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# Examination of CPUE indices for southern bluefin tuna



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# Summary

Nominal catch per unit effort (CPUE) and abundance indices for southern bluefin tuna (SBT) derived from CPUE data have increased strongly over the last three years (2008-2010). Whilst this is a positive signal for the stock there are reasons to be cautious about interpreting the observed increases in CPUE, such as potential changes in fishing practices and the current low level of the spawning stock biomass.

Considerable uncertainty around the relationship between currently applied CPUE indices and the abundance of the SBT stock means that continued examination of CPUE remains a high priority.

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# 1 Introduction

The catch per unit effort (CPUE) for southern bluefin tuna (SBT) caught in the longline fishery (LL1) is measured as the number of SBT 4 years and older caught per thousand hooks. Currently the operating model (OM) uses monthly totals of catch and effort data aggregated to the 5 degree square level. The base model used to standardise SBT CPUE, models aggregated CPUE as a lognormal random variable which is influenced by various spatial and temporal factors, the extent of targeting SBT as measured by bigeye tuna and yellowfin tuna CPUE, and a number of interactions (Itoh et al., 2003).

Rodriguez Boero (2009) suggested a simpler model that has been referred to as the reduced model. The reduced model excludes interactions with year. Exclusion of the interaction terms produces considerable savings in model complexity. Consideration of model selection is warranted as the current trend in abundance suggested by the reduced model is less optimistic than the current trend suggested by the base model.

It is important that the index of abundance derived from CPUE be as reliable as possible because it is an influential input in the OM and candidate management procedures (MPs).

Recently there have been concerns that the representativeness of the CPUE index might have been affected by changes in the behaviour of the longline fleet as SBT catch has been constrained by reduced quotas.

We explore current trends in the CPUE LL1 longline fishery data; compare models for standardisation of CPUE data; and examine the appropriateness of other aspects of the method currently used for calculation of indices of abundance.

# 2 Data

The data used for this analysis are Japanese longline (LL1) logbook data from 1986 to 2009 aggregated into 5 by 5 degrees squares. For 2010, these data are augmented with Real Time Monitoring Program (RTMP) data multiplied by a factor to make it equivalent to the logbook data, also aggregated into 5 by 5 degrees squares as supplied in May 2011. The RTMP data does not include New Zealand joint venture operations. The variables used for modelling are:

- 1) CPUE Monthly aggregated number of 4+ SBT caught in grid square divided by monthly aggregated effort in grid square (effort measured in thousand hooks set).
- 2) Year categorical variable.
- 3) Month (April to September) categorical variable.
- 4) Area (CCSBT Areas 4 to 9, Areas 5 and 6 amalgamated) categorical variable.
- 5) Lat5 (5 degree band of latitude) categorical variable.
- 6) BETcpue5 (monthly aggregated bigeye CPUE per thousand hooks in grid square) non-negative continuous variable.
- 7) YFTcpue5 (monthly aggregated yellowfin CPUE per thousand hooks in grid square) non-negative continuous variable.

#### 3 Exploratory Analysis of Nominal Data

Time series plots of nominal CPUE in each of the CCSBT statistical areas (Figure 1) reveal that increases in nominal CPUE since 2007 have been largest in Area 7 (Figure 1, see Appendix 1). Similarly, there have been large increases in nominal CPUE in Latitude 40 and Latitude 45 (Figure 2). However, modest increases in nominal CPUE have also been observed in Areas 4 and 5-6 over this same period. Nominal CPUE in Areas 8 and 9 has remained at similar levels to those observed since 1986.



Figure 1 Time series of annual nominal CPUE by CCSBT statistical area.



Figure 2 Time series of annual nominal CPUE by 5 degree band of latitude.

Plots of nominal effort by area, as measured by total hooks set, reveals that effort in Area 9 has declined markedly in recent years. Total effort in Area 7 has been relatively low for the last five years (Figure 3).



Figure 3 Nominal effort by CCSBT statistical area at latitude bands and in months considered for CPUE analysis.

The total reduction in effort in the longline fishery has declined substantially since the late 1990s (Figure 4). The reduction in total effort should also be considered when interpreting the reductions in the number of grid squares fished in recent years.



Figure 4 Total recorded effort in LL1 fishery (thousand hooks).

# 4 Calculation of CPUE index for SBT

Currently CPUE is modelled by fitting a lognormal generalised linear model (GLM) to aggregated monthly CPUE from 5 degree grid squares between the latitudes of 30 degrees S and 50 degrees S from CCSBT statistical areas 4-7, between the months of April and September. Relative abundance in fished squares is taken to be given by model predicted values.

Assumptions about the relative abundance in unfished grid squares are made which aim to account for the possibility that the spatial distribution of the SBT stock might change over time and that such changes would be reflected by the spatial distribution of fishing in the longline fishery.

Unfished squares are dealt with using two alternative weighted averages of what are considered to be opposing extreme assumptions about SBT density in those unfished squares. The most pessimistic assumption about the density of SBT in unfished grid squares is that there are no SBT in those squares. This assumption leads to the Variable Squares Index (see Campbell, 1998). An optimistic assumption is that in a given year, the unfished squares have abundance equal to the average abundance of fished squares in that year. This assumption is referred to as the Constant Square Index.

Annual indices of abundance are calculated as weighted averages of modelled values for fished squares and assumed values for unfished squares (Itoh et al., 2003).

### 5 Standardisation models

#### Base model

The base model was adopted after it was the favoured model among those considered by Itoh et al. (2003, CCSBT-ESC/0809/09).

The model assumes that the log transform of observed average monthly CPUE in each grid cell will be normally distributed about its expected value according to the model.

The base model is written as:

# $log(CPUE_{i} + 0.2) = Intercept + Year_{i} + Month_{i} + Area_{i} + Lat5_{i} + \beta_{1}BET\_CPUE_{i} + \beta_{2}YFT\_CPUE_{i} + Month_{i} : Area_{i} + Year_{i} : Lat5_{i} + Year_{i} : Area_{i} + Error_{i}$

Where  $\beta_1$  and  $\beta_2$  are constants defining the effect on log transformed CPUE due to a unit change in bigeye and yellowfin CPUE. The error term is assumed to be normally distributed with constant variance and the other subscripted terms on the right hand side of the equation denote the effects of factors on log CPUE relative to the predicted value for a reference category given by the intercept term.

The contribution of each term in the base model is given in Table 1. All variables are highly significant. Main effects for area and latitude band explain the greatest proportion of variance in log transformed SBT CPUE. Overall, the base model explains around 61 per cent of variance in log transformed monthly aggregated CPUE.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
year	24	94.005	3.917	7.827	< 0.001
month	5	152.047	30.409	60.768	< 0.001
area	4	503.57	125.892	251.576	< 0.001
lat5	3	565.8	188.6	376.887	< 0.001
BETcpue5	1	180.444	180.444	360.589	< 0.001
YFTcpue5	1	72.069	72.069	144.018	< 0.001
month:area	20	97.008	4.85	9.693	< 0.001
year:lat5	72	109.409	1.52	3.037	< 0.001
year:area	96	139.818	1.456	2.91	< 0.001
Residuals	2435	1218.511	0.5	NA	NA

Table 1 ANOVA table for the base model.

When fit to data from 1986 to 2010, the model yields diagnostics shown in Figure 5. The linear pattern in the plot of residuals versus fitted values is due to a moderate number of grid squares

where zero catch rates of SBT were observed. The Normal Q-Q plot suggests the residuals have slightly fatter tails than a normal distribution with similar variance. The scale-location plot suggests some departure from constant variance of residuals. The residuals versus leverage plot suggests that whilst some observations have high leverage, these are reasonably well fitted. Three observations with leverage 1 were not plotted. The observation identified as 671 is perhaps the most poorly fitted. This observation relates to a grid square in Area 9 in 1991 where high bigeye tuna CPUE was observed.



Figure 5 Default diagnostics for the base model.

Fitting an ordinary least squares model to the aggregated data is not ideal because the number of longline sets represented by different data points varies considerably. CPUE of data points that represent many shots are averaged over these shots and consequently would be expected to have lower variance. This effect can be seen by plotting model residuals against total hooks set (Figure 6).

The variance of the residuals from the base model decreases with increased effort (Figure 6). This suggests that the assumption of constant error variance is violated and, strictly speaking, a lognormal model is not appropriate for the aggregated CPUE observations. Ordinary least squares models fit to shot by shot data would be less likely to violate the assumption of unequal residual variance.



Figure 6 Plot of residuals from base model versus monthly aggregated effort in grid square.

#### Reduced model

The reduced model assumes that relative catch rates between areas and latitude bands do not change between years (Rodriguez Boero 2010). The reduced model is written as:

 $log(CPUE + 0.2) = Intercept + Year_i + Month_i + Area_i + Lat5_i + \beta_1 BET \_CPUE_i + \beta_2 YFT \_CPUE_i + Month_i : Area_i + Error_i$ 

Comparison of model diagnostics for the base model (Figure 5) and the reduced model (Figure 7) provide little basis for choosing between them. Since the reduced model is nested within the base model and has fewer parameters, greater mean squared error is to be expected. The reduced model explains around 53 per cent of the variance in log transformed monthly aggregated CPUE.



Figure 7 Default diagnostics for the reduced model.

#### Information criteria

The base model is preferred over the reduced model according to Akaike's Information Criterion (AIC) (Table 2). By contrast the reduced model would be selected on the basis of the Bayesian Information Criterion (BIC). Currently an unknown proportion of the variance in log transformed CPUE is accounted for by aggregating monthly catch and effort in each grid square. Model selection based on information criteria would yield different results if fit to finer spatial scale or shot by shot data.

Table 2 Akaike's Information Criteria and Bayesian Information Criteria for the base model and reduced model.

	AIC	BIC
Base model	5930	7272
Reduced model	6090	6443

#### 6 Results

Indices derived for the base and reduced model exhibit some disagreement, particularly in 2010 (Figures 8, 9). The reduced model CPUE decreases slightly between 2009 and 2010 whereas the base model increases strongly.



Figure 8 CPUE indices derived from the base model and reduced model under the w0.8 weighting scheme. Both indices were divided by their average value so that each series has a common mean of 1.

Comparing the values for the indices derived from each model under the alternate weighting schemes (Figures 8, 9) also reveals differences between the models depending on the weighting applied.



Figure 9 CPUE indices derived from the base model and reduced model under the w0.5 weighting scheme. Both indices were divided by their average value so that each series has a common mean of 1.

# 7 Discussion

The recent increases that have been observed in CPUE suggest that some improvement in the abundance of age classes vulnerable to the longline fishery may have occurred in recent years. Likewise, there have been positive signals from other fishery indicators, such as the scientific aerial survey. However, Hillary et al. (2011) suggest that some of the observed increase in nominal and standardised CPUE in recent years might be due to changes in catchability in the longline fishery, and/or due to changing fishing/targeting practices in response to management actions (Itoh, 2010). Moreover the increase in abundance suggested by the recent increases that have been observed in standardised CPUE are difficult to explain given the long lived nature of SBT. Abundance indices derived from the reduced model, which makes stronger assumptions about the spatio-temporal distribution of the stock, suggest a more modest increase in abundance than suggested by the base model. In addition, the effect on CPUE indices of unknown levels of historical overcatch in the LL1 fishery and more recent evidence of unreported release/discarding of small SBT (Sakai et al., 2010) is uncertain.

Overall, recent improvements in longline CPUE should be interpreted cautiously until the magnitude of any abundance increases are better determined. The analysis and broader provision of longline catch and effort data at a finer spatial scale (i.e. shot-by-shot) would allow greater interpretation of CPUE trends and the calculation of potentially more reliable CPUE based indices of abundance.

The importance of CPUE to the performance of MPs and hence stock and fishery outcomes suggest that efforts to address concerns about the uncertainty of CPUE indices should remain a priority.

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### Appendix 1

#### Map of CCSBT Statistical Areas

