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Recommended approaches for standardizing CPUE data from pelagic fisheries

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Indices of relative abundance derived from catch and effort data are often the most influential inputs to stock assessment models. This influence rests on the assumption that there is a relationship, generally linear, between standardized catch rate and abundance. This assumption breaks down in some circumstances (e.g. Harley *et al.* 2001), but, given appropriate analysis and awareness of their limitations, CPUE indices are extremely useful.

Many factors affect the relationship between abundance and catch rate, and the analyst must make choices about appropriate methods at multiple stages. The methods selected can influence the resulting abundance index, the stock status, and ultimately the management advice.

The purpose of this paper is to identify the most important factors that the analyst should consider when analysing CPUE data and deriving CPUE indices, and to recommend effective approaches. The paper also recommends approaches for presenting the results in a consistent, standard, and sufficiently thorough manner. This is intended to facilitate the review of CPUE indices presented to WCPFC scientific meetings. As well as data analysts, the target audience of the paper is members of scientific working groups who must review CPUE indices developed for individual fisheries, and assess their suitability for inclusion in stock assessments. We hope that the use of this document will improve the robustness of individual CPUE analyses and the utility of the resulting indices.

We focus mostly on pelagic longline CPUE because indices based on these fisheries are the ones most commonly used in WCPFC stock assessments. However many of the same issues apply to purse seine CPUE and pole and line CPUE. We devote the last section of the report to the particular issues involved in standardizing purse seine CPUE data.

There are many sources of information about CPUE standardization, and methods continue to develop with ongoing research. For additional background we particularly recommend Maunder and Punt (2004) for an overview of CPUE standardization methods, and other papers in the same volume of Fisheries Research. For statistical background to generalized linear modelling, and information about diagnostics we recommend McCullagh and Nelder (1989). We also recommend Campbell (in press) for a summary of the methods used to construct abundance indices, particular in regard to spatial effects.

The information content of CPUE indices

While indices of abundance can be based on annual research surveys, they are more often based on data from the commercial fleets in the fishery. This is usually the case for indices used in WCPO stock assessments of species caught by pelagic longliners, because alternative information sources such as fishery-independent surveys and absolute abundance estimates are rarely available. Information from tagging data is available for some species, but is only informative about part of the stock and for part of the time series. Therefore much of the information content of the assessment model comes from the interaction between the time-series of CPUE indices and catches. This information defines the overall abundance of the stock (via key parameters such as average recruitment and unfished biomass) and temporal trends in stock abundance. Size frequency data provide information on the length (and or age) of the fish in the fishery-specific catches and, for the longline fishery, mediate the relationship between the CPUE indices and the overall population through the estimated selectivity function.

For spatially stratified models, seasonal variability in the CPUE indices may also inform the model about seasonal movement between model regions. Different trends in the CPUE indices amongst model regions may indicate different historical patterns in exploitation amongst the different areas.

How indices are used in stock assessment

When developing indices of abundance it is helpful to be aware of how they are usually used in stock assessment. Each index is associated with a fishery. Each fishery has a selectivity associated with it, which defines the relative catchability at size (or age) of the fish in the population. CPUE as an abundance index therefore reflects the numbers at the ages (or sizes if selectivity is size-based) defined by the fishery's selectivity. On average the population has fewer individuals at older ages, so that changes in the selectivity of a fishery can be expected to change the CPUE. Note also that the age composition of the fish indexed by the CPUE series is not completely defined by the selectivity, but also depends on the age composition of the population.

Longline catch data are usually reported in numbers, and catch rates based on these data therefore index population numbers-at-age rather than biomass. The same generally applies to pole and line catch data. Purse seine data are reported in weight, and their indices therefore index the biomass of the selected part of the population.

Some stock assessment models, for example the WCPO bigeye, yellowfin and skipjack assessments (Davies *et al.* 2011; Hoyle *et al.* 2011; Langley *et al.* 2011) have multiple regions, in which case each CPUE index is associated with a fishery (and abundance trend) in just one region. Other models have only one region (e.g. the south Pacific albacore assessment, Hoyle 2012; the WCPO silky shark assessment, Rice and Harley 2013), and each CPUE index is associated with the abundance trend of the selected age classes for the entire stock. It is possible to define fisheries that represent effort in only part of a region (e.g. in the south Pacific albacore assessment), but the model will interpret the CPUE index as representing the abundance trend throughout the entire region.

In most stock assessment models it is assumed that the selectivity of a fishery does not change through time. However, problems can arise when the distribution of size classes is not homogeneous across the area defined by a fishery, because effort is very likely to move around through time resulting in temporal shifts in the size class of fish being caught and represented in the CPUE time series. It is therefore important to check that the assumption of uniform selectivity is valid, and that fisheries have been defined appropriately, by investigating spatial variation in sizes (e.g. Bromhead *et al.* 2009; Lennert-Cody *et al.* 2013). For cases where size varies spatially, analysts should consider spatially partitioning the fisheries within a region, which reduces bias in model results (Hurtado-Ferro *et al.* 2013). For example, investigations of south Pacific albacore sizes (Bromhead *et al.* 2009) found spatial variation north-south and east-west, and also seasonally. Spatial boundaries in the fishery definitions were moved to make the sizes more uniform within each fishery, and fisheries and their associated CPUE indices were also separated seasonally (Hoyle and Davies 2009).

Standardization models

A key assumption behind CPUE standardization is that catch rate is proportional to fish density. The relationship is CPUE = $C/E = qD$, where C is catch, E is effort, D is density, and q is the catchability coefficient, which is related to the efficiency of fishing. The population size of the fish in the area of interest is a function of average density D and the size of the area A, with equation $N = DA$.

It follows that changes in CPUE through time are due either to changes in the stock density (or number of fish on the fishing grounds) or to changes in the catchability coefficient. The need to standardize arises because q and D are not constant. Catchability varies between vessels and skippers, and with changes in fishing gear or fish detection technology. Density varies spatially and seasonally, as well as with overall changes in population size. Standardization can account for changes in q and for spatial and seasonal changes in D, so the remaining changes in CPUE can be related to longer term changes in stock density. This is the basic idea underlying what is known as the standardisation of catch rates.

The standardisation models predict CPUE based on a range of predictor variables that are assumed to influence the CPUE of the species of interest (e.g. depth of set, time of set, bait-type, gear-type and configuration, oceanic conditions, etc.). Logbooks may report the fishing practices used and prevailing oceanic conditions for each set, but in most cases only a limited amount of information is recorded and this limits the information available for the standardisation analyses. In such situations some information, such as oceanic conditions, may be derived from external data sets.

The model may use catch rate (e.g. number of fish caught per 1000 hooks) as the response variable, or simply the catch (e.g. number of fish). In the latter case, an effort variable(s) will usually be included as a predictor (e.g. 1000s of hooks). Both categorical (e.g bait-type) and continuous (e.g. sea-surface temperature) may be included in standardised CPUE analyses. The relationship between a continuous variable and the response need not be linear, although the modelling is simpler if this is the case. Initially it may be helpful to use GAMs to explore the shape of the relationship with a continuous variable. Subsequently, nonlinearity can be modelled directly using splines or polynomials, changed to linearity by transforming the variable, or modelled by breaking the variable up into categories.

It is important to note that CPUE is related to the density of fish of a particular size, based on the selectivity of the fishery. We assume that selectivity remains constant throughout the time-series, although factors that influence catchability may also affect selectivity.

Standardization is the statistical process intended to adjust for the factors that influence catchability so that one can estimate the contribution to changes in CPUE made by the temporal changes in abundance alone. Various approaches have been used to standardize catch and effort data, with generalized linear modelling (Gulland 1956; McCullagh and Nelder 1989) the most common. Other approaches include generalized additive models (Bigelow *et al.* 1999; Hastie and Tibshirani 1990; Swartzman *et al.* 1992; Wood 2006), generalized estimating equations (Bishop *et al.* 2000), neural networks (Gaertner and Dreyfus-Leon 2004; Maunder and Hinton 2006), habitat-based methods (Hinton and Nakano, 1996; Maunder et al 2006) and regression trees (Watters and Deriso 2000).

Generalized additive models (GAMs) are in many ways similar to generalized linear models (GLMs), but have a more flexible approach to fitting splines. They estimate a large number of parameters, but compensate by using a penalized likelihood and use cross validation to balance the likelihood with the penalty (Venables and Dichmont 2004). This makes them a good choice for data exploration when relationships with covariates are nonlinear. Splines can also be used with GLMs, but selecting the appropriate degrees of freedom is more difficult. Polynomials can also be used to model nonlinear relationships, but one problem is that the local behaviour determines the global behaviour, and good estimates in one region may be bought at the expense of very poor estimates elsewhere (Venables and Dichmont 2004).

Inference with GAMs may be more difficult than with GLMs, because the penalties complicate model selection. Related problems arise with confidence intervals. These issues are not straightforward for GLMs either (see later discussion).

Mixed effects models

Most statistical methods used to standardise CPUE assume that the observations (e.g. the CPUE associated with individual longline sets) are randomly sampled across the fishery. However, this is usually not the case given the often consecutive nature of fishing operations in a local region. Given this situation longline catch and effort data can be highly correlated. Generalised estimating equations (GEEs) extend the GLM framework to model correlations between observations (Hardin 2005), and should therefore be valuable for CPUE analyses (Bishop *et al.* 2004). Estimates of mean parameters are the same as for the equivalent GLM model, and they are unaffected by the choice of correlation or covariance structure. The main advantages of GEEs over GLMs are that they provide better confidence intervals and more reliable model selection.

Neural networks have the theoretical advantage that they can deal with complex relationships and nonlinearities. Some simulation studies have given results that are similar to generalized linear models. However, one problem with neural networks is that they are something of a 'black box', and it can be difficult to interpret the results, or identify whether the model is working correctly.

Regression trees are a useful approach for data exploration. They are well suited for exploring interactions and nonlinear relationships between parameters. However they can be unstable, and slight changes in the initial conditions or the dataset can lead to very different outcomes. It may also be difficult to estimate confidence intervals. Boosted regression trees and other numerical approaches can address these issues to some extent, but have not often been applied to catch rate standardization.

Habitat-based models (detHBS) (Hinton and Nakano 1996) and statistical habitat-based models (statHBS) (Maunder *et al.* 2006) were developed specifically for analysing pelagic longline data. They work in a GLM framework but attempt to model more directly the relationship between the distribution of the habitat preferred by a given species (as inferred from archival tagging) and the distribution of fishing gear (as inferred from depth monitors attached to longline gears). In comparison with detHBS, the statHBS approach always improves the ability to predict catch, and can produce quite different results. However although the methods are attractive in principle, the results from standard GLM approaches have been preferred for stock assessments. This may be due to uncertainties or errors in the oceanographic data used to describe the habitat or the archival data used to describe habitat use; mismatch between the oceanographic and archival tag data due to differences in scale; or limited understanding of the biology of the species being considered.

Use of operational and aggregated data

The majority of the catch and effort data held by the WCPFC and other tuna RFMOs is aggregated by 5 degree square and month. However, a considerable amount of operational data (i.e. set-by-set data) is also held, and indices for many assessments are derived from operational data not submitted to the WCPFC.

Standardization methods are available for both aggregated and operational data. Operational data are almost always better for standardization, for a number of reasons. Aggregating data across covariates removes their associated information, and analyses of operational data can therefore resolve CPUE problems that are intractable with aggregated data:

1. Clustering into targeting types can help resolve issues with target change through time. For example, clustering operational data at the trip level based on species composition per set significantly changed CPUE trends for albacore in the south Pacific (Bigelow and Hoyle 2009; Bigelow and Hoyle 2012).
2. Standardization with covariates such as vessel effects can help adjust for changes in fishing power that are associated with changes in the fleet. Accounting for variation in fishing power among vessels has long been a feature of CPUE standardization (Allen and Punsly 1984; Gulland 1956). For example, standardizing Japanese longline data with vessel effects significantly changed CPUE trends for bigeye and yellowfin across all regions of the Western and Central Pacific (Hoyle *et al.* 2010)
3. Operation-specific data (e.g. bait-type, use of light-sticks, time-of-set) can help account for changes in fishing power associated with changes in targeting. For example, swordfish targeting by Japanese longliners in the WCPO can be identified by the use of fewer than 5 hooks between floats after 1975, or the use of squid bait before 1975 (Hoyle and Okamoto 2011).
4. Operational data are easier to model, because they conform better to distributional assumptions. Individual sets can be assumed to be samples from a common distribution, while aggregated data have lost that characteristic. Variance will tend to be greater for cells with fewer sets, and sets per cell usually changes systematically, with more sets where and when catch rates are higher. However, models generally assume that individual rows of data are i.i.d.: independent and identically distributed.
5. The greatest advantage of working with operational data is the potential to understand the processes involved in fishing.

Nevertheless, much of the advice below is applicable to both aggregated and operational data.

Error distributions

When undertaking a statistical analyses of catch and effort data, the structure of the model (and modelling approach) should account for the underlying structure of the distribution of the catch rate data. An initial examination of the distribution of the unstandardized CPUE observations may be informative regarding the most appropriate error structure for modelling the data (e.g. lognormal, negative binomial). However, alternative error structures should be considered during model testing and diagnostic tools should be applied to select the most appropriate error structure. The analyst should select an appropriate distribution after examining the fit of the alternative options. The issues applying to aggregated data and operational data are similar, but with some points of difference.

The distribution traditionally used to fit CPUE data is the lognormal distribution. This may suffice with aggregated data for common species, such as target tuna species, since there are few zeroes. Models can be fitted with the lognormal distribution after omitting the zeroes, if there are only a small proportion of zero catch records in the dataset, there is no temporal trend in the proportion of zeroes, and they are not concentrated in one region.

However, set-by-set longline catches usually include an appreciably higher proportion of zero catches, and require a different approach since the natural logarithm of zero is undefined. In the past it was common practice to add a small constant to all values (e.g. 10% of the mean value, Campbell *et al.* 1996) so that data with zeroes could be modelled with the lognormal distribution, but the approach is now generally avoided because it introduces bias (Punt *et al.* 1996). Models that can predict zeroes include single-part models such as the Poisson or negative binomial, two part models such as the zero inflated negative binomial, and hurdle models such as the delta lognormal (i.e. combining the use of a Binomial model for the probability of obtaining a non-zero catch and a lognormal model for the size of the positive CPUE) or zero truncated negative binomial. In many cases longline data are best fitted by two part or hurdle models, because they require more flexibility than can accommodated by single-part distributions, particularly for rare and non-targeted species (Zuur *et al.* 2012).

Overdispersion should be expected in catch rates, because fish are often aggregated (i.e. in schools) rather than individually randomly distributed; catch rates are usually affected by factors not available to the analyst, such as by setting behaviour; and consecutive sets by an individual vessel are not independent. For this reason the Poisson distribution rarely provides the best fit to pelagic longline catch data. The negative binomial distribution comes from the same (exponential) family as the Poisson but allows for overdispersion with a more general form of the variance function ($\mu+k\mu^2$). Delta lognormal models may also be effective. The gamma distribution, which allows a variance function of the form ($k\mu^2$), should also be considered when modelling CPUE, a continuous variable.

The Tweedie and Weibull distributions may also be explored. The Tweedie is a general form that includes the Normal, gamma, and Poisson distributions as special cases, and can be flexible enough to provide a good fit to CPUE data with excess zeroes (Shono 2008). The Weibull is a continuous distribution often used for predicting failure rates over time, but can also be used for CPUE (e.g. Schmidt *et al.* 2005).

Splitting CPUE indices

Sometimes, when a distinct and ongoing operational change is thought to have occurred in the fishery, such as a change in targeting practices, CPUE indices can be split into separate time-series (e.g. Hiraoka *et al.* 2013). Using split indices in a stock assessment can be problematic unless another index is available to fill the gap, and effectively join the indices together. When indices are split the catchability in the stock assessment model is free to change between the sections of the index. The model choses values that give the best fit to all the data in the model. This tends to change the biomass in order to improve another part of the likelihood, usually associated with the length frequency data, with unpredictable consequences. It may be useful to check that the estimated catchabilities are consistent with the reason for the split.

Using multiple indices in a stock assessment

It is often the case that multiple indices from different data sources are available for a stock assessment, with the indices representing similar age/length classes of the fished population and covering the same time periods, but having trends that differ to some degree. Effectively, each index represents a hypothesis about the true state of nature. It may seem an obvious point, but two conflicting indices cannot both be true at the same time, so the appropriate response is not to combine the indices in a single model, but to include the two indices as alternative scenarios in separate models (Schnute and Hilborn 1993). Management advice can then take the uncertainty into account. It is not good practice to 'average' indices by (for example) including multiple indices in a single model and giving them relative implied weightings.

Schnute and Hilborn (1993) make this point for conflicts among all data sources, but the issue is particularly clear for CPUE indices. Multiple indices for the same stock are reasonable when they do not conflict, and when they index difference age or size classes in the population (e.g. Bigelow and Hoyle 2012). In such cases, different trends need not conflict but may be consistent with changing population structure.

Methods for model selection and comparison

Analysts should be cautious about including too many explanatory variables in CPUE standardizations. Given the very large sample sizes often seen, and the fact that model assumptions are never met perfectly, it is often the case that many variables explain enough variation to be statistically significant. However, we recommend a conservative approach for several reasons. First, statistical significance does not imply biological significance. Including too many independent variables may increase complexity (and confusion) while adding little insight. There is no such thing as a true model, and it wastes effort to try to find it. Secondly, CPUE data often include substantial pseudo-replication/autocorrelation and are generally overdispersed, both of which unless modelled carefully tend to result in spurious significance. Testing multiple variables and interactions without *a priori* justification will inevitably uncover variables that are statistically significant by chance (type 1 errors). Given un-modelled dependencies in the dataset, the chance of spurious significance may be much higher than 5% per test. The best approach is to explicitly model the dependencies, but this can be technically difficult, and the required variables are often unavailable.

For model selection the Akaike Information Criterion (AIC) (Akaike 1973) is useful but sensitive, and limiting the number of variables requires another criterion. A common approach is to include only variables that increase the R^2 by a predetermined percentage (Maunder and Punt 2004). We also recommend testing only variables for which there is good *a priori* reason to expect a relationship, based on expert understanding of the data and the fishery.

The purpose of modelling CPUE data is usually to obtain a time-series of indices. Therefore, it is usual practice to include the temporal variable (e.g. year or year-quarter) in the CPUE model without considering its explanatory power. Moreover, the influence on the temporal index of including each additional variable should be examined to determine which factors influence the standardised indices (Bentley *et al.* 2011). It may be reasonable to drop variables from the model if they do not substantially influence the final CPUE indices, but influential variables should be treated with respect.

The Bayesian Information Criterion (BIC) (Schwarz 1978) is sometimes preferred to the AIC, we suspect because it has a higher threshold for acceptance and therefore selects fewer variables. However, we argue that if oversensitivity is a concern then it is better to use the AIC and apply an R^2 criterion to explicitly reduce the sensitivity to an appropriate level for known reasons, than to use the BIC and be constrained by its default level of sensitivity. The AIC has a sound theoretical foundation, and generally performs better than BIC when there are many effects of varying size (Burnham and Anderson 2004).

The AIC is not available for all analyses and distributions. For example, quasi-likelihood methods do not provide a likelihood, and it may be difficult to determine the degrees of freedom when working with random effects and generalized linear mixed models. There are nonetheless appropriate model selection methods for each of these approaches, but exploring them is beyond the scope of this paper.

Methods for estimating uncertainty

Estimating the uncertainty associated with CPUE indices can be complicated, because there are multiple levels of uncertainty. These levels include the observation error associated with the estimated time effects, and the process error associated with catchability, the relationship between the time effect and abundance.

The observation error in the time effect after accounting for covariate effects is estimated in the model fitting process. The standard error associated with the time effects may be determined in R using the predict() function with type=”terms”, and se.fit=T. Using the standard error associated with each time interval in the model is not recommended because each time effect is calculated relative to the base time (e.g. base year or base year-quarter), which has no standard error. An alternative approach is to calculate canonical confidence intervals (Francis 1999).

Confidence intervals for two-step delta or hurdle models can be estimated using parametric (Shono 2008) or bootstrap (Ichinokawa and Takeuchi 2012) methods.

However, the estimates from the standardisation model usually underestimate the uncertainty because they do not fully account for the dependencies in the input data. As discussed elsewhere in this document, consecutive sets by a vessel are not independent of one another; and nor are sets by vessels from the same company which may communicate with one another, or may even be fishing together in a coordinated way. Data are usually overdispersed due to both aggregation of fish and the unavailability to the analyst of important factors affecting catch rates. It may therefore be assumed that, as a rule, CPUE analyses underestimate observation errors in the time effects.

Process errors occur when the average catchability across the fleet varies between time intervals. Effectively, the relationship changes between the abundance index and abundance, so that there is more uncertainty in the abundance index than predicted by the observation error. This variability is often larger than the observation error in the time effects.

While the precision associated with the CPUE indices are likely to be under-estimated, the standard errors do provide an indication of the relative reliability of the CPUE indices over the time-series and for this reason it may be appropriate to incorporate the relative precision of the CPUE indices within the assessment model.

Targeting

Pelagic longliners catch multiple species on each set, but can use different fishing methods to increase the catch of one species or group of species. Targeting strategy can substantially affect catch rates for the species of interest, and is therefore a very important issue for CPUE standardization. Targeting strategies may vary among vessels, spatially, and temporally. The most important concerns arise when targeting strategies change through time, affecting the index of abundance.

Identifying targeting strategies is, however, not always straightforward. When recorded and reliable, information about the targeting strategy used in a set should be used either to separate data into different groups, or as a covariate, or as an interaction term if the relationships amongst different target categories are not linear.

However in many cases information about targeting strategies may not be recorded, or the recorded information may be unreliable. In such cases it may be possible to identify and adjust for targeting by analysing the data.

The approach most commonly used in pelagic longline CPUE analysis to identify targeting strategy is to use an indicator variable, particularly hooks between floats (HBF). HBF tends to be correlated with set depth (Bigelow *et al.* 2006), which can affect the catch rate of different species. In the Japanese longline fleet, vessels targeting swordfish after 1975 tended to use HBF between 3 and 5, while tuna targeting has used more HBF. However, HBF has limitations as an indicator of targeting strategy. It has only been broadly available to analysts of Japanese longline data since 1975, and in Taiwanese longline data since the early 1990s. More seriously, the relationship between set depth and HBF values have changed through time as gear materials have changed. For example, the mono-filament gear used in more recent decades is more neutrally buoyant than the older kuralon rope material, and requires more HBF to attain the same depth. In addition, the targeting strategies associated with different HBF values appear to vary spatially (Hoyle and Okamoto 2013).

Bait type may also be a useful indicator of target species. The use of squid bait is a powerful indicator of swordfish targeting in Japanese longline data prior to 1975, when HBF was not available (Hoyle and Okamoto 2011). However bait type often varies along the length of the longline, and has only been recorded for Japanese longline operational data for a limited time period, i.e. not since 1994.

Vessel identity can also be a useful indicator of targeting strategy. Vessels may be set up to follow a particular approach, and adopt consistent behaviour through time. For example, during the 1970s the introduction of vessels with super-cold freezers made it economic to target bigeye tuna for the high value sashimi market. This target method was not feasible for vessels with earlier freezer technology. Another example is the southward expansion of the northwest Pacific albacore longline fishery during the 1990s, reaching south of 20N. Including vessel effects in the standardization demonstrated that many of the vessels in this area with low bigeye catch rates were new to the area, and not part of the bigeye targeting fishery (Hoyle *et al.* 2010). Including vessel effects in a CPUE standardization can account for changes in fishing power due to target change as well as efficiency change.

Species composition of the catch can also be used as an indicator of targeting strategy. This approach gets at the fundamentals of targeting, which aims to affect the species composition of the catch. Care must be taken however, for several reasons. Set by set variation in species composition is usually greater than the variation between targeting strategies, so it is necessary to examine a vessel's species composition over a longer time period, such as at the trip level. Factors other than targeting affect species composition, including the relative abundances of individual species, which vary in space and time. The identified targeting signatures should be based on prior knowledge that distinct targeting practices exist. The targeting signatures should have species compositions that are distinct from one another, because non-discrete groups lead to confounding between targeting categories and the abundance trends of the constituent species. If the species of interest is a major component of the species composition then the analyst must take care that its abundance does not affect both the dependent and independent sides of the standardisation model, which will obscure the abundance signal in the data.

Two main approaches have been used to separate data using species composition: cluster analysis and catch ratios. Cluster analysis groups catch records into categories by automatically identifying similar species-composition groups in the data (He *et al.* 1997; Rogers and Pikitch 1992; Ward *et al.* 1996). This approach has been used for south Pacific albacore tuna using data from vessels in multiple fleets (Bigelow and Hoyle 2009, 2011, 2012). We recommend using this approach if *a priori* evidence and data exploration indicate that discrete targeting strategies exist.

Catch ratios have also been used as targeting indicators in analyses for WCPO stock assessments. This approach uses the ratio of two species, often including the species of interest, in the catch as an indicator of targeting strategy. The ratios are then grouped by percentile frequency either over the whole time period (e.g. Mejuto *et al.* 2009) or by year (e.g. Chang *et al.* 2008; Hiraoka *et al.* 2012), and the percentile group is used as a categorical variable in the standardization analysis.

There are several problems with these approaches. First, if the ratios are grouped over the whole time series, then there will inevitably be overlap between the groups. This overlap results in confounding between abundance and the catch ratio. If the abundance of the species of interest changes through time then the abundance index should reflect this change. However, with the species of interest in the catch ratio, the effort shifts from one category to another and reduces the change in the abundance index. Thus this approach will tend to remove CPUE trends from abundance index (Chang *et al.* 2011). On the other hand, if the abundance of the second species in the catch ratio changes through time, it will bias the abundance index for the species of interest.

Second, if the ratios are grouped by year, the same number of sets will be in each catch ratio category in each year. In this situation it can be demonstrated that the catch ratio indicator has no influence on the index of abundance, even though it may be highly statistically significant in the standardization. A measure δ_y^A of the influence of parameter *A* on year effect *y*, can be calculated as follows (Bentley et al. 2011).

$$p^A = \frac{\sum_{i=1}^{i=n} \alpha_{a_i}^A}{n}$$

$$\delta_y^A = \frac{\left(\sum_{i=1}^{i=n_y} \alpha_{a_i}^A - \rho^A\right)}{n_y}$$

In the catch ratio approach described, given *x* percentile groups, each of the *x* values of $\alpha_{a_i}^A$ occurs n_y/x times in year *y*, and so the measure of influence δ_y^A is always equal to zero. Thus this form of targeting indicator is not recommended because it has no effect on the CPUE time series. It appears to address targeting, but does not.

A new method to account for targeting in multispecies CPUE based on species composition has recently been developed (Winker *et al.* 2013; Winker *et al.* 2014), which uses scores from Principle Component Analysis as predictor variables in a GAM. Simulations suggest that it may be more effective than the cluster analysis approach. Investigation of this approach with pelagic longline catch and effort data is recommended.

Further work in this area is recommended. The suitability of any proposed approach should be investigated using simulation testing to investigate the potential biases that may be introduced under a range of differing multi-species stock trajectories.

Consideration of catchability change through time

The fishing power of longline vessels (as with most other types of fishing vessels) tends to change through time, due to technological progression, and changes in fishing and targeting strategy. For a review of factors associated with fishing power change see Ward and Hindmarsh (2007). CPUE is generally estimated with effort measured in terms of hooks, whereas vessels make a profit based on total catch, so a vessel may catch more by setting more hooks without increasing CPUE. However some changes such as the use of remote sensing sea-temperature plots to identify favourable fishing locations, and improved hooks and line types are likely to have improved fishing power per hook.

Fishing power change can be estimated using operational data for variables that are available to the analysis. However, usable variables are rarely available to the analysis. Where available, error in the recorded data on vessel characteristics, and limited temporal overlap within the fleet, can also reduce the reliability of estimates of fishing power change. Some information is available in longline observer data but few such analyses of these data have been carried out. Furthermore, the coverage of longline fleets by observer data is, to date, poor and the spatial and temporal coverage is unrepresentative of the activities of the entire fleet.

Changes through time in one component of the average fishing power of the fleet can be estimated from logbook data. As outdated vessels leave the fleet and new vessels are introduced, the average fishing power of the fleet is likely to change. Modelling CPUE with vessel identity included as a categorical variable produces abundance indices that account for this component of fishing power change (Hoyle 2009; Hoyle and Okamoto 2011; Hoyle *et al.* 2010). The degree of fishing power change can be estimated by comparing indices standardised with and without vessel effects. The estimated rates of fishing power change may be informative about the rates of such change in general, and used to help parameterise effort creep for indices where vessel identities are not available. Note however that these vessel effects may include the effects of target change not accounted for in the standardising model, if vessels with different targeting strategies are included in the standardization.

Assumptions about spatial CPUE variation

In most standardisations of catch and effort data, area effects are included to account for spatial differences in density (and trends) of the resource. However, spatial variation in CPUE trend within each area modelled by a single CPUE trend is an important issue that must be considered carefully, especially where the area effects included in the model are large. It is best to avoid this issue by defining stock assessment regions so that the fish are well mixed, and the trend within the region is close to the same throughout. This makes the stock assessment conclusions more useful for management, since inferences about biomass trend can be generalized across the region. With this in mind, CPUE analyses can be used to identify areas within which the CPUE trend is relatively uniform (e.g. Langley 2006).

However, sometimes abundance indices must be estimated for regions within which the temporal CPUE trends vary in space. CPUE may fluctuate seasonally as fish move; vary in response to oceanographic conditions; or change due to range contraction, or because fishing pressure is higher in one area and the stock is not well mixed. Such situations may require models with interactions between spatial and temporal terms. This causes a number of difficulties, including large computational demands due to the number of parameters to be estimated, and questions about what to do with cells with no data, particularly at the start and end of the time series and on the edges of the spatial domain. There can also be difficulties summing across space to calculate the overall abundance trend.

Given the difficulty of including an interaction term with the main temporal variable in the model, such an approach needs to be well justified both statistically and in its effect on the resulting indices. Computational demands can be reduced by standardizing smaller sub-regions separately and combining the results into a pooled index for the full region; increasing the area covered by each spatial term; reducing the temporal resolution; or otherwise reducing the parameter space by, for example, reducing the numbers of vessel effects estimated. For details of approaches for generating a CPUE index in this situation, see Campbell (in press).

Where data are missing for areas, the analyst must make assumptions about the trends during the period without data. Walters (2003) and Campbell (2004) discuss the issue, and imputation methods are proposed by Carruthers *et al.* (2011; 2010). However, it is clear that the appropriate assumption in each individual area will depend on the situation and the history of that area, and a one-size-fits-all approach to imputation is inappropriate. For example, data may be missing at the beginning, middle or end of a time series; may be missing before effort has expanded into an area; or because catch rates are too low or costs are too high to be economic; or because a fleet is excluded from an EEZ. McKechnie et al (2013) discuss this issue, and compare alternative ways of dealing with it, in the context of WCPO tuna fisheries. Imputation essentially involves making assumptions about CPUE trends in the absence of information, so it may add bias and produce an index that underestimates the uncertainty. The analyst should consider whether using imputation is better than the alternatives.

Being able to assume that a CPUE trend is constant within a region considerably simplifies the modelling. However, spatial variation in average CPUE should always be expected within the area defined by a single CPUE series, due to variation in habitat quality. Such variation can easily be dealt with by using sub-regional grid squares as factors in the standardization model, with the formulation CPUE ~ time + grid + other factors + error. Using grid squares as factors is equivalent to a categorical lat*long interaction term but makes computation simpler. Two dimensional smoothers, which may also be used, often cause problems with extreme values at the edges if data are sparse, and may not fit well when there are abrupt changes in CPUE in some areas but not in others. Individual lat and long variables, without interactions, may also be used but fail to account for interactions, which are usually present. Given the large datasets usually involved, and the degree of spatial variation usually seen, interaction terms are statistically significant in most cases.

Standardizations for WCPO stock assessments normally include spatial factors at the 5 degree grid squares resolution at which aggregated data are reported (Chang *et al.* 2011; Hoyle *et al.* 2007; Langley 2003). Higher resolutions including 1 degree and 3 degrees have been tested for bigeye and yellowfin tuna, but have made relatively little difference to indices of abundance (Hoyle and Okamoto 2011). Lower spatial resolutions have been used in the past, particularly when computing power limitations made it difficult to analyze large datasets with many parameters. However, such analyses cannot discriminate between abundance change and movement of fishing effort to areas with different density. Such problems will be apparent in analyses of residuals by location, although the pooled distributions of residuals may appear normal (Chang *et al.* 2011).

Effort concentration through time

During the history of a fishery, effort will tend to move around and concentrate in different areas. These shifts in effort concentration also change the amount of data used to estimate effects in each area, which changes the weight assigned to each area effect. This variation in weights will influence the abundance indices derived from the data, unless the weights are adjusted appropriately. Temporal trends in effort concentrations will result in temporal biases in the abundance index (Campbell 2004). To resolve this problem the analyst should weight the data for each time interval so that the sum of the weights in each area are the same at each time interval (Punsley 1987, Campbell 2004). This can be achieved for area k and observation i with effort $e_{i,k}$ with weights of $e_{i,k} / \sum_{i=i:N} e_{i,k}$. Alternatively, one may include certain interactions in the model so that each spatial-temporal stratum is individually parameterised, but this can greatly increase the complexity of the model and can cause problems when constructing the abundance index.

Furthermore, in order to overcome the potential biases which can result from using catch and effort data from a fishery with a high degree of spatial targeting, analysis of catch and effort data should be carried out at a spatial scale which adequately accounts for these spatial shifts in effort.

Ultimately, the interpretation of catch rates and the construction of indices of stock abundance should be based on an understanding of the dynamics underlying the spatial distribution of both the stock and the fishing effort, and preferably on the relationship between them.

Environmental variables

Aspects of the aquatic environment, such as water temperature and oxygenation at depth, affect both fish density and catchability and can have these effects in numerous ways, such as via recruitment and survival. However, when considering CPUE for stock assessment indices of abundance we are mainly concerned with factors that affect local catchability. In most cases the environment should not be permitted to explain factors that affect overall stock abundance, since they will not then be captured by the time effect, which needs to track abundance. For example, if long-term temperature change affects stock abundance by, for example, reducing recruitment, then it may be best to exclude temperature from the analysis so that the CPUE index tracks abundance. Alternatively, the average annual value of the environmental variable can be included in the prediction process that generates the abundance index, but this approach adds complexity and is often ignored in practice.

On the other hand, environmental effects that alter the local availability of fish to the fishing gears (such as effects that cause fish to move around within a region, or alter the depth profile of the targeted species) may usefully be included in the analysis, but not without also including spatial effects.

Environmental variables can be well correlated with CPUE, but variation is usually better explained by spatial-temporal effects such as 5 degree grid squares and quarter (or month). Once these effects are in the model, environmental effects often explain little additional variation. In some regions, environmental effects such as sea surface temperature show consistent spatial patterns through time, so that spatial effects can act as proxies. Environmental effects used in abundance indices must be available over very long periods with broad spatial coverage, and are often derived from models. These models have uncertain reliability, in contrast to spatial variables for which the data are comparatively reliable and consistent across the whole time series (Evans *et al.* 2014). A further concern with using environmental variables in CPUE standardization is that environmental variables are strongly spatially confounded with one another, we only have data for a very limited subset of variables, and we are often unsure of the mechanisms by which environmental variables affect resource density. We can therefore expect that many environmental relationships that appear to be significant are in fact driven by another parameter for which we have no data.

Purse seine catch and effort data

In tropical tuna fisheries, including the WCPFC fisheries, the purse seine fishing method accounts for most of the tuna catch. These fisheries generally catch a mixture of skipjack, yellowfin, and bigeye tuna, with species composition varying spatially, temporally, and by fishing mode.

The catch and effort data collected from the purse seine fleets, primarily from vessel logsheets, are routinely summarised to monitor trends in purse-seine fishing performance, typically expressed in terms of average species catch per day for the main fishing fleets and the main types of fishing operation, free-school, drifting Fish Aggregation Device (FAD) and anchored FAD (Williams and Terawasi 2013).

In tuna fisheries, catch and effort data are readily available and are routinely analysed to derive a time series of CPUE indices that can be incorporated in stock assessment models. The CPUE indices are often the most influential data included in the stock assessment as they provide long time series that can be assumed to represent trends in population abundance.

In WCPFC stock assessments, the primary CPUE indices are derived from the longline fisheries, with the exception of the WCPO skipjack stock assessment (Hoyle *et al.* 2011) which includes a CPUE index derived from the Japanese pole-and-line fishery (Kiyofuji *et al.* 2011; Langley *et al.* 2010). The reasons for selecting CPUE indices derived from longline catch and effort data have been discussed in earlier in this document. Skipjack tuna are not effectively targeted using the longline method and insufficient data are available to derive a reliable time-series of CPUE indices.

Catch and effort data from the purse seine fisheries are likely to include some information that is related to the abundance of the main tuna stocks. However, it is generally accepted that purse seine CPUE metrics (e.g. catch per set, catch per day or catch per area searched) are likely to be relatively insensitive to changes in stock abundance over a relatively wide range of stock sizes (hyperstable), primarily due to the concentration of fishing effort on fish aggregations (schools). They are also unlikely to provide the consistent long term abundance indices needed, due to the rapid increases in fishing efficiency associated with technological development of the purse seine fleets and changes in the operation of the fishery (ISSF 2012). The use of FADs introduces an additional problem by fundamentally changing the nature of the effort (search) variable.

Recent studies have applied standard analytical approaches, such as GLMs, to derive CPUE indices from purse seine catch and effort data (e.g. Soto *et al.* 2013; Soto *et al.* 2009). The authors of these studies acknowledge the deficiencies of the resulting indices as indices of stock abundance. Nonetheless, purse seine CPUE indices, either as standardised or unstandardized indices, are included in a range of tuna stock assessments.

For the WCPFC tropical tuna assessments, the unstandardized catch and effort data from the purse seine fishery are incorporated in a manner that means that these data are not informative regarding trends in stock abundance. The inclusion of uninformative purse seine CPUE indices in an assessment model provides the opportunity to estimate trends in the fishing efficiency of the purse-seine fleet within the model framework (ISSF 2012).

Some other tuna assessments, usually those that lack alternative indices of stock abundance, have fitted to the purse seine CPUE indices and assumed that they index stock abundance (e.g. IATTC yellowfin tuna dolphin associated CPUE, ICCAT eastern Atlantic skipjack tuna, IOTC Indian Ocean skipjack tuna). In those cases, the deficiencies of the CPUE indices have been documented in the assessment report. Some assessments (e.g. ICCAT eastern Atlantic skipjack tuna) have also attempted to account for potential biases in the CPUE indices by applying estimates of change (increase) in fishing efficiency derived from external analyses of the characteristics of the fishing fleet or inferred from other tuna stock assessments (see above).

Criteria for review of purse seine CPUE indices

The various statistical techniques described in the longline section of this report can be used in exploratory analysis of purse seine catch and effort data, and may improve understanding of the main factors that influence the performance of the fishery. However, it is generally accepted that the resulting CPUE indices are unlikely to reliably index species abundance. New and innovative approaches for analysing and modelling purse seine catch and effort data may improve the utility of these data and, at a minimum, increase the understanding of the dynamics of the purse seine fishery, although there has been limited progress in this area to date.

The WCPO tropical purse-seine fisheries harvest three main tuna species: bigeye, yellowfin, and skipjack. The majority of the WCPO tuna catch is skipjack tuna, and the proportion of each species in the catch varies spatially, seasonally, and annually. Variation in species composition of the catch will reflect the relative catch (and catch rate) of the three species and, consequently, changes in the abundance and availability of one species may directly influence the catch and catch rate of the primary species of interest. There may also be strong market preferences for one species or fish size grade that may influence the operation of the fleet. Therefore, preliminary analyses of the species catch composition data should be undertaken to understand the operation of the fishery. This may identify different components of the fishery that should be analysed separately; for example free-school purse seine fishing targeting yellowfin or skipjack schools. A review of market price information may provide some insights into the relative preferences of each species.

Analyses of purse seine catch and effort data need to be based on a clear understanding of the underlying structure of the fishery. The fishery's operation differs markedly among the three main fishing modes (free-school, drifting FAD and anchored FAD), although there may be considerable overlap between the modes at different levels of temporal resolution (e.g. within a fishing day or during a fishing trip). Furthermore, the three fishing modes differ in the size and species composition of the catch, the search method and its implications for the unit of effort, and in the management regulations applied to the fishery. These differences in both inputs and outputs have important implications for analysis methods, the first of which is that data from each fishing mode should be analyzed separately.

Fishing effort from individual fishing trips should be partitioned among the modes of fishing based on pre-screening of the operational data from the fishery. At a minimum, this requires processing of sequential fishing records from logsheet data and, where available, should be corroborated by the analysis of auxiliary data (such as observer data and VMS data). Where feasible, robust data partitioning routines should be developed to apportion fishing effort between modes, especially for fishing trips that conduct multiple types of fishing activities (set types).

There are large difference in size composition between free-school and FAD (drifting or anchored) based fishing. Free school fishing selects larger fish, particularly for yellowfin tuna. Consequently, the relationship between purse-seine CPUE and stock abundance will vary between the different fishing modes.

Species composition varies considerably between the fishing modes, with bigeye tuna almost absent from free school sets. Analysts should be aware that estimates of the amount of a species taken in a set are uncertain, and are affected by the estimation method (Lawson 2013). Estimates from logbooks often underestimate the proportion of bigeye in the catch in comparison with observer estimates. Observer estimates differ considerably between spill sampling and grab sampling, and both differ from logbook estimates. All methods are biased, but to date the biases in each method are not well understood.

The operation of the purse seine fishery, either at the vessel level of fleet level, will be influenced by the prevailing management framework. Clearly, recent changes in the management of the purse seine fishery, such as the introduction of the vessel days scheme (VDS), FAD closures, and increased observer coverage, will have affected the behaviour of the fleet and should be referenced in any analysis. Patterns in catch and effort data should be contrasted under different management regimes to investigate the likely impact of the change on the resulting CPUE indices.

Purse seine data are generally a mixture of zero catches, representing effort resulting in no catch, and positive sets with a catch quantity in weight. Most recent purse-seine CPUE analyses have used such a two component 'hurdle' (delta) model with a probability of species catch component (binomial) and a positive catch component (typically lognormal). These two components represent different aspects of the fishing process, and provide a useful framework for evaluating the data assumptions inherent in the analysis of purse seine catch and effort data. At a minimum it would be informative to monitor the number of unsuccessful purse-seine sets ("skunk" sets). This would include an appraisal of the reliability of the reporting of unsuccessful sets.

Both components are standardised, either explicitly or notionally, against a variable that relates to the level of fishing effort. An analysis of the catch and effort data relative to the range of elements outlined below should be used to inform the analyst of the most appropriate measure of fishing effort for each model component and/or the nature (parameterisation) of the relationship between the dependent variable and the effort variables.

The following list includes some of the key factors that are likely to influence the two model components. These are in addition to the factors associated with species abundance such as year, quarter, and location. The list is not exhaustive, but gives an overview of the issues that the analyst should consider.

1) The ***probability*** of catch of the species of interest depends on two steps: finding a school, and successfully making the set. Together these processes are influenced by the following factors:
    a) The spatial operation of the vessel/fleet relative to the density of tuna schools. The distributions of tuna schools and fishing operations will each vary considerably. It is useful to investigate the concentration of fishing operations with respect to the density of the tuna species of interest (relative to other areas). For FAD fishing operations, the search effort is carried out by the FAD array, so similar analyses should be applied to consider the spatial overlap between the FAD array and the stock.
    b) The effective area searched by a vessel. The definition of search effort will vary between fishing modes.
        i) For free-school fishing, the effective search area is affected by vessel design (vessel cruising speed, crow's nest height) and with the adoption of new technology and/or improvements in existing technology (bird radar, helicopters, etc).
        ii) For FAD fishing, effective fishing effort is affected by the number and design of FADs deployed, the aggregating behaviour of tuna that associate with the FADs, given the local characteristics of the tuna population and the environmental conditions, and the frequency of monitoring FADs either by the vessel or service vessels or electronically (utilising GPS buoys).

c) Technology such as the use of oceanographic products derived from remote sensing, which will concentrate searching activity into areas of tuna habitat.
d) The sharing of information regarding the location of tuna schools amongst vessels within the fleet (code groups).
e) The sizes of the individual fish schools encountered and/or the species and fish size composition of the school. The characteristics of the school may determine whether or not the fishing operation commences on the school.
f) Factors associated with setting successfully, such as technological advances in monitoring a tuna school (using sonar), and improved net design, net deployment and net monitoring. Knowledge of the subsurface conditions is also likely to influence the decision to initiate a set on the school.
g) The speed of handling the catch from a set will reduce the time required to complete the set and allow the vessel more time to conduct searching activities.
h) The reliability of reporting of a positive catch will depend of the reliability of the estimates of the catch from individual fishing operations. Small catches of a specific species may not be reported, especially if the species represents a very small fraction of the total catch.

2) The ***magnitude*** of the species-specific catch may be influenced by:
   a) The size of the species-specific tuna schools that were detected in the searching phase of the operation, and mixture of species in the school.
   b) The capacity of the vessel to catch and handle the catch from a school. The relationship between school size and catch is unlikely to be directly proportional, particularly at larger school size as the catch will be limited by a vessels capacity.
   c) Time of day, which may be associated with set size for free-school sets. As the end of the fishing day approaches a vessel may choose to set on smaller schools rather than keep searching and potentially miss out on a set.
   d) The reliability of species catch estimates available at the level of the fishing effort (per set or per day).
   e) Interaction with the magnitude of the catch of another tuna species (other than the species of interest). There may be changes in the preference for a species that influence the species composition of the sets and this may increase or decrease the magnitude of the catch of the species of interest.

A thorough analysis of purse-seine catch and effort data should involve a consideration of the above elements. Analysts should also investigate the potential for significant interactions to exist between the behaviour of the fleet and the technological advancements; i.e. the introduction of new technology may change the overall operation of the vessel. A detailed list of technological changes in provided in ISSF (2012).

We recognize that there is likely to be insufficient data to adequately consider many of the factors listed above, and that many of the factors may be intractable or insufficient resources are available to thoroughly investigate the key elements. However, a thorough CPUE analysis should at least consider the biases that may exist in the analysis so that these can be investigated for in any subsequent analysis.

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