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RESEARCH OUTLINE FOR SIZE DATA IN WCPO LENGTH-BASED STOCK ASSESSMENTS

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Introduction

The purpose of this paper is to outline a structured research approach aimed at better understanding factors affecting the size data used in WCPO tuna stock assessments, and subsequently to allow for more appropriate use and modelling of available size data in the assessments.

The sizes of yellowfin, bigeye, albacore, and skipjack tuna vary considerably between tuna fisheries, in time and space, and even between individual fishing operations on the same trip. The stock assessment model MULTIFAN-CL (Fournier *et al.* 1998) is designed to use size data, and the observed size variation, to provide information about stock status. Multiple factors contribute to this variation, some of which are accounted for in the model, and some not. The factors modelled by MULTIFAN-CL include fish growth (which is currently assumed within the model to be uniform across time and space), recruitment (temporal and between regions), selectivity (between fisheries), fishing mortality (temporal and between regions), and movement (between regions). It also models random variation around the expected sizes around the mean predicted by the growth model. The contributions of the "unaccounted for" factors to size variation in stock assessment data are uncertain, and so are their effects on stock assessment results.

This research outline divides issues into four categories: potential causes of size variation in observed size data, strategies to investigate the nature of size variation, the effects of unmodeled size variation on MULTIFAN-CL results, and changes suggested for the way size data are used for stock assessments using MULTIFAN-CL.

This document was prepared for SPC's 2011 pre-assessment workshop, and subsequently updated for the 2011 Scientific Committee. It largely focuses on work done by SPC for WCPO stock assessments.

Causes

The sources of size variation in the observed size sampling data can be classified into three sources: fish sizes in the population, selectivity effects, and catch sampling effects.

The size structure (number of fish in each size class) of a fish population can be affected by a number of factors, each of which can vary over time and between regions. These factors include fishing mortality and recruitment (modelled by MULTIFAN-CL at a quarterly and regional level), movement (modelled regionally but without temporal or (usually) age variation), and growth and natural mortality (modelled as age-dependent but constant across time and space). However, these processes may vary at smaller spatial and temporal scales than they are currently modelled. For example, growth may vary spatially and/or temporally, due to factors such as environmental variation (temperature, productivity) and density-dependence.

Fishing gears differ in their size selectivity (the size of fish they most commonly catch) and, even within a fishing gear type, variation in size selectivity can occur due to variations in how the fishers set up or use that specific gear type (e.g. due to variations in time of set, bait, hook size etc). Selectivity is often found to vary between fleets, areas, seasons or through time. Some of these factors can be accounted for when setting up fisheries in MULTIFAN-CL. However, some effects on selectivity can be more difficult to identify because they are not reported in much of the available size data, such as the effects of line type, bait, time of set, or hook type.

As with CPUE analyses, the effect of environmental factors on the sizes of fish sampled (relative to the sizes of fish in the time-area being fished) still requires significantly more investigation and understanding. Environmental factors can drive both the size of fish in a time-area (e.g. tuna may move to find their preferred conditions, and preferences may vary by size), and the availability of fish of different sizes to the fishing gear (e.g. size-depth preferences may vary according to conditions).

Sampling effects can also affect the reported sizes. These effects include sorting of catches before sampling, unrepresentative sampling that does not stratify across sources of variation, inappropriate data substitution, falsification of data, and effects such as grab sample bias. A related and interesting cause of bias in stock assessments is failure to realize that MULTIFAN-CL and similar programs model a fishery's size data as if it is representative of the exploitable population, not the catch. This has implications for the approach to sampling stratification, which is particularly important when fish sizes vary spatially within a fishery.

Effects

Size data that do not truly represent the population directly affect the catch estimates from Multifan-CL, and also act on the likelihood in a number of ways.

For fisheries where catch is reported in weight, and subsequently converted to numbers using mean weights-at-length from sampled length distributions, the model estimates a predicted catch that is affected by selectivity. If the average of a set of size samples is biased, then the fishery's selectivity estimate will be biased and the catch in numbers will also be biased. This effect is suspected in Philippines purse seine size data, which may have in the past combined samples from 'baby' purse seine fisheries (small scale purse seining operations - equivalent to ring nets) catching smaller fish with under-represented sampling from the larger purse seine fishery, which catches a greater weight of fish. This may have caused the number of purse-seine-caught fish to be overestimated. Note that a time period's catch in numbers is not particularly affected by the size samples in that period, but by the combined effects of all size samples for that fishery.

Possibly more important are the effects of size biases on the likelihood. Scientists generally programme MULTIFAN-CL to put substantial weight on the fit to the size data, and trade-offs occur between fits to the various components of the size data and other components, such as CPUE and tagging data. Average size affects the model's estimate of total mortality, and this feeds through into the estimates of fishing mortality and biomass. If the observed sizes in a time period or region are larger than the model predicts, the model will tend to compensate by underestimating fishing mortality and therefore (since catch is known) overestimating biomass. Such effects can occur due to biased size samples, errors in the growth curve, unrecognized spatial or temporal variation in the growth curve or selectivity, or other unrecognized effects (such as size-dependent movements or sex ratio variation) that can cause fish sizes to vary in space or time. Biased data (size, CPUE, or tag) can also cause data conflict and poor fits to multiple data types, as well as recruitment trends as the model uses recruitment to adjust biomass estimates.

A further effect of inconsistent size sampling is that it can obscure modal progression in length frequencies, which makes it more difficult to directly estimate growth rates. A comparable situation is that strong modal progression in regions 1 and 2 tends to drive growth rate estimates in the yellowfin stock assessment, since the more spatially and temporally variable recruitment in regions 3 and 4 does not provide such consistent length frequency modes (Langley *et al.* 2007).

Further research is needed to examine how biases in size data and growth rate estimates affect MUTLIFAN-CL stock assessment results, to help prioritize further work on growth rates and size data. This can be investigated by adjusting assumed growth rates to alternative values, by adjusting size data in individual regions and fisheries, and by running the assessment using data from individual regions.

Investigating size data

A number of strategies are available for analyzing size data. The initial aim here is to observe the patterns in the size data, and the factors driving or associated with those patterns. Subsequently, we can identify strategies to adjust for the observed patterns and accommodate them in models. The following strategies are grouped according to the data inputs.

Fleet and operational data can be investigated for size patterns associated with fishing method, space, time, season, and sex. This kind of investigation is a high priority for a number of fisheries. In particular, spatial size variation is apparent in longline fisheries for bigeye and yellowfin, and appears to significantly affect the stock assessments. Size patterns in Indonesia and Philippines fisheries also require investigation, since they have strong implications for the very large catch numbers currently estimated for these fisheries. Unexplained spatial size patterns are also apparent in skipjack fishery data, for all gear types.

Straightforward approaches for investigating size patterns, such as direct comparisons of fish size by gear type or fleet, are often effective. Statistically-based methods, which may be needed in more complex situations, include generalized linear models (GLM), generalized additive models (GAM), and regression trees. A comparative approach can be used across species and oceans. For example, (Bromhead *et al.* 2009) used GLM and GAM methods to investigate size patterns for south Pacific albacore. I am currently using GLM methods to investigate size patterns for bigeye, yellowfin and skipjack across the Pacific, and factors affecting sex ratio at length. Distributional regression trees have been used to characterize size variation in eastern Pacific longline fisheries (Lennert-Cody *et al.* 2010). Previous work has examined spatial patterns in bigeye and yellowfin size data to help define regional structure (Langley 2006), and albacore data to help define spatial and seasonal fishery structure (Hoyle *et al.* 2008a).

Factors affecting distributions observed in the fleet and operational size data can also be investigated using functional models. For example, residuals from MULTIFAN-CL can be analyzed to identify the factors affecting them. It is also useful to remove size data components and investigate the effects on recruitment and effort deviates, e.g. albacore (Langley and Hoyle 2008), and bigeye (Harley *et al.* 2010).

Sampling effects on the fishery size data also requires further investigation. In a number of cases the sampling methods used to obtain the data used in stock assessment models are unclear – efforts to obtain better descriptions of sampling methods might be rewarding. A report and database describing the sampling methods for all size data used in WCPFC stock assessments, and identifying gaps in this knowledge, are needed. Initially, particular attention should be given to data that are outliers, such as the unusually small bigeye and yellowfin longline fishery length samples throughout most of the Pacific in the early 1960's. This approach has previously been taken with data for south Pacific albacore (Hoyle *et al.* 2008b) and bigeye (Harley, Hoyle, Williams, and Hampton 2010).

Direct size sampling effects due to grab sampling bias also require further investigation, regarding the size of the bias, its effects on current size sample estimates, and likely effects on past size samples. SPC is currently investigating these issues.

Tagging data and length at age data can be used to investigate spatial and temporal variation in growth. Spatial and sex variation in albacore growth rates is currently being investigated by SPC and CSIRO using length at age data. SPC is conducting a WCPFC-funded pilot project looking at bigeye growth rates. SPC holds a very large and long time series of tagging data, and analyses of growth have begun in 2011. SPC is currently modelling potential contributions of growth and natural mortality to spatial patterns of sex ratio at length.

Action

In many cases action can be taken to improve the modelling of size data.

Separating catch and effort into different fisheries is the standard approach to account for differences in fish size between fishing methods, such as different gear types. Current fishery definitions have been designed to take major size differences into account. However, there is considerable scope to improve these definitions and redefine fisheries - spatially, seasonally, by gear type, by flag, or by according to other characteristics of the fishing method.

Even when size differences between locations or seasons are due to size-dependent movement rather than selectivity, fisheries can be used within or between regions to account for the difference without introducing bias. This approach is used in many WCPO stock assessments, such as for seasonal and north-south differences in the south Pacific albacore stock assessment.

Changes to the input data are also possible. Where data are influential outliers and the sampling methods are suspect and/or not understood, the best approach may be to remove the data from the model, or effectively remove it by minimizing the effective sample size. This approach has previously been taken with data for south Pacific albacore (Hoyle, Sharples, and Nicol 2008b) and bigeye (Harley, Hoyle, Williams, and Hampton 2010). A less severe option is to reduce the effective sample sizes for some size data to low levels. This has been done for the mixed flag fisheries in the south Pacific albacore stock assessment, because they comprise a mixture of fisheries that catch different sized fish, so observed sizes can change when the mixture of sample sources changes.

Post-stratification can also be applied across factors reported in the data, even when only time and location are reported, so that data are more balanced and informative about the vulnerable population for a fishery. In previous stock assessments, Japanese longline yellowfin length samples' source locations have been compared with catch locations in the same period and rejected if the size data were not representative of the catch (Langley, Hampton, Kleiber, and Hoyle 2007).

An improved post-stratification method is being applied in 2011 (Hoyle and Langley 2011), in which data are reweighted in order to improve the spatial consistency of the size samples. This is necessary because in a catch at length model like MFCL, the predicted catch is removed rather than the observed catch. The separability assumption ensures that the length distribution of the predicted catch = population length distribution x selectivity. Selectivity does not change from year to year in the model, so the model interprets changing observed lengths as changing population lengths. If length distributions change due to fleet movements rather than population length changes, the model results are biased. We have stratified the size data across the main source of variation, which is space. The size data are weighted by long-term average CPUE, which is the best estimate of average abundance distribution in space. The result is consistent size patterns in which temporal changes reflect the population dynamics, not the movements of the fleet.

Input data can also be adjusted for grab sampling bias in purse seine fisheries (Lawson 2010). This process is currently under way for some of the observer-sampled purse seine size data held by SPC.

Finally, the overall modelling approach can be adjusted, to take into account growth rate variation by sex, area, or time. For differences between sexes, MULTIFAN-CL is currently being modified to be able to model sexes separately, with their own growth rates (Davies et al 2011). Billfish show clear growth differences between sexes, as do some species of tuna. Spatial growth rate variation is more problematic, and may require a major rewrite of MULTIFAN-CL. Currently there is no clear evidence about how WCPO tuna growth might vary spatially. Temporal growth rate variation may be easier to implement, but it is not clear that it is an important feature of WCPO tuna population dynamics.

Research recommendations

Further work should be considered in the following areas:

1. Investigate the effects of grab size sample bias on size frequency estimates, and simultaneously adjust both present and historical size frequency data for these effects.
2. Examine potential effects of biases in size data and growth rate estimates on MUTLIFAN-CL stock assessment results, adjusting assumed growth rates to alternative values, by adjusting size data in individual regions and fisheries, and by running the assessment using data from individual regions.
3. Investigate fleet-sourced data for size variation associated with space, season, gear type, flag, and fleet, using GLMs, GAMs, regression trees, and other approaches. Identify which effects are due to selectivity and movement, and use these observed patterns to design consistent MULTIFAN-CL fisheries that take fish of similar sizes.
4. Investigate growth variation by location, sex, and time, using data on length at age, sex ratio at length, modal progression, and tag recapture. Develop modelling strategies to include growth variation in stock assessments, or strategies robust to these sources of variation.
5. Investigate the sources of sampled size data, remove unrepresentative data, and adjust both the size data and the effective sample sizes where necessary to reflect the representativeness of the data.

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