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Longline CPUE series that account for changes in the spatial extent of fisheries

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1. Summary

There have been large changes in the spatial extent of the Japanese longline fishing fleet in the WCPO which may have consequences for the reliability of CPUE indices. This paper presents preliminary analyses that attempt to account for the spatial distribution of fishing through time. We compare a number of approaches including methods that use generalized additive models and rule-based back-filling to impute CPUE values for cells where fishing did not occur in a given year-quarter. Most approaches produced indices relatively similar to the currently-used indices for the WCPO BET/YFT assessment region 3. There were exceptions however, and several of the indices showed more promising performance than others. The next step will be to formulate robust methods, such as cross-validation and/or simulation studies, that will allow formal comparison of the indices. It would be very valuable to undertake further analyses with refined methodology on more complete datasets of operational longline data that are not currently held by the SPC.

2. Introduction

Indices of relative abundance of fish over time are an extremely important input for stock assessment models (Hilborn and Walters 1992). It is common for indices to be developed by standardizing commercial fisheries data to account for changes in catch rate that occur due to factors other than fish abundance. CPUE for the Japanese longline (JPLL) fishing fleet in the WCPO are vitally important for the assessments of bigeye (BET) and yellowfin tuna (YFT) in that region (Davies *et al.* 2011, Langley *et al.* 2011) and are estimated using generalized linear models (GLMs). Given the value of these time-series, considerable effort has been invested in improving the standardisations since the early stock assessments, including; a shift from aggregate to operational-level data, accounting for targeting, methods for weighting data and the structure of the GLMs themselves, amongst others (e.g. Langley *et al.* 2005, Hoyle *et al.* 2010, Hoyle 2011, Hoyle and Okamoto 2011).

The use of standardised indices in stock assessment models assumes that they are directly proportional to numbers of fish available to the fishery in the assessment regions (Figure 1). Despite the progress that has been made several issues remain that may affect the validity of this assumption. One example is the failure to fully account for spatial changes in the effort of the fleet within regions. Fishing does not usually occur in all spatial cells in a region in every year, and this is certainly the case for the JPLL dataset. Consequently, standardisation analyses usually assume that the dynamics of catch rates are common to both fished and un-fished cells. Because catch rates vary between spatial cells (Hoyle and Okamoto 2011), and the pattern with which cells are fished is not random, analyses that ignore spatial effects can produce non-representative indices. Two examples are often provided to illustrate the idea. Firstly, during the early development of a fishery, the spatial extent of fishing expands as fishers search for the most productive areas, and each newly fished area may start with a high catch rate which then declines. Secondly, in well-developed fisheries fishing may contract to those cells where catch rates are highest, again giving an artificially high nominal CPUE for the region. The JPLL fishery has both these features: it expanded into new areas during the 1950's and 1960's, and has significantly contracted in spatial extent over recent decades (Figure 2-5). These changes have partly been due to changes in regulations on where these vessels are allowed to fish, and partly due to economic factors.

Currently-used standardisations of CPUE of BET/YFT in the WCPO typically use models that include effects for time (usually year-quarter) and area (usually 5×5° spatial cells), though not an interaction between them (Hoyle and Okamoto 2011). These models are capable of providing robust indices of abundance even for situations such as suggested above where fisheries expand or contract into cells with different catch-rates. However, to be valid, the trends in abundance must be the same for all cells, or at least, must not be different enough to result in significantly biased indices. In the event of the latter, a better approach would then be to adopt models with time-area interaction terms, although large datasets and large numbers of factor levels for the interaction often overwhelm the memory capabilities of available computers. Furthermore there will generally be missing data for many of the area-time combinations, which can lead to uncertain estimates and requires methods to impute values for these cells.

The importance of accounting for spatial extent in standardisations of CPUE has been recognised for some time (e.g. Walters 2003, Campbell 2004) and recent progress has been made in developing methods to correct CPUE indices using imputation techniques (Ahrens 2010, Carruthers *et al.* 2010, 2011). Most techniques focus on imputing values for cells where no fishing occurred in a given year and broadly follow one of three methods; kriging, spatial smoothing (often using generalized additive models; GAMs) and rule-based imputation. The general premise is common to all approaches; the values of CPUE (often after standardisation) in cells where fishing did occur provide information on the cells in close proximity (in space and/or in time) where fishing did not occur, and this information can be used to impute CPUE values for the cells where fishing did not occur.

The critical questions when attempting to account for the spatial extent of the fishery are therefore; are differences in trends in abundance between cells (especially between fished and un-fished cells) enough to warrant imputation approaches, and if so, which methods provide the most satisfactory estimates of abundance? Many choices must be made if these approaches are adopted. These include, but are not limited to; how to define the region that the index will represent, the spatial scale to focus on, the method of standardising CPUE in the cells where fishing did occur and the method of imputing CPUE in cells where fishing did not occur. With these issues in mind, this paper presents analyses of BET/YFT CPUE using techniques that account for the spatial extent of the JPLL fleet in the WCPO. We will continue to develop the methodology over coming months to provide updated standardised CPUE indices for the 2014 BET/YFT stock assessments. The CPUE indices for Japanese vessels used in the reference case models for the latest BET/YFT assessments (Davies *et al*. 2011, Langley *et al.* 2011) were estimated using operational-level data held by the National Research Institute of Far Seas Fisheries (NRIFSF) in Japan (Hoyle and Okamoto 2011). This dataset is not available to either the Western and Central Pacific fisheries commission (WCPFC) or the Secretariat of the Pacific Community (SPC)[2]. The SPC

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[2] Except under strict conditions and onsite in NRIFSF in Japan

holds a dataset that mostly consists of fishing effort within the exclusive economic zones (EEZs) of the Pacific Island nations. The best data coverage is for region 3 of the WCPO BET/YFT stock assessments, and this is the data analysed here.

This paper begins by examining the JPLL fishery's spatial extent over time. The CPUE data is then adjusted to account for differences in fishing practices over time by incorporating appropriate covariates into GLMs and removing their estimated effects from the raw data. We then develop indices using GAM-based spatial smoothing and rule-based imputation methods, and compare them to the nominal indices and indices calculated using the currently-used GLM-based method and its variants. The SPC-held aggregate-level data at the 5×5 degree square scale is much more complete than the operational-level data, and so further analyses are conducted on that dataset to investigate whether increased spatial data coverage would provide more robust results than the operational-level analyses.

The purpose of this paper is to develop and compare several methods of accounting for spatial extent of fishing, and compare them to currently-used methods for inferring trajectories of stock abundance. We identify issues relating to each method, and discuss how their performance may change if other data sets are used. All indices presented in this paper are preliminary, and we outline in the discussion how these analyses are expected to develop between now and the next stock assessment.

3. Methods

3.1. Data preparation

3.1.1. SPC-held operational-level data

Operational-level data at the set-level were most complete between 1979 and 2011 for Japanese longline vessels. Records outside this period were excluded. Fine-scale latitude and longitude were available for each set and this was used to assign them to 1×1° and 5×5° spatial cells. Hooks-between-floats (HBF) were available for most sets. The few sets with more than 22 HBF were pooled into the 22 HBF category and all sets with missing HBF values were removed. All sets were removed for vessels that fished for less than 10 quarters as it is difficult to accurately estimate vessel effects with fewer records and vessel effects use up considerable degrees of freedom. The effects of data grooming on the characteristics or the data are shown in Table 1.

The data were separated into the six regions currently used in the BET/YFT stock assessments, and only sets within region 3 were retained for the analyses. Available data were very sparse for all other regions. Once the final dataset was established the analyses for BET and YFT were conducted separately.

Fifty-five 5° cells of the 72 in region 3 were fished (in the dataset available) at least once over 1979-2011. It should be noted that cells will often be referred to as 'fished' or 'unfished' when in reality for the operational data some of the cells with missing values would have been fished by JPLL but are not held by SPC. Furthermore, other flags will be fishing in some cells considered 'fished' and 'unfished' for JPLL analyses. For the indices that require a total region to be specified for imputation of missing values, these 55 cells were designated as that region. Most of the missing cells are largely land or continental shelf, with no significant tuna population. Also, while imputing values for cells that are never fished is possible for GAM-based spatial imputation, it is more difficult for rule-based imputation which relies on CPUE being available before and/or after the missing value. For these reasons and for purposes of comparison among methods we considered the 55 cells to represent the total region.

Due to the contraction of the JPLL fleet another dataset was extracted that included vessels under multiple flags (flags with at least 3,000 sets fished). Data grooming followed the rules carried out for the JPLL data except that sets without HBF were not removed as this information is not available for data under most flags. The results of the data grooming are displayed in

3.1.2. Aggregated data

The full Japanese longline dataset aggregated at the 5°-square-scale is held by SPC and provides almost complete spatial coverage of effort of this fleet in the WCPO, though considerable detail of fishing efficiency is lost when the data is aggregated (Langley 2007). With full operational-level data unavailable, many of the analyses were repeated on the aggregated data to examine the benefits of the greater spatial coverage they provide.

The aggregate data were extracted and assigned to the six spatial regions. Data outside the period 1975-2012 were removed. For simple GLM-based indices of abundance (sections 3.3.1, 3.3.3) only data from region 3 were retained for analyses. Due to the abundance of data in the surrounding regions (in comparison to the operational-level data where little data was available outside of region 3) data from all regions were retained for the GAM-based analyses (section 3.3.2) so that they could provide information about the CPUE surface at the edges of region 3. In the latter case the CPUE index is still calculated from only cells in region 3 – data from the surrounding regions merely influence the imputation in cells within region 3 with missing values.

One further GLM-based index was developed that uses data from flags other than Japan to impute CPUE values for cells at time-steps lacking Japanese data. This necessitated extracting aggregated data for vessels of all flags (including Japan), using the approaches described above. Only data within region 3 was retained for this analysis.

The aggregate data was used to calculate indices of spatial concentration of catch and effort, in addition to the indices of abundance. The two indices calculated here are the Gini index for measuring concentration of catch and Gulland's index of measuring the concentration of effort in cells with higher density (as estimated by CPUE). Methods followed those presented by Harley (2009) and a higher Gini index indicates higher proportion of catch being taken from a smaller number of cells, and a higher Gulland's index indicates more fishing effort being expended in cells with higher catch-rates.

3.2. Indices calculated for operational-level data

3.2.1. Currently used CPUE indices

The CPUE indices used in the reference case models for the latest BET/YFT assessments (Davies *et al.* 2011, Langley *et al.* 2011) were estimated using delta lognormal models (Lo *et al.* 1992, Stefansson 1996). The probability of catch being zero (w) is modelled using a binomial GLM (with a logit link function) and the distribution of the positive catch rates is modelled using a standard GLM with normally distributed errors (and an identity link function) after log transforming the catch rate. More formally this model can be described by

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

where y is the CPUE calculated as numbers caught in the set divided by the number of hooks fished in the set. The link function and linear predictor of the binomial GLM are given by $g(w)$ = Intercept + Year-quarter + Cell + Vessel + h(hooks) + h(HBF), where g is the logit link function, Year-quarter and Cell (spatial cell; in current standardizations this is 5° squares) are categorical variables, hooks is a covariate calculated as the number of hooks per set, HBF is a covariate calculated as the number of hooks between floats for the set, and in both cases h is a 6_{th} order polynomial function. The $f(y)$ is the distribution of the positive CPUEs and the model for this component is given by

$$\log(y) = \text{Intercept} + \text{Year-quarter} + \text{Cell} + \text{Vessel} + h(\text{HBF})$$

where the variables have the same form as in the binomial component.

Because this approach only includes marginal effects it assumes that the change in CPUE between year-quarters is the same across spatial cells. Furthermore, it assumes that the CPUE trends for spatial cells not observed (fished) in a given year-quarter are the same as those that were observed.

Because the imputation methods presented in the following sections have been developed under a simplified model structure for ease of developing methodology, the delta log-normal method was not appropriate for comparison. Instead, the reference-case standardised index was estimated using GLMs with a similar structure to those used for spatial imputation in the sections below. This GLM is given by

$$\log(y) = \text{Intercept} + \text{Year-quarter} + \text{Cell} + \text{Vessel} + h(\text{HBF})$$

where y = catch/hook+c, where catch is the number of fish caught in the set, hook is the number of hooks fished in the set and c is a constant added to prevent taking the logarithm of zero for sets where no catch occurred. The offset was set at half of the minimum observed value of y. The independent variables again have the same form as presented in the delta log-normal model. The index of abundance is calculated from the estimated Year-quarter effects and is denoted the 'traditional' index.

3.2.2. *Rule-based imputation*

A rule-based method for imputing CPUE in spatial cells where fishing did not occur has been proposed by Walters (2003) and was implemented by Carruthers *et al.* (2011) for CPUE indices of a range of pelagic species, including BET and YFT in the Indian and Atlantic oceans. CPUE in all cells fished is standardised to remove the influence of factors other than the abundance of fish, before CPUE values are imputed for the missing cells where fishing did not occur in that time step.

Carruthers *et al.* (2011) compared several models of standardisation and identified a GLM with a time-cell interaction as the best performing. Their imputation then proceeded depending on the nature of the cell that needed imputing (the 'missing cell') with the rules being:

1. If the missing cell has CPUE values in at least one year-quarter before, and one year-quarter after, then the mean of the two nearest values is imputed.
2. If the missing cell has no CPUE values in any year-quarter before it then the mean of the first three values occurring after it is imputed.
3. If the missing cell has no CPUE values in any year-quarter after it then the last CPUE occurring before it is imputed.

These rules are ad hoc, for instance the choice of taking the mean of three values in rule 2 as opposed to only one value in rule 3 appears to be arbitrary, and they do not seem to have been formulated based on empirical relationships at different time scales. It is also not a complete set of rules. For example, three values must occur before the first observed CPUE in rule 2 and this will not always be the case. The rules also ignore the reasons that effort is missing from an area.

The rule-based approach was implemented for the SPC-held JPLL data to compare it with currently used standardised indices (section 3.2.1) and GAM-based imputation indices (section 3.2.4). The memory costs of implementing GLMs with time-area interaction terms for the JPLL datasets precluded their use in the time available for this analysis, and so a preliminary approach was used to control for changes in fishing power over time. A log-offset GLM model was fitted with the structure

$$\log(y) = \text{Intercept} + \text{Year-quarter} + \text{Cell} + \text{Vessel} + h(\text{HBF})$$

where y was calculated $y = \text{catch/hook} + c$ where catch is the number of fish caught in the set, hook is the number of hooks fished in the set and c is an offset term which is a constant added to prevent taking the log of zero. The offset was set at half of the minimum observed value of y. The observed log CPUE values ($\log(y)$) were then adjusted for the variables representing changes in fishing practices over time by calculating

$$\log(y)^* = \log(y) - \beta ves - \delta_{hbf}$$

where $\log(y)^*$ is the adjusted log CPUE, β_{ves} are the coefficients of vessel effects and δ_{hbf} is the effect of hooks between floats estimated for the value of HBF in the given set, which was calculated as a function of the coefficients of the polynomial relationship estimated by the GLM. These adjusted CPUE represent the best estimates of standardised log-catch rate at the set-level (which can now be aggregated to the year-quarter-level) in the absence of being able to fit GLMs with time-area interactions.

The means of the log(y)* over all sets in each cell, in each year-quarter, were calculated to produce a spatial set of CPUE values for each year-quarter. These are the 'observed' CPUEs for cells where fishing occurred in that year-quarter. The rule-based approach was then applied to impute values for the remaining cells in each year-quarter where fishing did not occur. The rules used were the same as Carruthers *et al.* (2011)'s and presented above except that the first value after the missing value was imputed for rule 2 rather than the mean of the first three values. The CPUE index was then calculated by summing the CPUEs across all cells (both observed and imputed) in each year-quarter and is denoted the 'Carruthers' index.

It was quickly apparent that many cells were unfished for long periods of time and so the Carruthers method imputed CPUE for some missing cells as the mean of CPUEs widely separated in time. This is not ideal as, if CPUE is changing through time, the change will be underestimated by the imputation. Three datasets were therefore analysed; the full dataset where data from all cells was retained, a dataset where data from cells fished in less than 50% of year-quarters was discarded, and a dataset where data from cells fished in less than 50% of year-quarters was discarded.

3.2.3. GLM-based backfilling

An alternative approach attempts to account for possible synchronicity in the temporal fluctuations in catch-rate across cells. Instead of using previous or future CPUE to impute values, the predicted value for the missing cells was taken as the prediction of CPUE for the individual cell in that particular year-quarter, based on the original GLM model used to adjust for fishing efficiency (section 3.2.1). This approach can therefore be considered to be a hybrid of the traditional marginal effects GLM model for the imputed cells where we lack information on trends, and a model similar to one with an area-time interaction for the cells where fishing did occur and we therefore have information on trends, and is denoted the 'hybrid' index. The CPUE index was again calculated by summing the CPUEs across all cells (both observed and imputed) in each year-quarter. It accounts for some spatial and temporal effects when imputing values, while also allowing different cells to have different trends in catch-rate where there is evidence (i.e. where fishing occurs). As the number of cells that were not fished increases we expect that this index will approach the traditional index in section 3.2.1 because the index will be made up of an increasing number of cells where the CPUE has been imputed based on the traditional model itself.

3.2.4. Spatial imputation using GAMs

An alternative method of accounting for spatial extent in CPUE standardisation uses GAMs to spatially smooth the CPUEs and simultaneously predict the missing values in the cells where fishing did not occur. A preliminary analysis of the SPC-held JPLL dataset using this approach was undertaken through the following methods. The same adjusted CPUE (log(y)*) as used in section 3.2.2 was modelled at the set level using GAMs in the R package `mgcv`. Data for each year-quarter was analysed separately to produce a time-specific spatial CPUE surface. The model formula was

$$\log(y)^* \sim \mathrm{s}(\text{longitude, latitude})$$

where $\log(y)^*$ is the adjusted CPUE at the set-level for the year-quarter being analysed, s represents an isotropic smoother, and longitude and latitude are measured at the 1° scale. The standardised CPUE index for each year-quarter can then be calculated as the sum over the model estimates of mean CPUE in the cells that were fished and the model predictions of CPUE in cells that were not fished (the model-based imputed values). This is effectively the sum over the model predicted CPUE surface for the effective region being considered and is calculated using the `predict.gam` function in R and is denoted the 'GAM-based' index.

Predictions of CPUE from the GAM were highly unstable for certain cells in some years, particularly on the edges of the region where there are no surrounding cells to constrain the predicted gradient of catch-rate. This was more prevalent towards the end of the time-series when the spatial extent of the Japanese longline fishery had significantly contracted. Two rule-based approaches were used to limit the effects of this problem. If the predicted CPUE of a missing cell was higher or lower than the maximum or minimum adjusted observed CPUE (log(y)*) in that year-quarter then the value imputed for the cell was taken to be either 1) the mean of the fitted values in that year-quarter (from the GAM model), or 2) the predicted value for that cell in that year-quarter from the original GLM model (taken to be the prediction for the 5° cell to which the 1° cell in the GAM model is associated) used to adjust for fishing efficiency (section 3.2.1).

Each of these indices was also calculated for the full operational-level dataset which included data from vessels under all the main flags. The models for this dataset only differ in that HBF is no longer available for most sets and it is consequently removed from the models.

3.3. Indices calculated for aggregated data

3.3.1. Traditional reference indices

The reference indices used for the aggregated data broadly follow those previously estimated and used for stock assessments of BET/YFT (Hoyle 2009). Zero catches are less frequent in aggregated data and so it is common to remove these data and fit a GLM on the log-scale, which in this case has a model with the simple form of

$$\log(y) = \text{Intercept} + \text{Year-quarter} + \text{Cell} + h(\text{HBF})$$

where y is CPUE (with values of zero removed) and Year-quarter, Cell and HBF are the familiar time, area and hooks-between-floats effects, with the latter at the 5° scale. The standardised index for this model is then calculated by extracting the year-quarter effects and is again denoted the 'traditional' index.

To provide a direct reference index to compare to the multiple flag model developed in section 3.3.3, an additional model was fitted that allowed for differences in trends between cells. It has the form

$$\log(y) = \text{Intercept} + \text{Year-quarter-cell} + h(\text{HBF})$$

where the response is the same as above and the Year-quarter-cell is a factor with levels for each combination of year, quarter and cell for which there was data. This manual construction of the year-quarter-cell factor instead of including a three-way interaction between year, quarter and cell in the model was to prevent the instabilities that can result when missing values occur for some combinations of the factors in an interaction (which is relatively common for this dataset). The CPUE index was calculated as the mean over the predicted values for all cells with predictions in each year-quarter and is denoted the 'traditional-interaction' index. Note that the number of cells with predictions in each year-quarter varies as some cells in the region were obviously not fished in each year-quarter.

3.3.2. Spatial imputation using GAMs

It is difficult to standardise the aggregated data for temporal changes in fishing performance as relevant covariates at the set-level are clearly unavailable, and the data is pooled over vessels within each cell. Consequently, the spatial imputation for this dataset using GAMs was more straightforward than for the operational-level data. Due to more data being available in all assessment regions the GAM was fitted to all data instead of just region 3, to allow data in other regions to influence the CPUE surface on the edges of region 3. The GAM model was fitted to data from each year-quarter separately and was simply

$$\log(y) \sim \mathrm{s}(\text{longitude}, \text{latitude})$$

where $\log(y)$ is the CPUE (with zero catches removed) at the 5° scale for that year-quarter in question, s represents an isotropic smoother, and latitude and longitude are continuous variables. The CPUE index for each year-quarter can again be calculated as the sum over the GAM estimates of mean CPUE in the cells that were fished and the GAM-based imputations of CPUE in cells that were not fished and is again denoted the 'GAM-based' index. Note that this was the sum over all cells in region 3, including those that were never fished. Due to far fewer cells in this dataset being un-fished in comparison to the operational-level data, the imputations were more stable. However, on the very infrequent occasions that the predicted CPUE of a missing cell was higher or lower than the maximum or minimum observed CPUE in that year-quarter, the value imputed for the cell was taken to be the mean of the fitted values from the GAM model in that year-quarter.

3.3.3. Imputing using a GLM with multiple flags

Aggregated data for vessels of all flags were used to fit a GLM that allowed prediction of CPUE for Japanese vessels in cells where they did not fish, provided at least one other flag fished in that cell in that time period. The model was

$$\log(y) = \text{Intercept} + \text{Year-quarter-cell} + \text{Flag}$$

where y is CPUE (catch/hooks) after the small number of zero catch-rates were removed, Year-quarter-cell is a factor with levels for every combination of year, quarter and cell where fishing occurred and flag is a factor indicating the nationality for the CPUE being modelled. Again we manually constructed the year-quarter-cell factor instead of including a three-way interaction between year, quarter and cell in the model, to prevent the instabilities that can result when missing values occur for some combinations of the factors in an interaction. We predicted CPUE for each year-quarter-cell combination for Japanese flagged vessels, using the `R` function `predict`. The index was calculated as the mean over the predicted values for all cells with predictions in each year-quarter and is denoted the 'flag-imputation' index. Note that the number of cells with predictions in each year-quarter varies as some cells in the region were invariably not fished by any flag in each year-quarter. This means that the index will still be affected by the spatial extend of fishing, but will be less sensitive than the traditional index as some missing values (cells fished at some stage over the time-series) will be imputed.

4. Results

The number of cells in region 3 that were fished by Japanese vessels changed dramatically between the 1970's and 2012 for both the SPC-held operational-level data (Figure 2) and the aggregated data (Figure 3). The spatial pattern of contraction of fishing in the SPC-held operational-level data is shown at two spatial scales in Figure 4 and 5. The pattern of presence of fishing and CPUE in each year-quarter in individual spatial cells is displayed in Figure 6. This shows that 'missing data' (cells not fished) occurs as a mix of short-term absences of data in some cells and extended time-periods with no data in others. The latter includes cells where fishing did not occur for long periods at the beginning or end of the time-series.

Gulland's index of concentration for BET was variable and had periods where it was both lower and higher than one, indicating fishing effort was sometimes concentrated in cells where CPUE was lower and higher, respectively. For YFT it was generally above one in most years and showed a dramatic increase in the period after about 2008. The Gini index showed a steady increase from about 0.7 to about 0.9 over the whole time-series, for both species.

The general dynamics of the GAM-based spatial indices followed those observed for the nominal and GLM-based indices. The exception to this was the increased variation in the GAM-based index especially towards the end of the time-series (Figure 8b, 9b, 10c, 11c). This was especially the case for the operational-level data for both BET and YFT, presumably partly due to the sparseness of cells fished during this period for that dataset. Over this time period it was frequently necessary to constrain predictions of CPUE in the un-fished cells as they were often unrealistically high or low for many cells, especially on the edge of the region. This tended to result in the GAM index being higher than the traditional index in those years (Figure 8f, 9f) and resulted in a trend in the ratio of the GAM-based index to the traditional index over time for YFT but not for BET. The indices produced by constraining unstable estimates to be either the mean of the fitted values in that year-quarter or the predictions from the GLM model were essentially identical and hence only the former is displayed in the figures.

The GAM-based index was more stable for the aggregated data and except for a very few year-quarters it was unnecessary to constrain the spatial imputations of missing CPUEs. There were fewer differences between the GAM-based indices and the traditional indices for this dataset and there was less, to no trend detected in their ratios against the traditional indices (Figure 10g, 11g). Examples are shown for two contrasting year-quarters for the aggregate data, one with a high number of fished cells where imputation did not have to be constrained (Figure 12), and one where imputations for several cells needed to be constrained when the GAM-predicted values were unstable (Figure 13).

The Carruthers et al. (2011) method of rule-based backfilling produced indices that displayed the most significant deviations away from the nominal and traditional indices. For both species these indices exhibited different trends over the time-period, with the index for BET being generally higher than the traditional index in the early part of the time-series and lower in the later period (Figure 8c). For YFT the index was lower than the traditional index initially but was generally higher during the middle to latter periods of the time-series (Figure 9c). These indices also display substantially less year-quarterly variation than the traditional indices. This may be because the imputations dampen fluctuations as they are linked with CPUE in several surrounding year-quarters. The general trends remained when the cells with large proportions of year-quarters without CPUE estimates were removed, but the year-quarterly variation increased.

The hybrid indices that were calculated by imputing CPUE based on the main effects GLM model (the basis of the traditional index) produced indices that were relatively similar to the traditional indices for the operational-level data, although there was a slight negative trend in the ratio against the traditional index for BET (Figure 8d) and a positive trend for YFT (Figure 9d). Few changes in these indices were observed when cells with large proportions of year-quarters without CPUE estimates were removed.

The method that used aggregate data and multiple flags to impute CPUE values for cells where the Japanese fleet did not fish produced indices (the flag-imputation indices) for both species that were very similar to the traditional indices and the traditional-interaction indices (Figure 10d, 11d). The exception was for the period since 2008 when this method produced an index lower than the traditional and nominal indices for BET.

The indices performed similarly on the operational-level data where data from vessels under all the main flags were included (Figure 14 and 15). Carruthers indices were again more stable than the other indices and consequently displayed trends in the ratio against the traditional index. The GAM-based indices were more stable than those for the JPLL operational-level data in the later years.

Comparison of each of the traditional indices showed similar general patterns between each dataset, though there were differences in variability and periods where some indices differed from each other somewhat, most notably at the very end of the BET and start of the YFT time-series.

5. Discussion

The indices of concentration suggest that there has been a trend towards increased concentration of catches into a smaller number of cells, and at least for YFT, some concentration of fishing effort in cells with higher CPUE, especially in the last five years. While these dynamics must be accounted for by including cell effects within standardisation models they do not necessarily demand spatial imputation methods. The insights from these indices are valuable, but they could be improved for our purpose here (accounting for spatial extent when estimating relative abundance indices) by incorporating information on unfished cells. For example, Gulland's index shows the concentration of effort within the year-quarter, and within the cells that were actually fished in that year-quarter. It provides no information about CPUE in un-fished cells at that time or the patterns of concentration of effort between year-quarters for the full set of cells in the region, which is more important for CPUE standardisation. Development of further indices of concentration that consider unfished cell would certainly be beneficial for informing spatial CPUE standardisations, especially if they can identify differences in CPUE trend between cells and if so, whether fishing is becoming concentrated within cells with different trends.

Unfortunately indices of concentration and other diagnostics do not provide any information on the dynamics of CPUE in cells that are never fished. This highlights the problem with calculating CPUE indices for a region with different categories of data availability. For example, there are cells that are fished in every time-period, cells that are never fished and cells that are sometimes fished. Currently-used standardisations are robust if the trends in CPUE between these categories are very similar. The validity of this assumption depends on why the cells belong in these categories, for example, are they un-fished because of political regulations, the presence of other fleets etc., or the abundance of fish. Furthermore, it depends on the biology of the species, such as whether there is a high level of movement at a scale larger than the size of the spatial cells in the model that can reduce localized depletions from fishing as just one example. Imputation is desirable if trends are likely to be different between the categories and the reasons for the missing cells will affect the best way to do this. For example, the Carruthers and hybrid indices are only able to impute cells that are fished in at least one or more years, and so again assumptions are made about the cells that are never fished. Spatial imputation using GAM-based methods are capable of imputing for all missing cells, including those that were never fished, but this requires extrapolation, which has its own risks. Without being able to directly calculate relative changes in CPUE between cells in the different categories we are limited to comparing the different indices that accommodate variation in trends between cell and indices that do not.

The methods of accounting for spatial extent of fishing produced indices largely similar to the traditional indices. For BET this was a relatively variable index with little overall trend since about 1990. For YFT this was a sustained decline over most of the time-period investigated. The largest exception to this was the Carruthers index which generally flattened any trend observed in the traditional index for both species. However, this may be attributed to both the imputation rules and the large amount of missing data when using the SPC holdings of Japanese operational data. Thus this method may be less suitable for datasets with large gaps as the ratio of imputed to ‘real’ data increases. We did not apply this approach to either the all-flags operational data or the aggregate data. The relative stability of the index is a result of the frequency with which a large proportion of cells are un-fished in any year-quarter, and the long periods for which a cell might not be fished. This means that the index in any given year-quarter is made up of many cells whose imputed value is a function of abundance often a significant time prior to, or subsequent to the focal year-quarter. This effectively dampens between year-quarter variations. It is possible that it is adequate in other situations where variability is lower, a higher proportion of cells are fished and/or CPUE in a cell is only missing for a year or two straight (the simulated data of Carruthers *et al.* (2011) for example), rather than for multiple years such as for our datasets. Regardless, it will generally be possible to come up with improved imputation rules such as those used for the hybrid index which better accounts for year-quarter effects.

The GAM-based and hybrid indices also showed some deviations away from the traditional index for the operational data. For the former, some differences can probably be attributed to the high uncertainty in estimates in some year-quarters, especially in recent years where spatial coverage was lower. With high uncertainty on the log-scale the expected value on the nominal scale will tend to be higher and this led to a tendency for the GAM-based estimates to be substantially higher than for the traditional index in some of these later year-quarters. This would presumably be reduced for the full dataset and this is reflected in the GAM-based indices for the aggregate data which had fewer extreme positive ratios against the traditional indices and also for the operational-level data with all flags included. The hybrid index for YFT also showed an increasing trend in the ratio against the traditional index. The consequences of results such as this for stock assessments are significant and further work into whether these differences are real or a consequence of the limited data and preliminary model structures is important.

There are numerous future research avenues for improving indices that account for spatial extent of fishing effort. For example, there are many methodological improvements that could be made to the indices themselves:

- utilise more realistic error distributions (than those assumed for the simple log-offset methods used here) for the GLMs fitted to the observed data.
- account for zero inflation in the operational data.
- utilise more powerful computing resources to investigate the possibility of implementing models with area-time interactions for operational-level data.
- determine the optimal spatial scale for undertaking analyses.
- account for cells with large proportions of landmass occurring within them.
- weight data in the models based on the number of sets in the spatial cell to prevent cells where a lot of effort is concentrated from biasing the index
- investigate the effects of spatial correlation in residuals for models where time-area interactions are not accounted for.
- calculate reliable uncertainty around the point estimates, which are an important component of assessment models.

The results from this paper will form the basis of future work and have identified general methods that have promise and should be investigated further. Among the more promising is the hybrid index, which is some way between the traditional method and a full interaction model with imputation of missing cells. The GAM-based index of spatial imputation also has some attractive properties and its preliminary performance shows potential, however there are issues that need to be resolved. Perhaps most importantly is the difficulty in predicting CPUE for cells on the boundary of a region where there is little surrounding observed data to constrain predictions to be realistic. This is partly a consequence of extrapolating a statistical technique beyond the observed data which is a risky endeavour, although it should be noted that the risks of the alternative (of not imputing missing values) are also high, and are of course the motivation behind this paper. This was most prevalent when little data were available and so it is hoped that the issue will be reduced if the full operational-level data was available. However, whether this technique could be used in some other regions where spatial coverage is more limited (even in the full dataset), remains to be seen. Future work would benefit from investigating whether developments such as incorporating a time dimension into smoothers may lead to more robust indices.

Development of techniques to test and compare the performance of different approaches will be just as important as improving the fitted models themselves. A cross-validation approach to model comparison appears to be well suited when different methods are fitted to the same data. This approach aims to identify models with better predictive ability which is perhaps the most important property of an imputation method given that predicting unobserved CPUE is their main function. Development of cross-validation routines would significantly improve the comparisons of methods presented herein.

A more challenging, though complementary approach to model testing would involve construction of a simulation model to represent the temporal and spatial dynamics of BET/YFT in the WCPO, and the 'observation process' linking these underlying dynamics in each spatial cell with the CPUE observations that result from fishing within it. This is a difficult undertaking and careful thought must be given to each of the large number of simplifying assumptions to ensure that important properties of the system are captured with respect to the purposes of the study. The simulation approach was adopted by Carruthers *et al.* (2010, 2011) to test several methods of calculating abundance indices for pelagic fish, and a similar approach would benefit other aspects of the WCPO tuna research, such as analyses of the spatial dynamics of tuna tagging programmes.

Finally, if these methods and the resulting indices are to be the best possible – then they also need to be based on the best available data. It has been shown that operational data hold the best hope of being able to standardise for important factors such as vessel and hooks-between-floats. SPC holds some operational data for DWFN vessels, but this data only has reasonable coverage for region three. Ideally as this work is progressed we will have access to all available DWFN operational data under arrangements that are conducive to good and thorough scientific investigation. Alternatively, aggregated data in the non-equatorial assessment regions will have to be used.

6. References

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7. Tables

Table 1: Characteristics of the data for the full operational dataset for region 3 and the data remaining after removing years, after removing records without HBF information and after removing vessels fishing for less than 10 year-quarters for data for just JPLL and for all flags (AllLL).

Data	No. sets (thousands)	No. hooks (millions)	BET caught (thousands)	YFT caught (thousands)	No. vessels
JPLL					
Full	337	760	3,710	9,383	1,687
Yrs removed	335	755	3,700	9,277	1,680
HBF removed	308	687	3,424	8,384	1,543
Vessels removed	229	522	2,741	6,215	358
AllLL					
Full	972	1,657	6,912	13,370	4,917
Yrs removed	957	1,617	6,793	12,844	4,683
Vessels removed	679	1,203	5,299	9,401	1,048

8. Figures

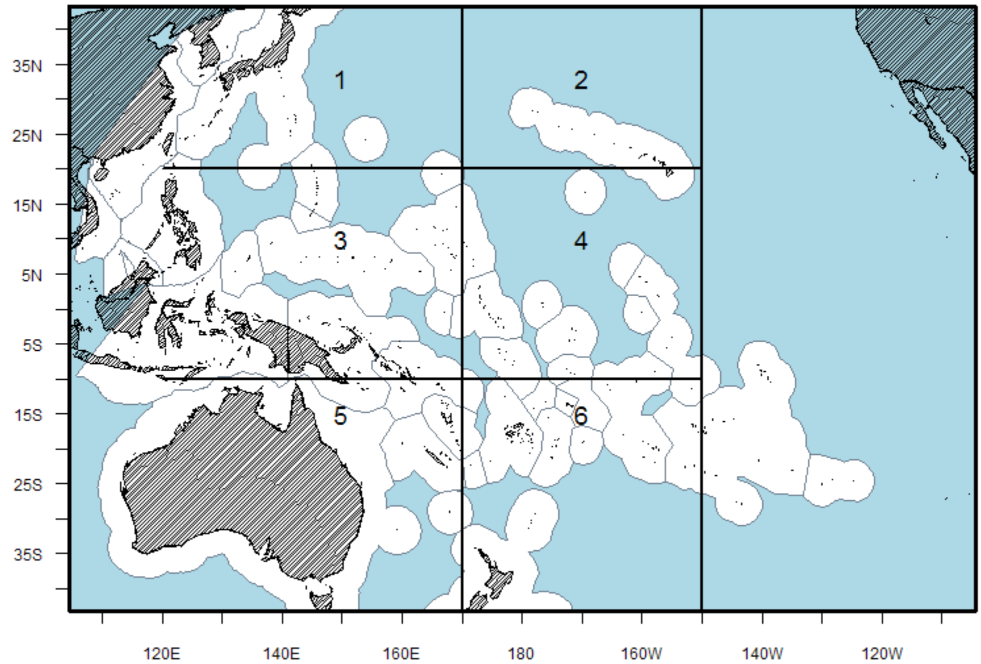

Figure 1: The regions used for the WCPFC BET/YFT stock assessments.

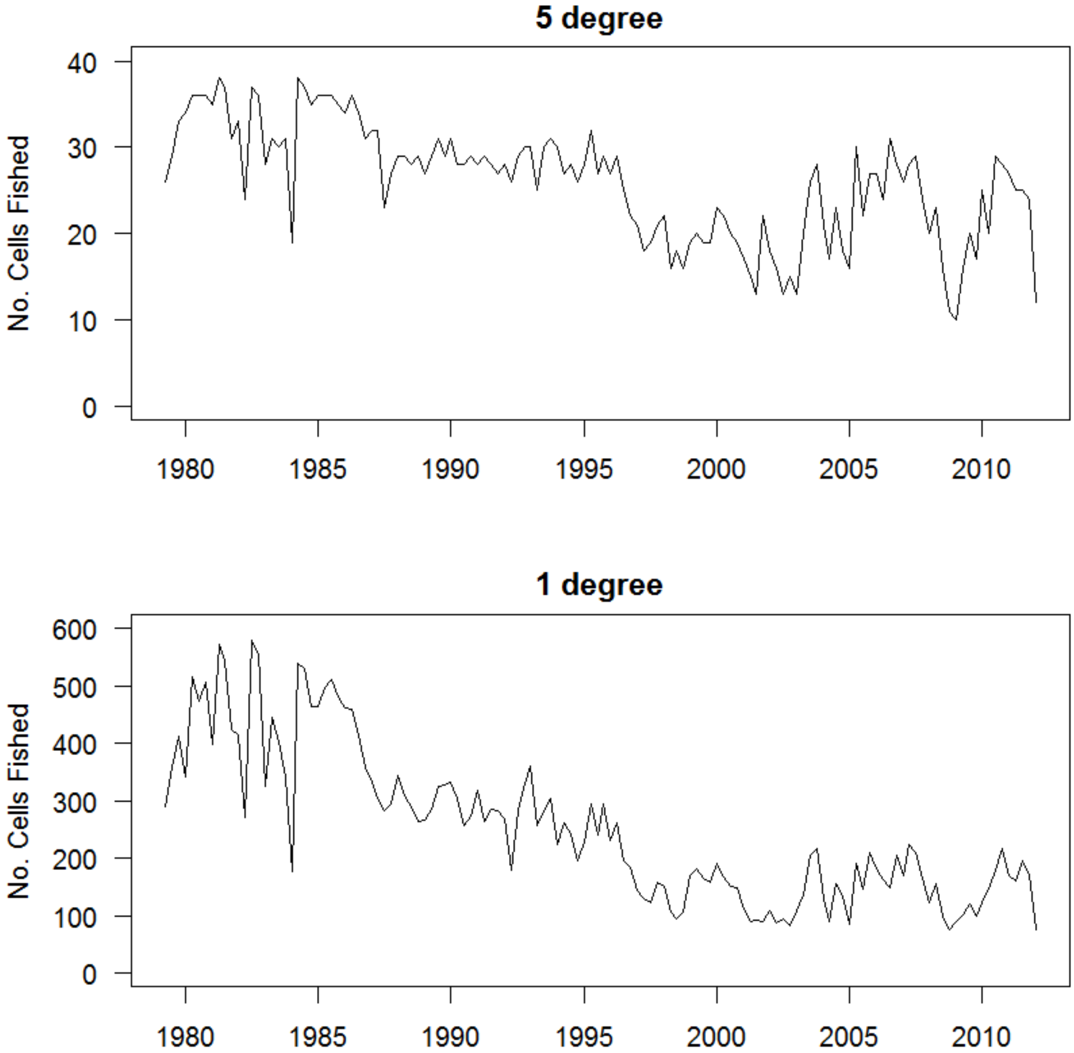

Figure 2: The number of spatial cells in region 3 fished in each year-quarter by Japanese longline vessels, for the SPC-held operational-level data. The top and bottom panels are at the 5×5° and 1×1° square scale, respectively.

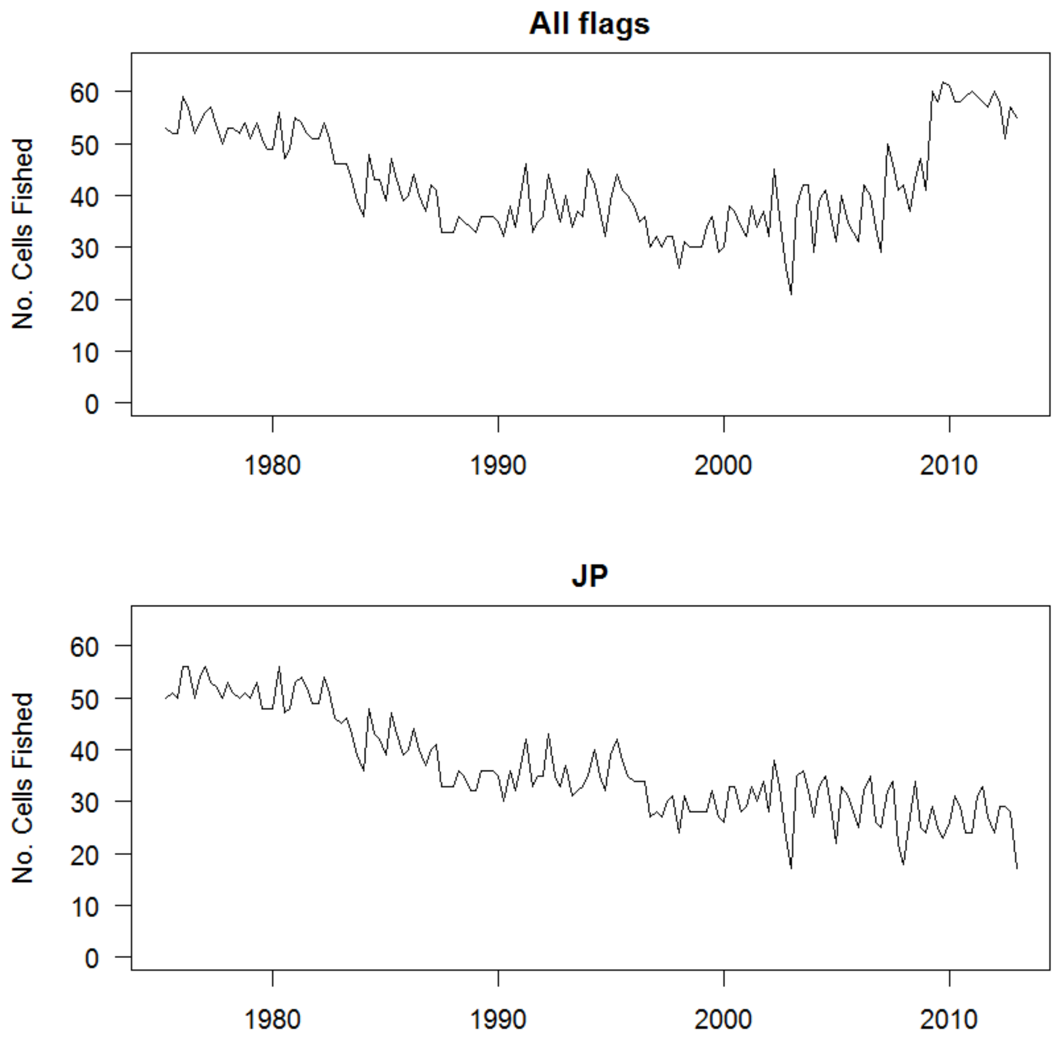

Figure 3: The number of 5×5° spatial cells in region 3 fished in each year-quarter by longline vessels of all flags (top panel) and Japanese longline vessels (bottom panel) for the aggregated dataset.

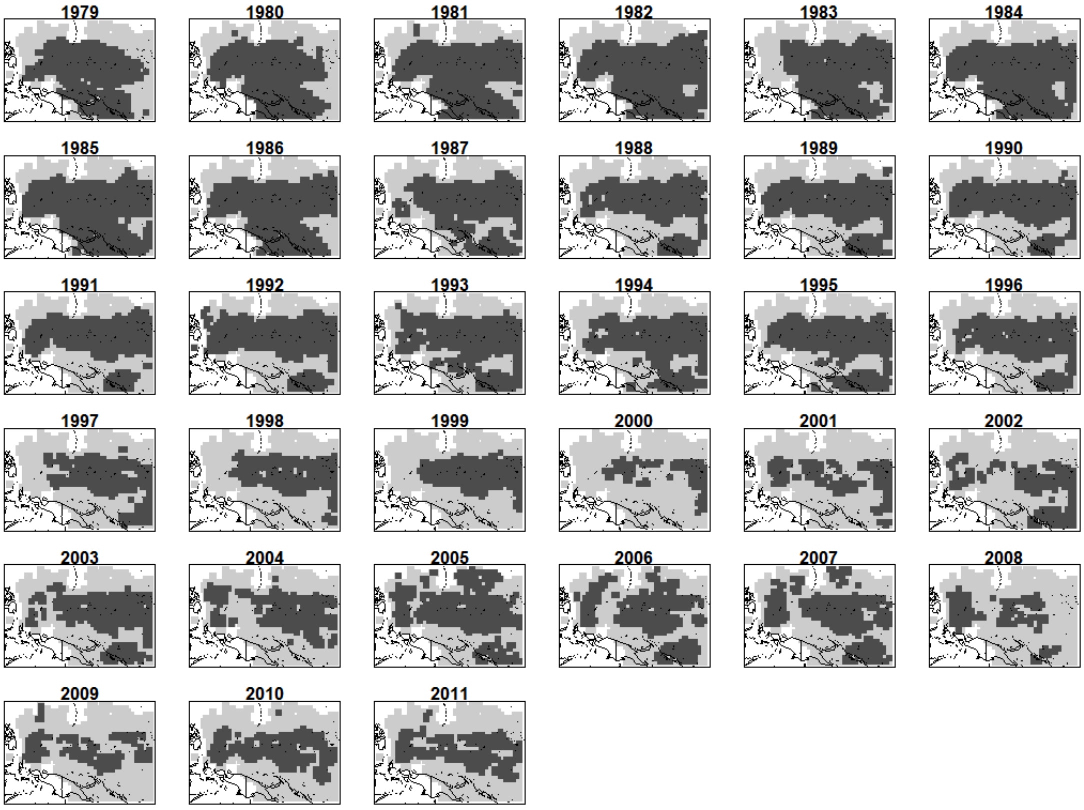

Figure 4: Spatial distribution of the 1×1° spatial cells with data in each year in region 3 by Japanese longline vessels for the SPC-held operational-level data.

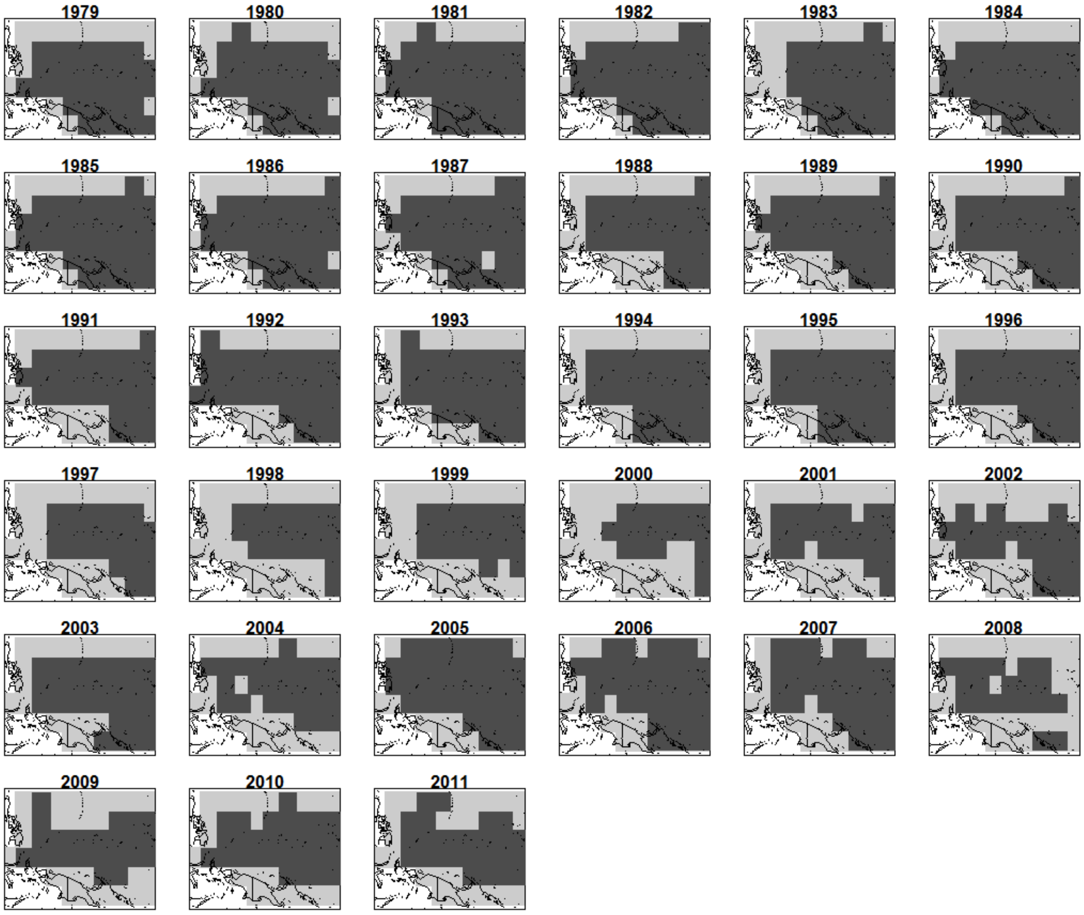

Figure 5: Spatial distribution of the 5×5° spatial cells fished in each year in region 3 by Japanese longline vessels for the SPC-held operational-level data.

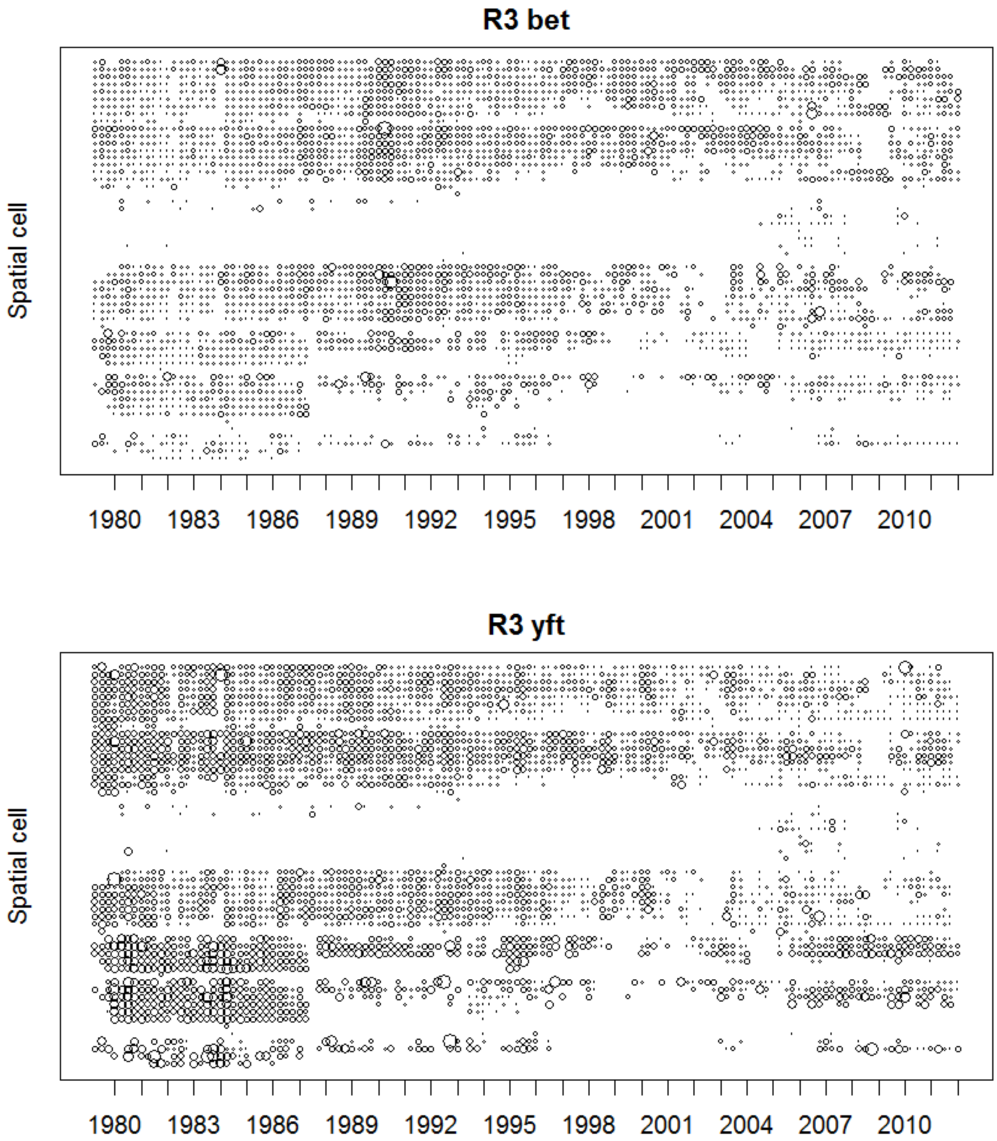

Figure 6: Nominal CPUE in each year-quarter for each 5×5° spatial cell for BET (top panel) and YFT (bottom panel) for the SPC-held operational-level data. Each row of bubbles represents an individual cell, the area of the bubble is proportional to CPUE and the absence of a bubble in a year-quarter indicates that no fishing data were available in the cell then.

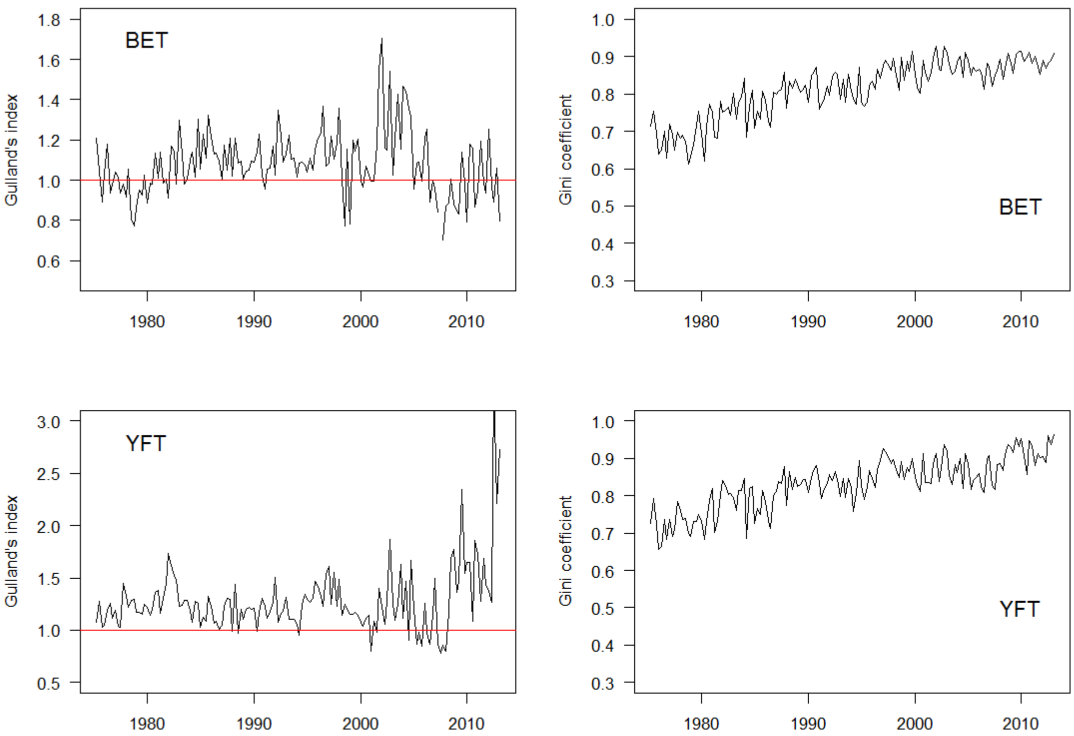

Figure 7: Gulland's index of concentration of effort (left panels) and the Gini index of concentration of catch (right panels) calculated from the aggregate data for BET/YFT in region 3.

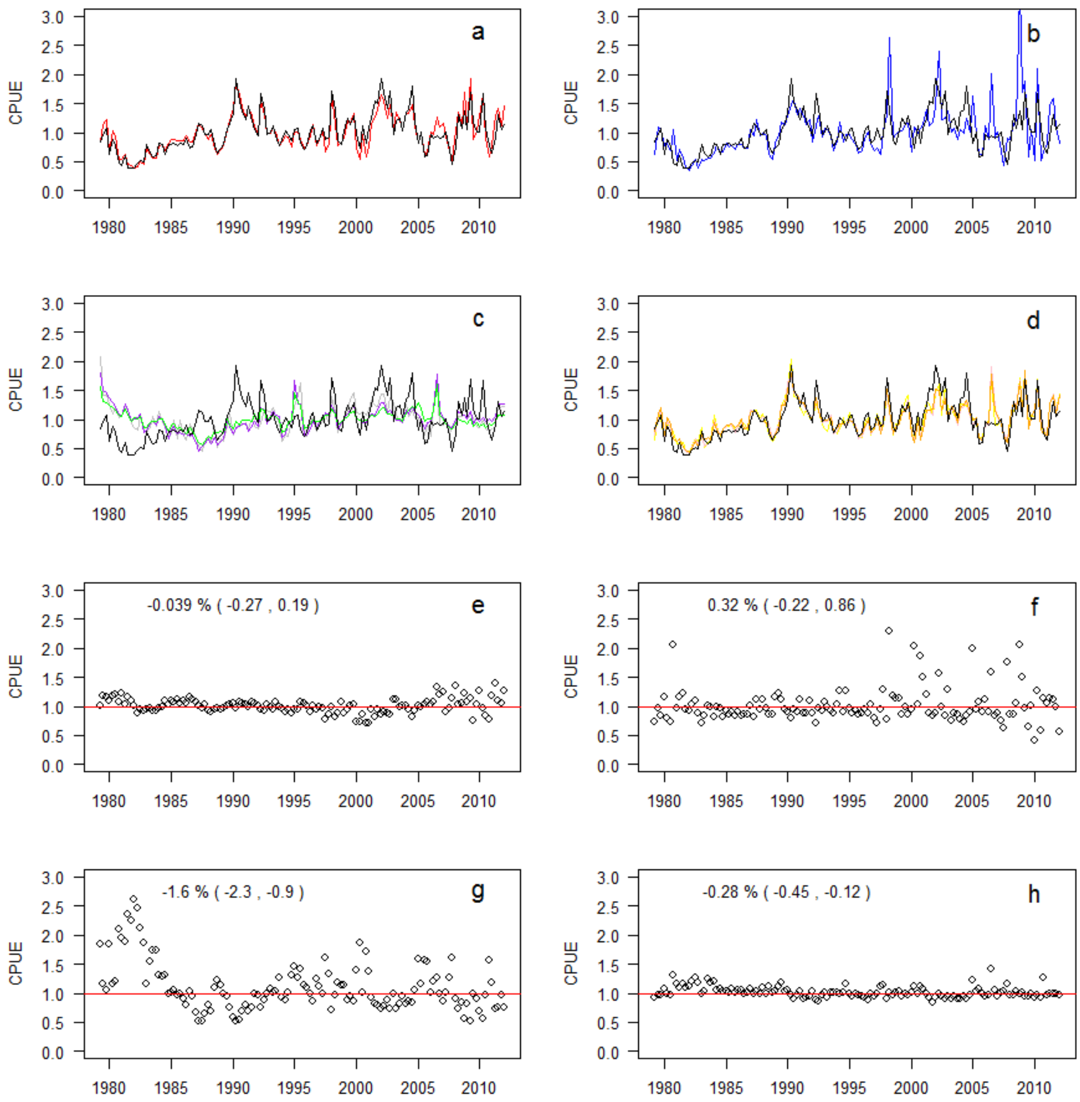

Figure 8: Indices of BET CPUE in region 3 for the SPC-held operational-level data for Japanese longline vessels. The black line in each panel is the nominal CPUE index. The red line in panel a is the traditional index and the blue line in panel b is the GAM-based index. The indices in panel c are Carruthers indices with the green, purple and grey lines representing indices when all cells are retained, when cells with less than 50% year-quarters fished are removed, and when cells with less than 70% of year-quarters fished are removed, respectively. The indices in Panel e are the hybrid indices with the orange, pink (obscured) and yellow lines representing indices when all cells are retained, when cells with less than 50% year-quarters fished are removed, and when cells with less than 70% of year-quarters fished are removed, respectively. Panel e shows the ratio of the traditional index to the nominal index, panels f, g and h show the ratio of the GAM-based, Carruthers and hybrid indices, respectively, against the traditional index. The numbers in panels e-h are the annual trend in the ratio estimated using a linear regression model fitted to the log ratios, with the 95% confidence interval for this trend given in brackets.

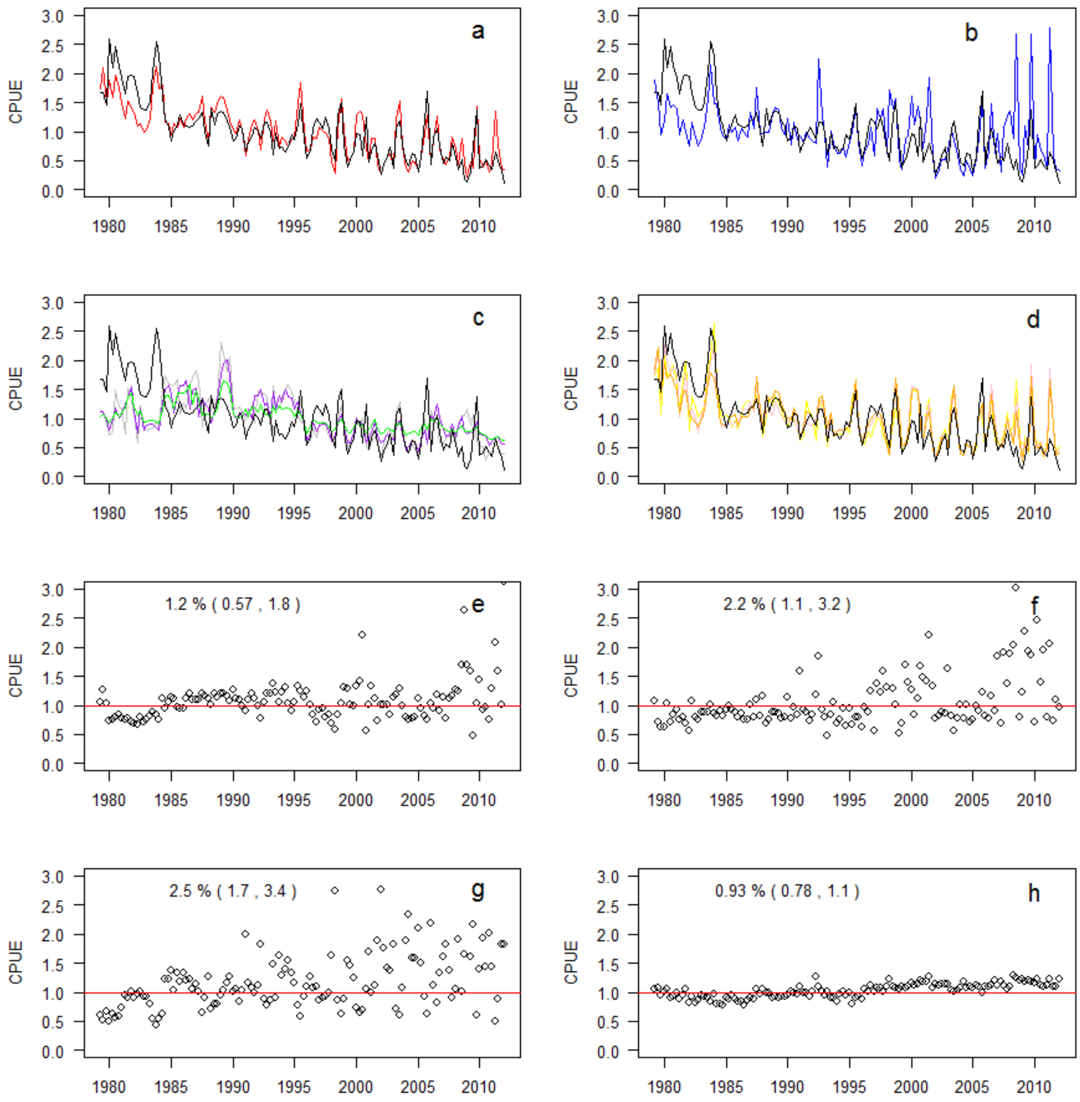

Figure 9: Indices of YFT CPUE in region 3 for the SPC-held operational-level data for Japanese longline vessels. The black line in each panel is the nominal CPUE index. The red line in panel a is the traditional index and the blue line in panel b is the GAM-based index. The indices in panel c are the Carruthers indices with the green, purple and grey lines representing indices when all cells are retained, when cells with less than 50% year-quarters fished are removed, and when cells with less than 70% of year-quarters fished are removed, respectively. The indices in Panel e are the hybrid indices with the orange, pink (obscured) and yellow lines representing indices when all cells are retained, when cells with less than 50% year-quarters fished are removed, and when cells with less than 70% of year-quarters fished are removed, respectively. Panel e shows the ratio of the traditional index to the nominal index, panels f, g and h show the ratio of the GAM-based, Carruthers and hybrid indices, respectively, against the traditional index. The numbers in panels e-h are the annual trend in the ratio estimated using a linear regression model fitted to the log ratios, with the 95% confidence interval for this trend given in brackets.

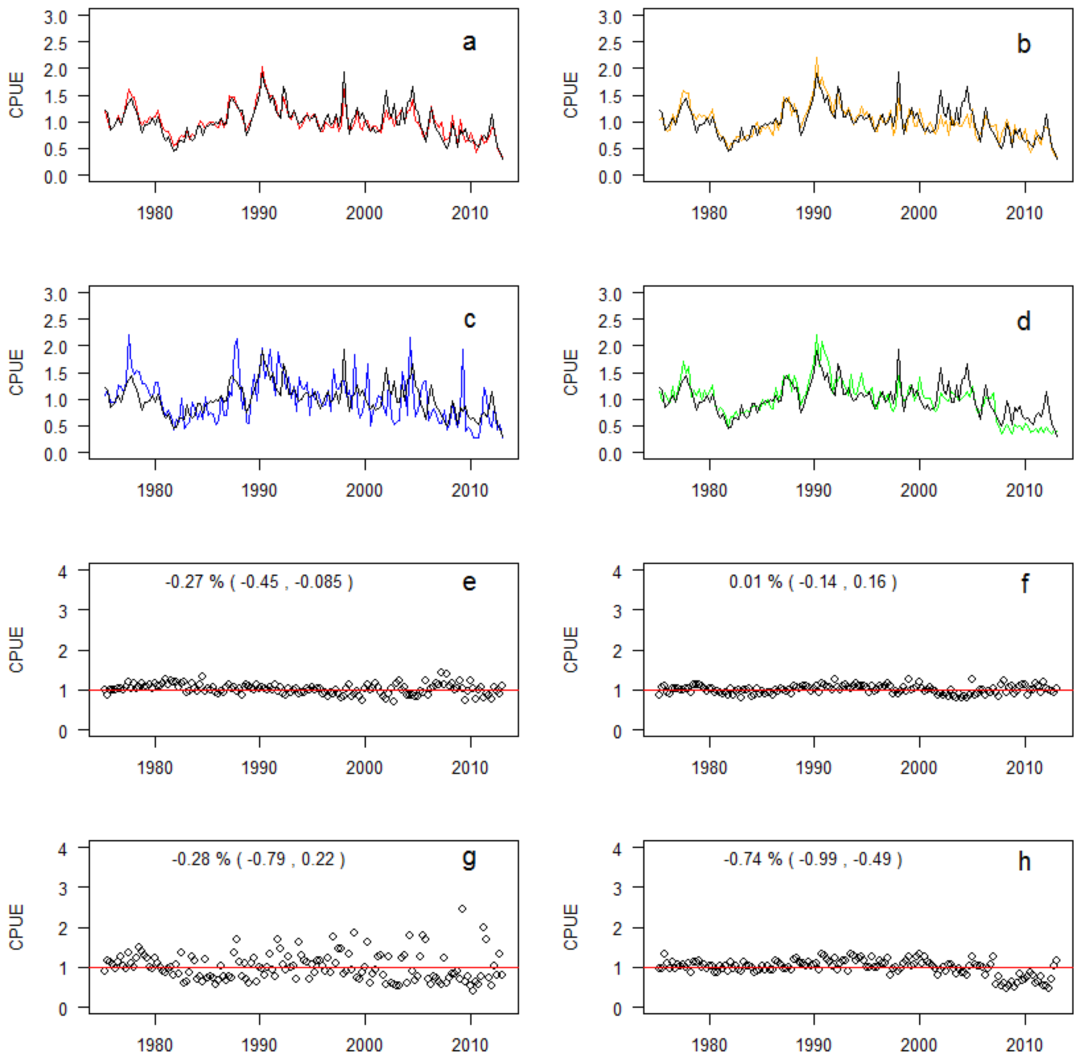

Figure 10: Indices of BET CPUE in region 3 for the aggregate data for Japanese longline vessels. The black line in each panel is the nominal CPUE index. The red line in panel a is the traditional index, the orange line in panel b is the traditional- interaction index, the blue line in panel c is the GAM-based index and the green line in panel d is the flag-imputation index. Panel e shows the ratio of the traditional index to the nominal index, panels f, g and h show the ratio of the traditional-interaction, GAM-based, and flag-imputation indices, respectively, against the traditional index. The numbers in panels e-h are the annual trend in the ratio estimated using a linear regression model fitted to the log ratios, with the 95% confidence interval for this trend given in brackets.

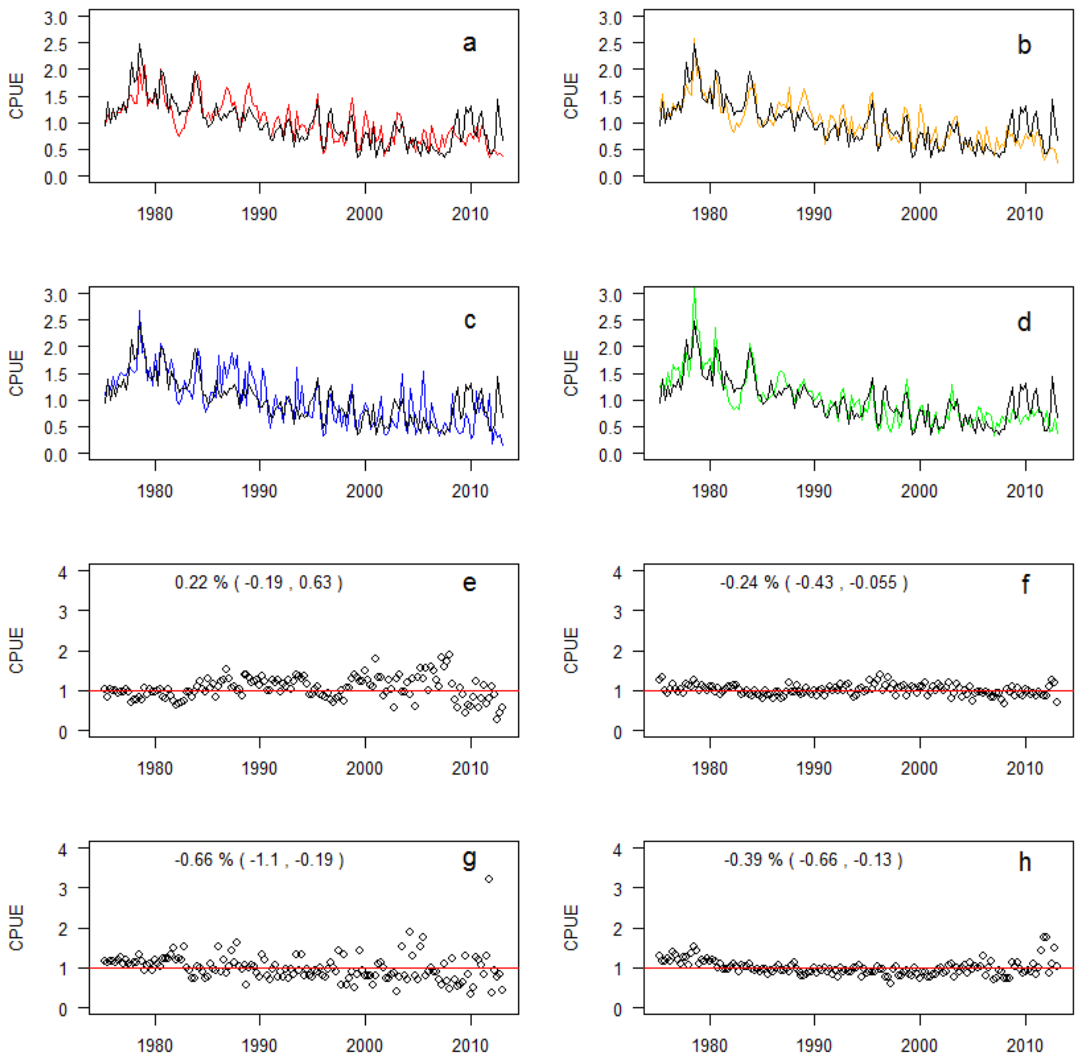

Figure 11: Indices of YFT CPUE in region 3 for the aggregate data for Japanese longline vessels. The black line in each panel is the nominal CPUE index. The red line in panel a is the traditional index, the orange line in panel b is the traditional-interaction, the blue line in panel c is the GAM-based index and the green line in panel d is the flag-imputation index. Panel e shows the ratio of the traditional index to the nominal index, panels f, g and h show the ratio of the traditional-interaction, GAM-based, and -flag-imputation indices, respectively, against the traditional index. The numbers in panels e-h are the annual trend in the ratio estimated using a linear regression model fitted to the log ratios, with the 95% confidence interval for this trend given in brackets.

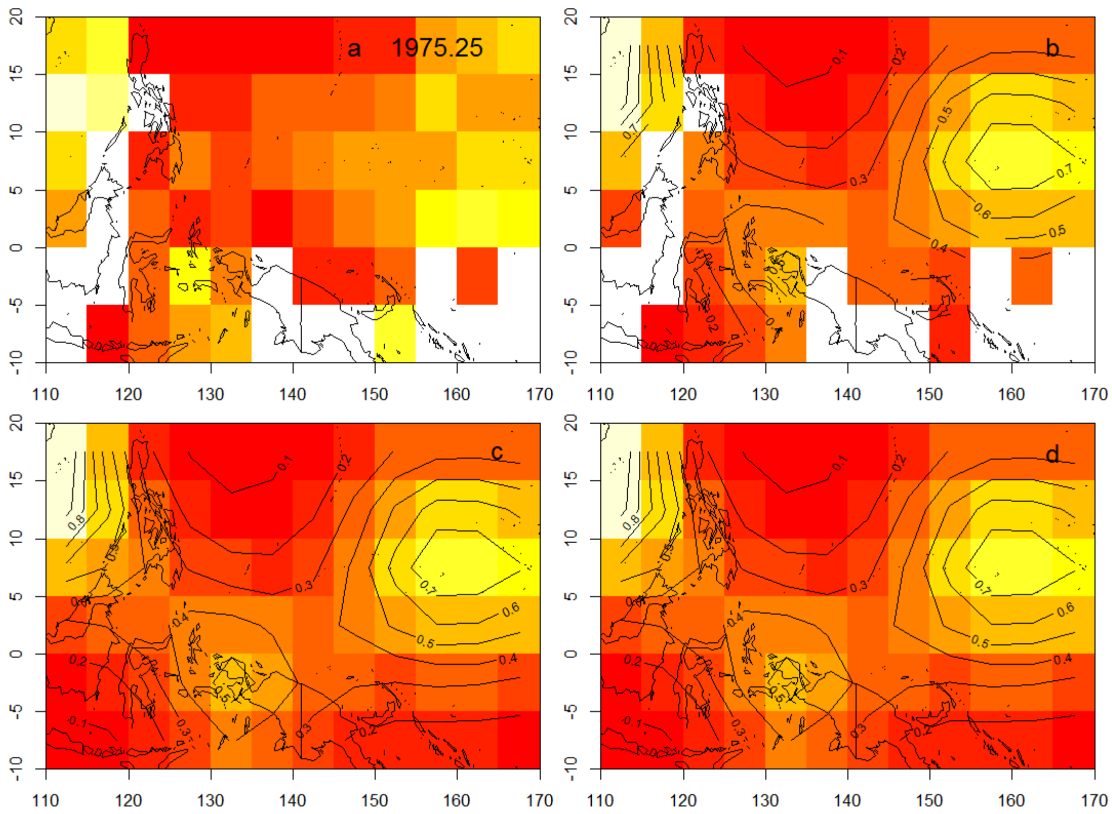

Figure 12: An example of the GAM-based method of spatially imputing CPUE values for cells that were not fished in the 1st quarter of 1975, for the aggregate data for Japanese longline vessels in region 3. Panel a shows the observed CPUE data for each 5° spatial cell, panel b shows the fitted values resulting from the GAM, panel c shows the CPUE surface for all cells (fished and un-fished) before constraints are applied and d shows the same as c but after the constraints have been applied (in this case the constraints did not affect the surface). The sum of the CPUE values over all cells in panel d is the index of abundance for that year-quarter. The contour lines and colours indicate the relative CPUE with red being lowest through to yellow being highest.

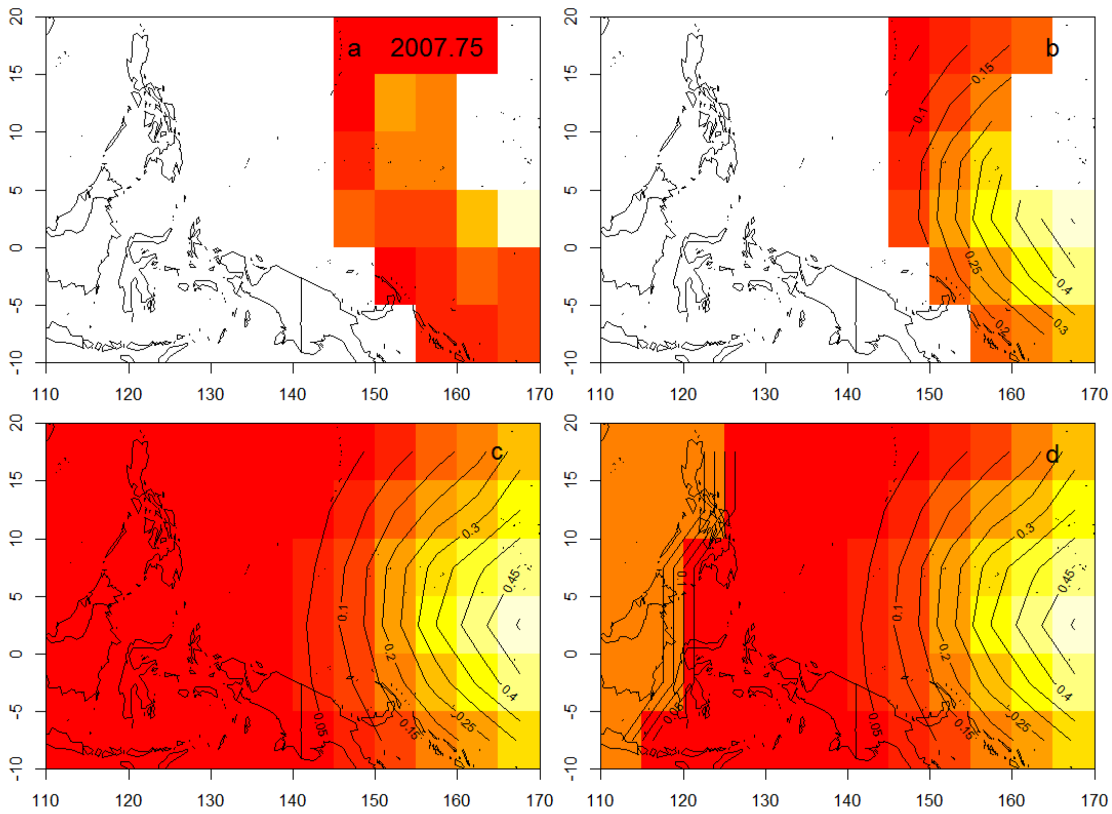

Figure 13: An example of the GAM-based method of spatially imputing CPUE values for cells that were not fished in the 3rd quarter of 1975, for the aggregate data for Japanese longline vessels in region 3. Panel a shows the observed CPUE data for each 5° spatial cell, panel b shows the fitted values resulting from the GAM, panel c shows the CPUE surface for all cells (fished and un-fished) before constraints are applied and d shows the same as c but after the constraints have been applied (in this case the cells in the far west of the region were constrained to be the predictions from the traditional GLM model as the GAM-based predictions for these cells were outside the range of CPUE values observed in that year-quarter). The sum of the CPUE values over all cells in panel d is the index of abundance for that year-quarter. The contour lines and colours indicate the relative CPUE with red being lowest through to yellow being highest.

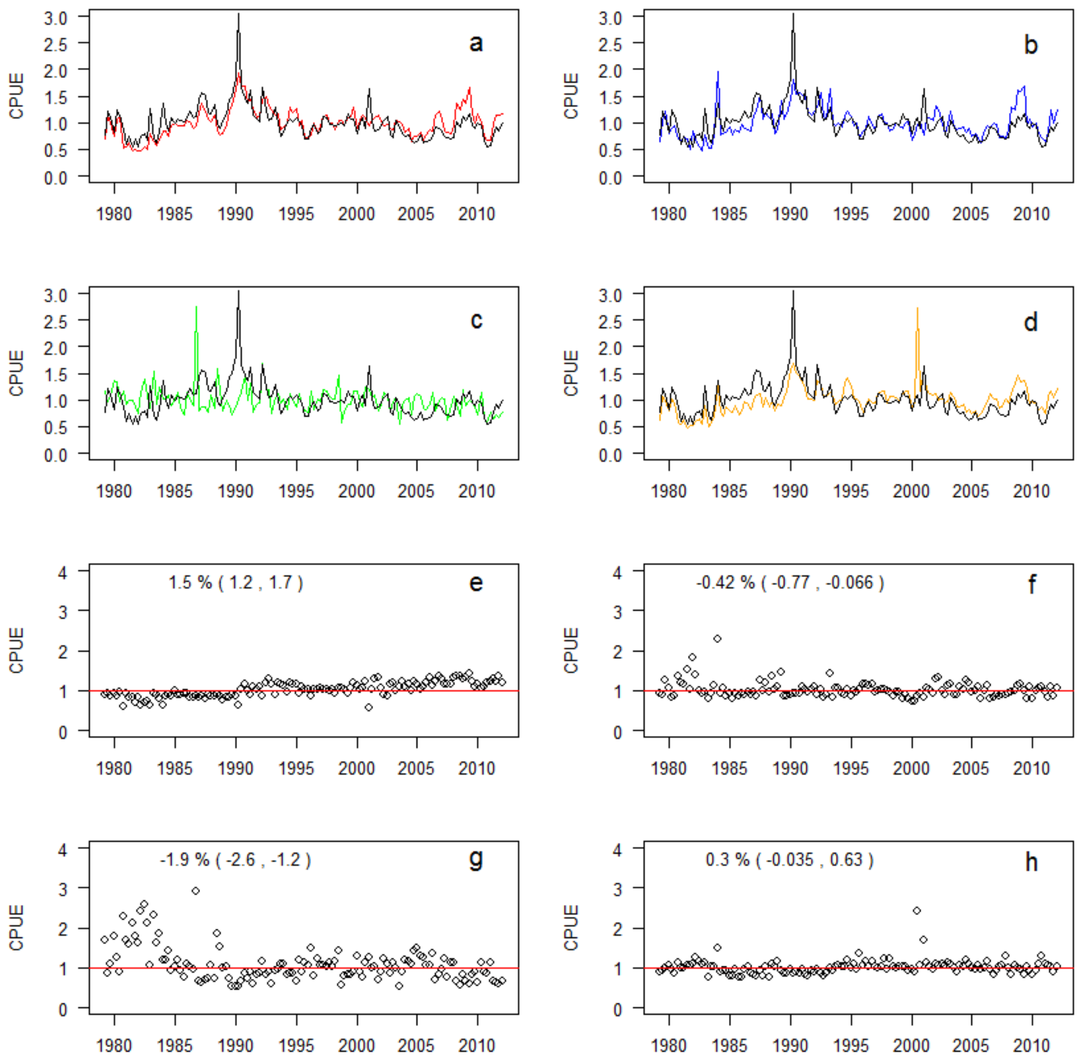

Figure 14: Indices of BET CPUE in region 3 for the SPC-held operational-level data for vessels under all flags. The black line in each panel is the nominal CPUE index. The red line in panel a is the traditional index, the blue line in panel b is the GAM-based index, the green line in panel c is the Carruthers index when all cells are retained, and the orange line in panel e is the hybrid index when all cells are retained. Panel e shows the ratio of the traditional index to the nominal index, panels f, g and h show the ratio of the GAM-based, Carruthers and hybrid indices, respectively, against the traditional index. The numbers in panels e-h are the annual trend in the ratio estimated using a linear regression model fitted to the log ratios, with the 95% confidence interval for this trend given in brackets.

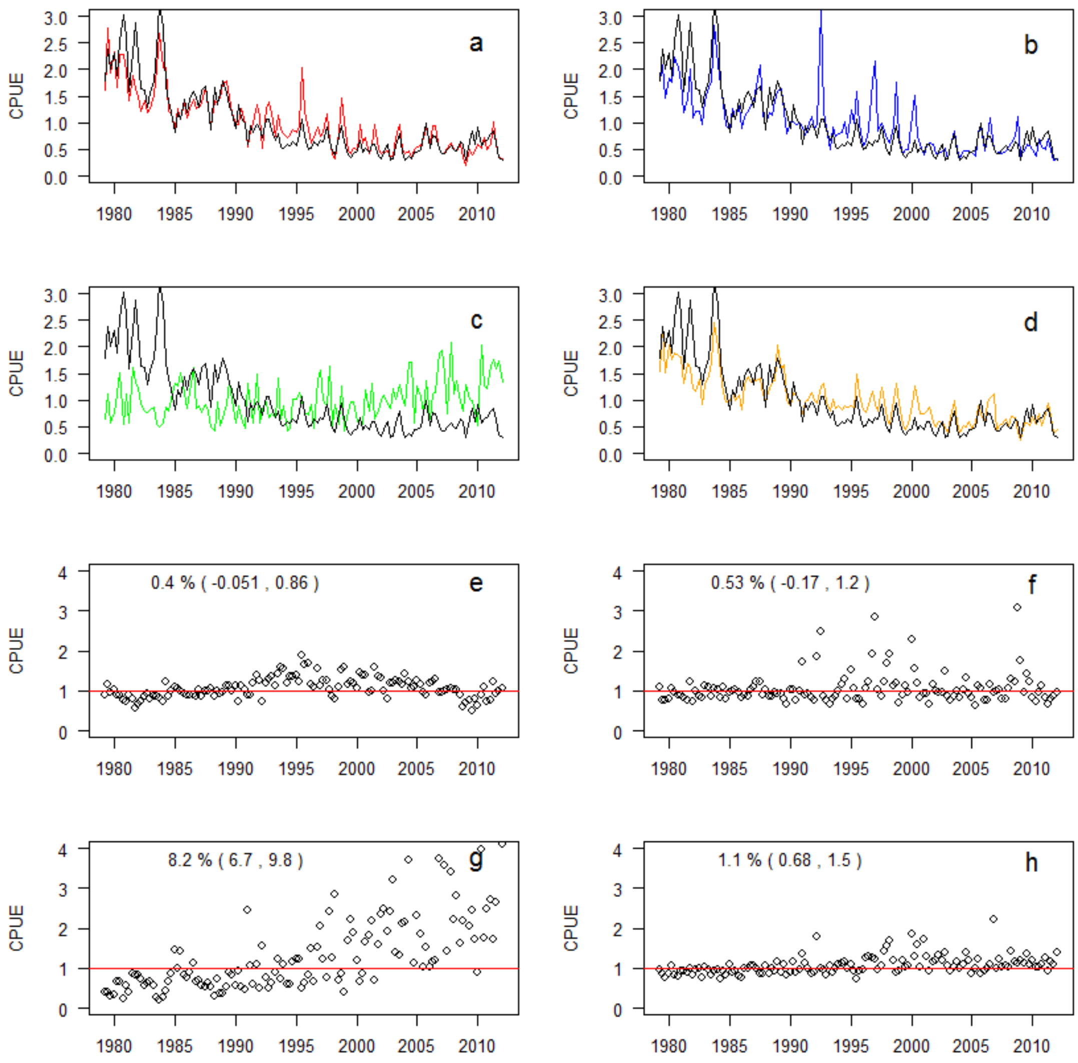

Figure 15: Indices of YFT CPUE in region 3 for the SPC-held operational-level data for vessels under all flags. The black line in each panel is the nominal CPUE index. The red line in panel a is the traditional index, the blue line in panel b is the GAM-based index, the green line in panel c is the Carruthers index when all cells are retained, and the orange line in panel e is the hybrid index when all cells are retained. Panel e shows the ratio of the traditional index to the nominal index, panels f, g and h show the ratio of the GAM-based, Carruthers and hybrid indices, respectively, against the traditional index. The numbers in panels e-h are the annual trend in the ratio estimated using a linear regression model fitted to the log ratios, with the 95% confidence interval for this trend given in brackets.

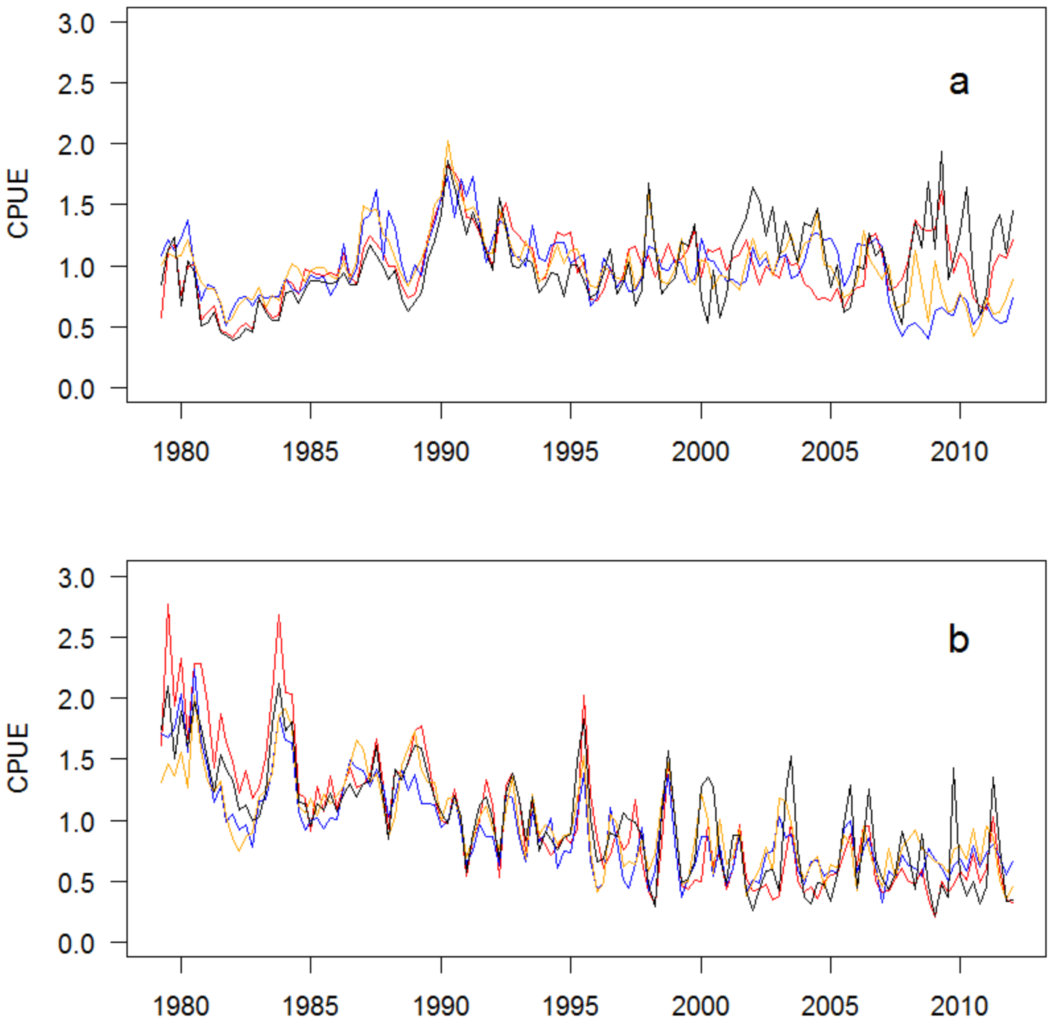

Figure 16: Comparison of traditional indices for BET (panel a) and YFT (panel b) in region 3. Black, red, orange and blue lines are the indices for the Japanese operational-level data, all flags operational data, Japanese aggregate data and all flags aggregate data.