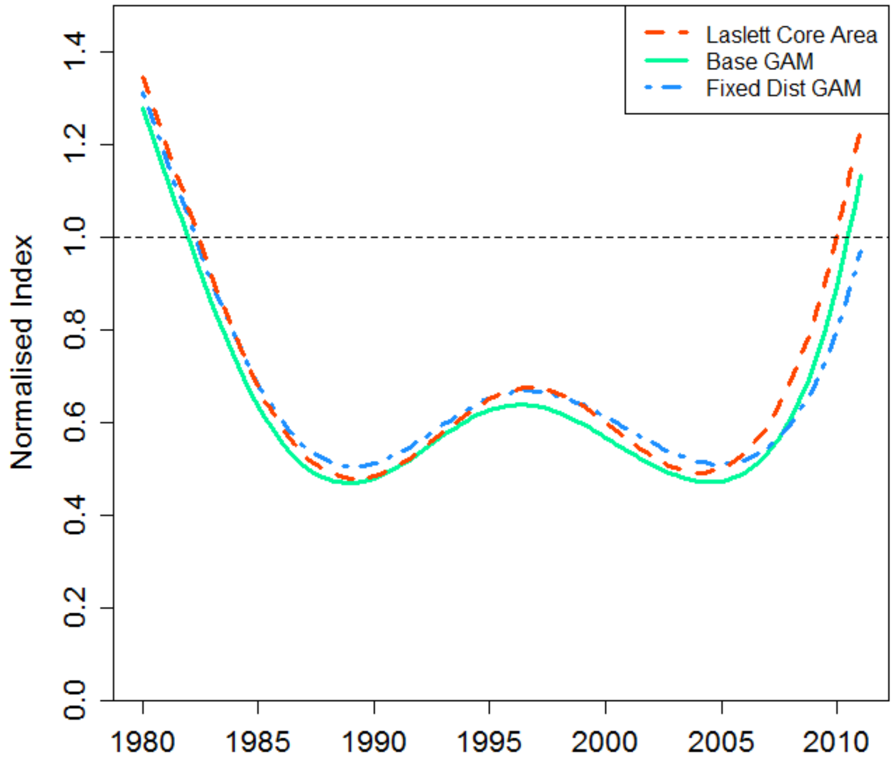


Figure 10: Effect of flexibility in annual spatial distribution of CPUE. Indices derived from 3 alternative models used to predict CPUE on the Laslett Core Area domain.

Table 3: Explanation of CPUE indices compared in Figure 10.

Index	CPUE Model	Calculation Domain	Smoothed?
Laslett Core Area	Laslett spline model	Laslett Core Area	Yes
Base GAM	Base GAM	Laslett Core Area	Yes
Fixed Dist GAM	Fixed Dist GAM	Laslett Core Area	Yes

The distribution of residuals exhibits positive skew. Residuals from the Fixed Dist GAM model (Figure 11) are consistently positive in STAT_AREA 7 beginning in 2008. This demonstrates that CPUE in Statistical Area 7 relative to other areas has been higher than in previous years.

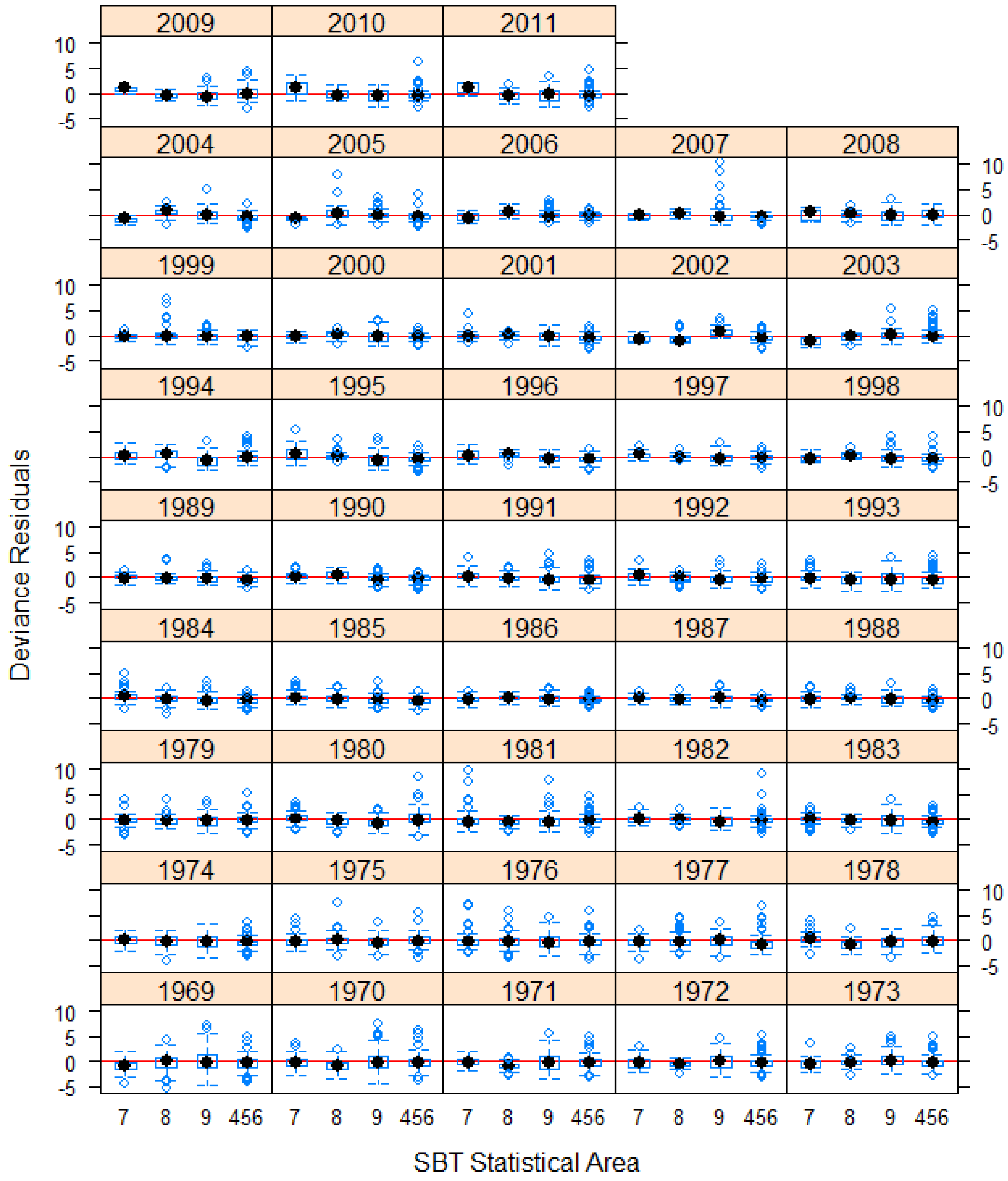


Figure 11: Boxplots of deviance Residuals for FixedDist GAM model by year and Statistical Area.

Variance in CPUE is noticeably lower in the 1990s and early 2000s than at other times (Figure 11 and Figure 12).

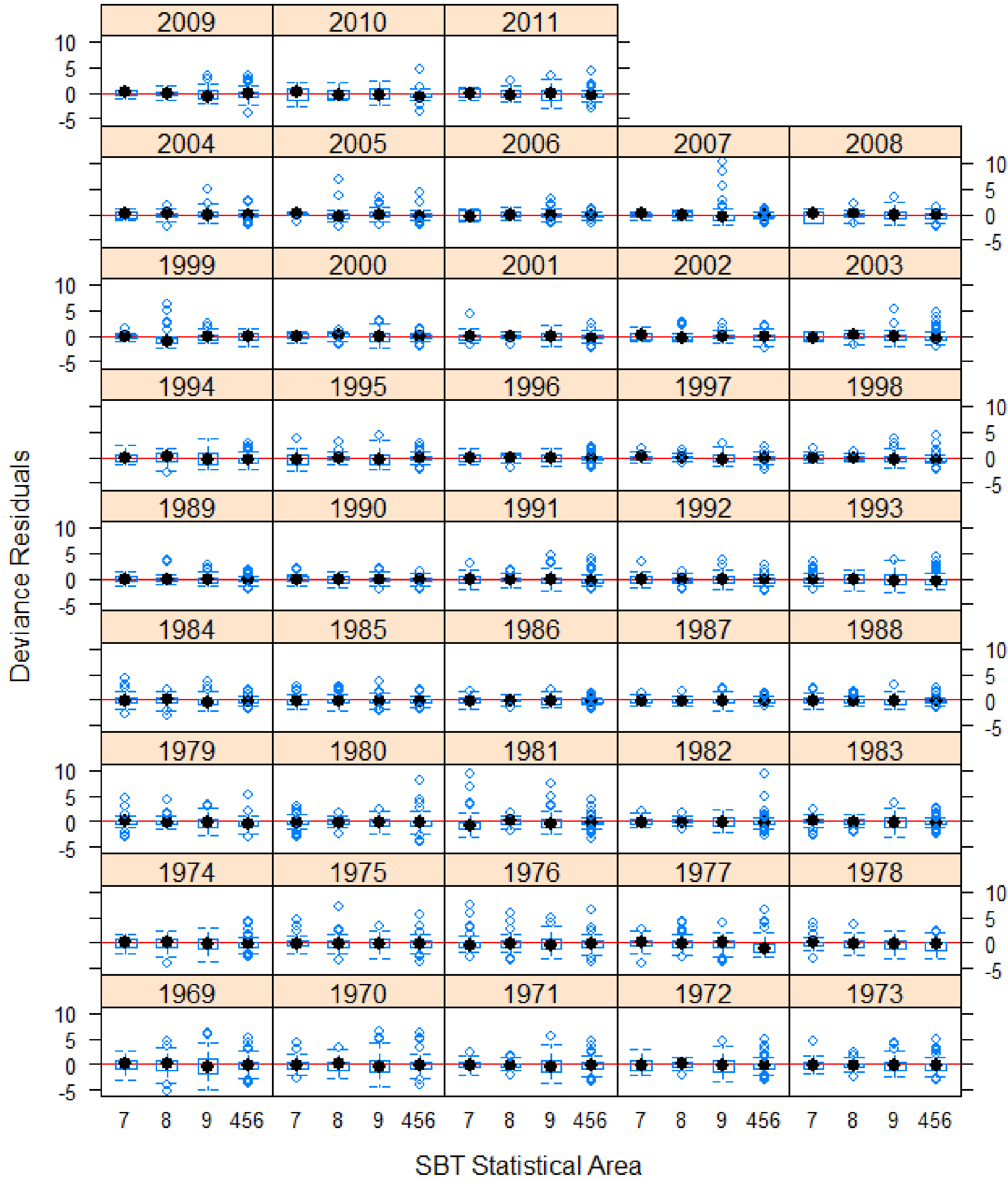


Figure 12: Boxplots of deviance Residuals for FixedDist GAM model by year and Statistical Area.

Additional insights into the causes of differences between the LCA index and the ST-Windows index can be gained by fitting models such as GAMs and using the fitted models to predict CPUE on the LCA domain and the ST-Windows domain.

Indices based on predicted CPUE in the LCA increases more in recent years than do indices based on predicted CPUE in the ST-Windows domain (Figure 14). This is unsurprising given increases in observed CPUE over this time have been largest in Area 7 which is not considered in the ST-Windows index.

The difference in trend in CPUE in the 1990s between the Laslett Predicted ST-Win index and the Base GAM Predicted ST-Win index (Figure 13) is interesting. The major difference between the models used to estimate these indices is that the Laslett model allows for the spatial trend in CPUE across a fishing season to vary each year, whereas the Base GAM allows for relative mean CPUE in each of the SBT statistical areas to vary each year, but for the latter case the pattern of movement in CPUE across the season is fixed. The Base GAM model and Laslett model give very similar indices when the index is derived from predicted CPUE in the LCA (Figure 13).

The Base GAM Predicted Variable ST-Win Sum index is the closest to the proper ST-Windows CPUE index because it is directly affected by the number of cells fished. The difference in recent years between this index and the other ST-Windows indices (Figure 13) is perhaps an indication of the effect of the reduction in fishing effort on the ST-Windows CPUE index.

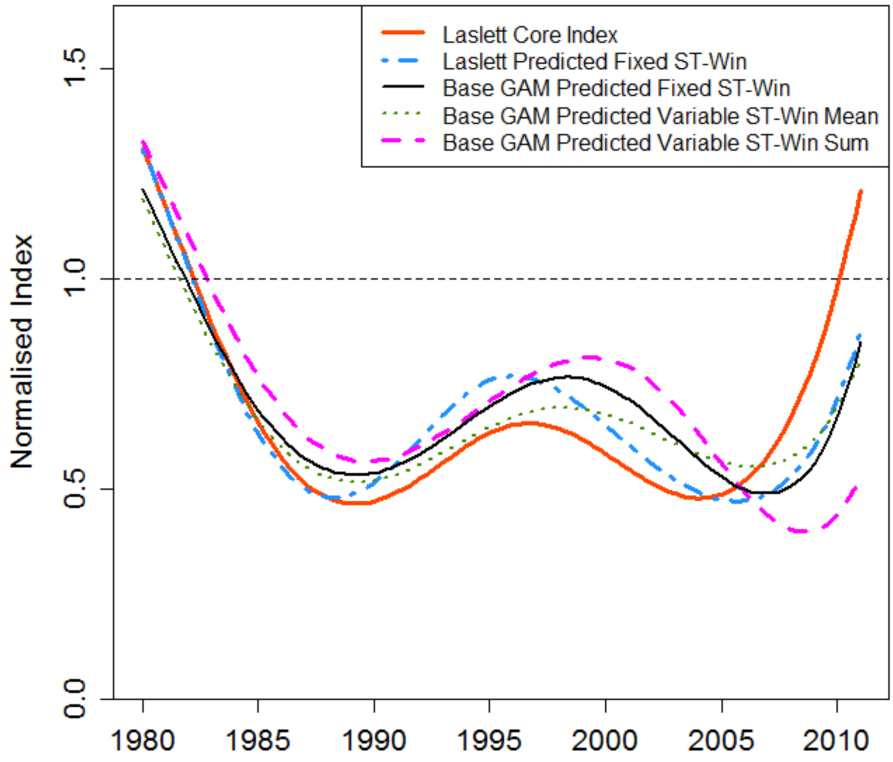


Figure 13: Comparison of smoothed Laslett Core Area CPUE index with smoothed indices based on CPUE fit to Laslett and Base GAM models predicted on Fixed and Variable ST-Windows domains.

Table 4: Explanation of CPUE indices compared in Figure 13.

Index	CPUE Model	Calc. Domain	Smoothed?
Laslett Core Area	Laslett	Laslett Core Area	Yes
Laslett predicted Fixed ST-Win	Laslett	Fixed ST-Win	Yes
Base GAM predicted Fixed ST-Win	Base GAM	Fixed ST-Win	Yes
Base GAM predicted Variable ST-Win Mean	Base GAM	Fished ST-Win	Yes
Base GAM predicted Variable ST-Win Sum	Base GAM	Fished ST-Win	Yes

7 Conclusions

The observed difference between the LCA and ST-Windows CPUE indices in recent years is found to be due to a combination of a reduction of the number of cells fished in the ST-Windows domain and an increase in CPUE in Statistical Area 7 relative to Statistical Area 8 and Statistical Area 9. Both of these factors result in an increase in the LCA index relative to the ST-Windows index and the size of the effect of each of these factors appears to be about equal.

Inter-annual variation in CPUE about its underlying trend appears to be substantial and seems fairly consistent between the various CPUE indices considered. Given the population of SBT exploited by the longline fishery comprises a number of age-classes, this inter-annual variability is more likely to be due to fluctuations in catchability than in abundance. This provides a theoretical basis for estimating relative abundance as a smooth curve through annual modelled CPUE index values.

GAMs are a highly flexible family of models that enable spatial and temporal smoothing of CPUE and can accommodate a range of error structures. It is straightforward to fit GAMs that are similar to the spline models fitted in the LCA index and would be expected to result in similar indices.

Appendix A - Spatial CPUE Effects by Month

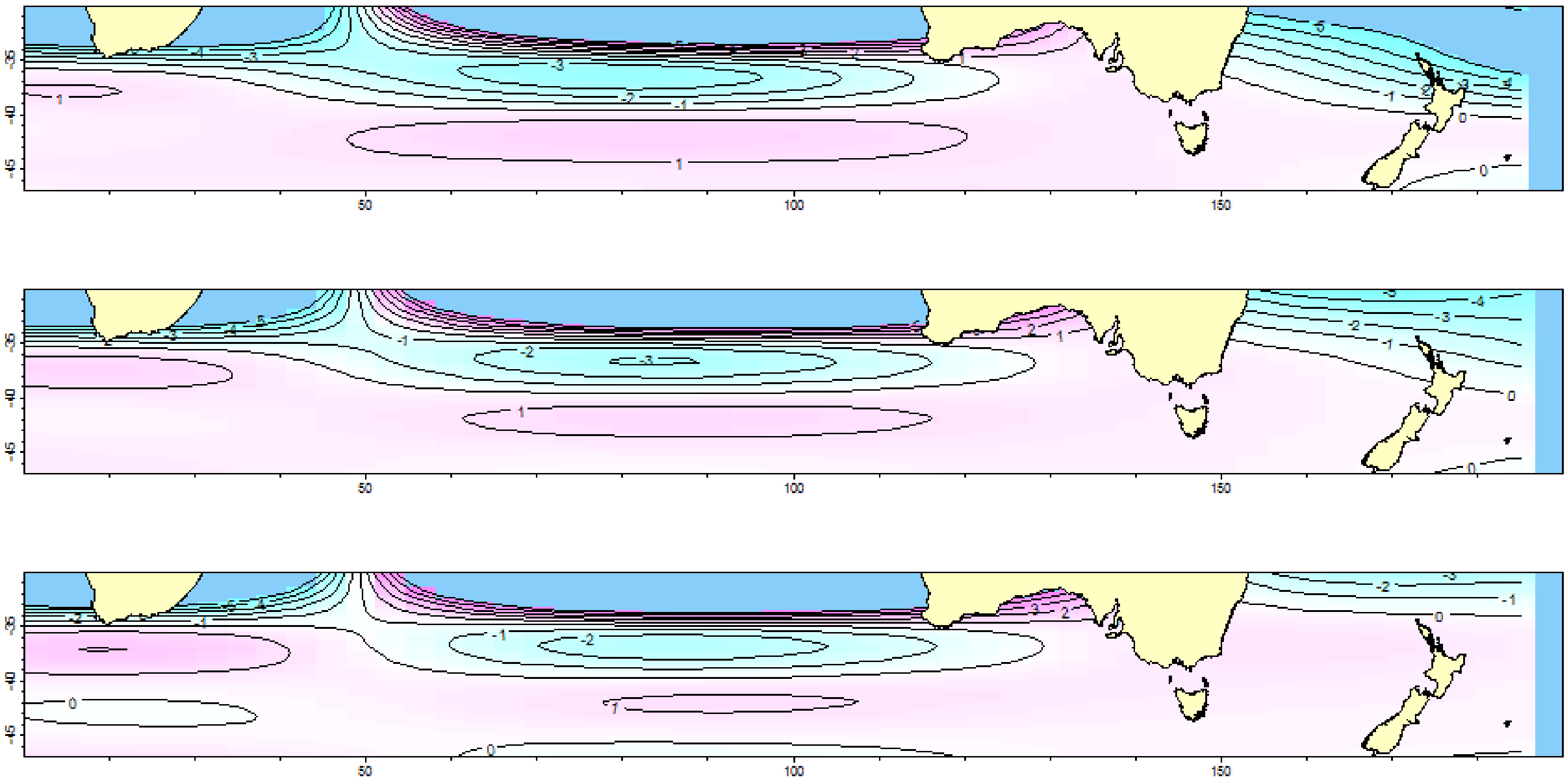


Figure 14: Contour plot of jointly modelled effect of longitude and latitude on CPUE (1969–2011) in April (top), May (centre), and June (bottom). Effects estimated using the Fixed Dist GAM model (no Year by Area interaction).

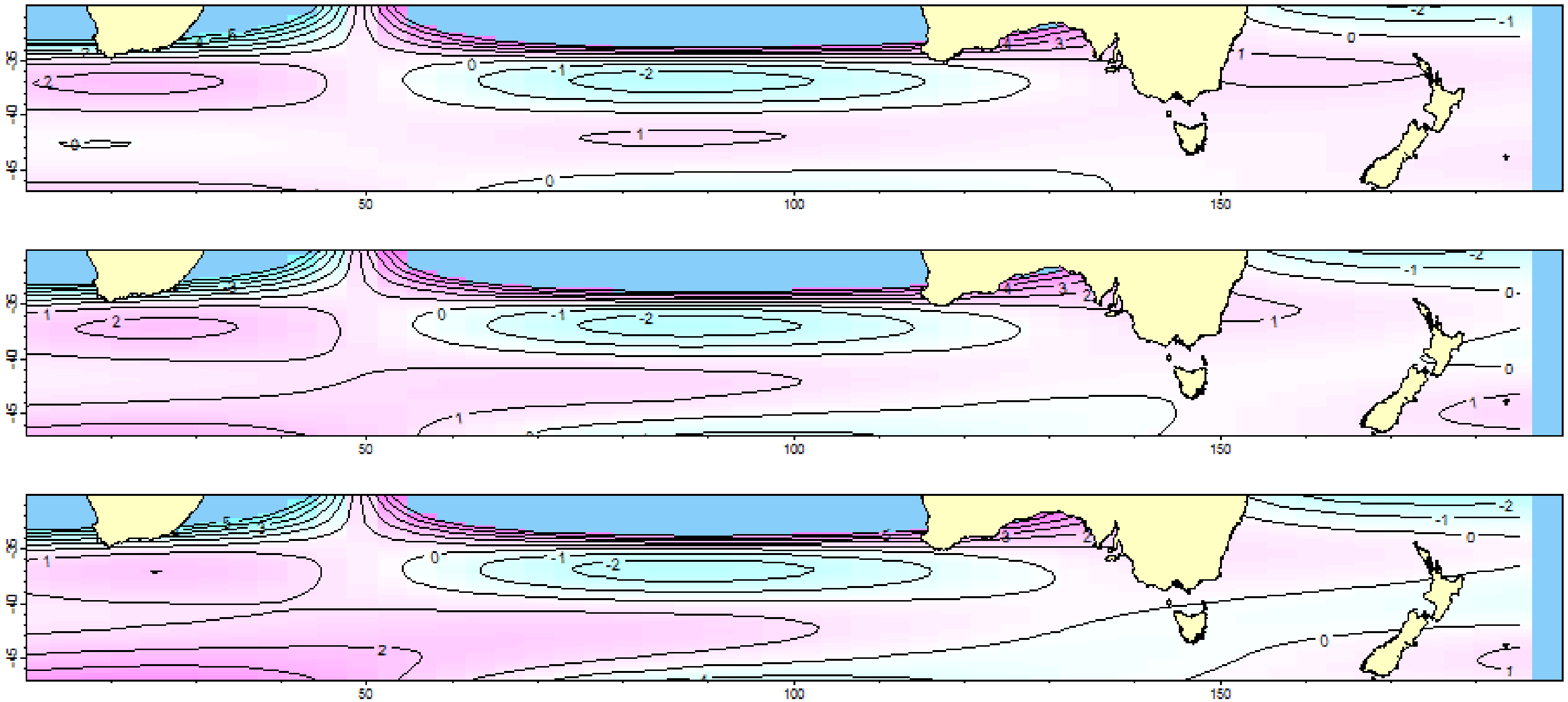
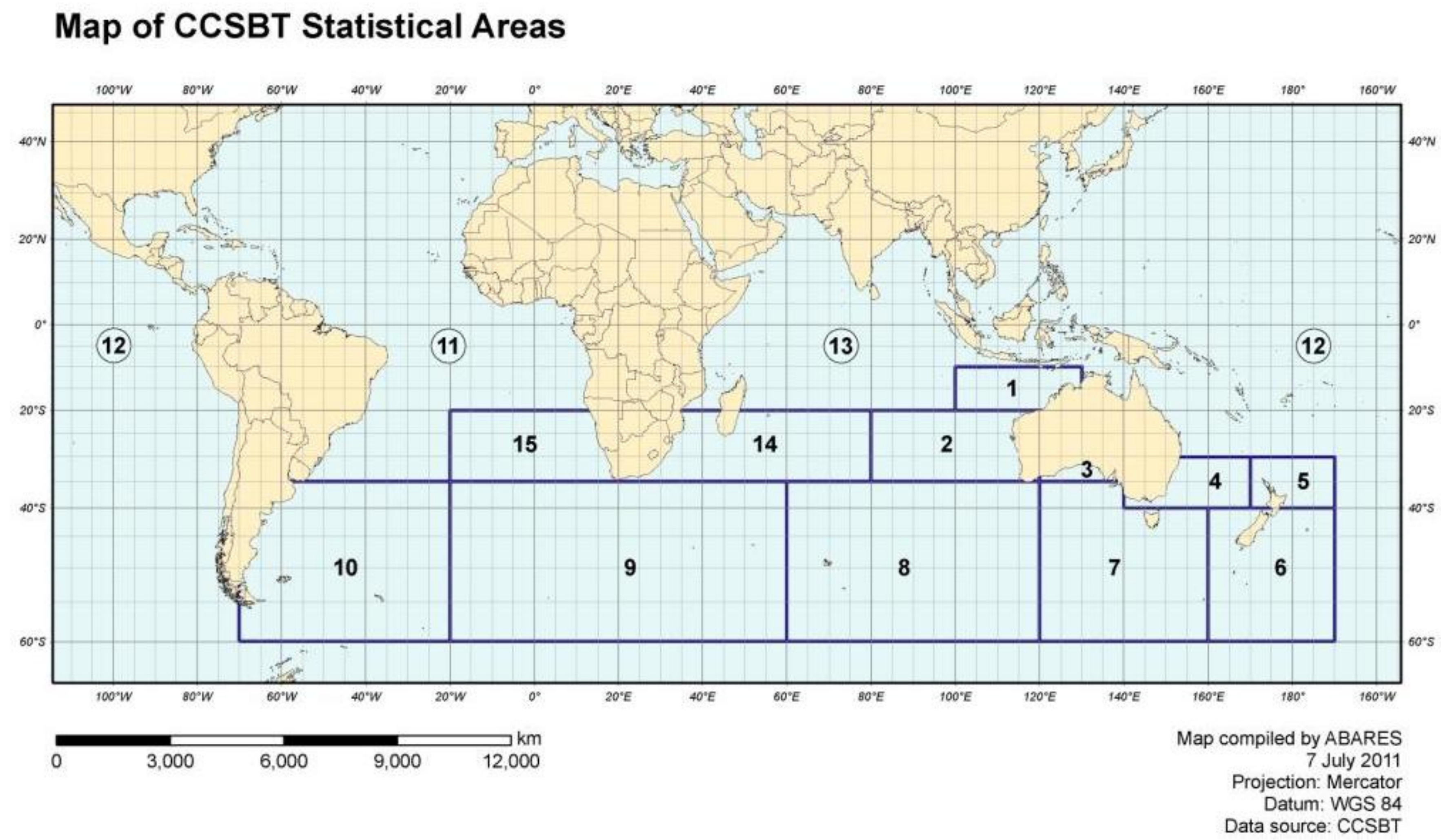


Figure 15: Contour plot of jointly modelled effect of longitude and latitude on CPUE (1969–2011) in July (top), August (centre), and September (bottom). Effects estimated using the Fixed Dist GAM model (no Year by Area interaction).

Appendix B Map of CCSBT Statistical Areas

Map 1: CCSBT Statistical Areas



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