What is CPUE standardisation and why is it important for stock assessments?

Nicholas D. Ducharme-Barth[1*]

One of the key elements of any stock assessment model is the abundance index. This provides information on how the population has changed over time. Combining the abundance index with the historical fishery removals (sometimes referred to as catch or landings) can allow scientists to estimate the reproductive potential of the stock (also referred to as the spawning potential or spawning biomass). Together these form the basis for sustainable fisheries management. Here we evaluate a new approach for catch per unit effort (CPUE) standardisation using western and central Pacific Ocean skipjack tuna (*Katsuwonus pelamis*) as an example.

How do we derive abundance indices?

Ideally, abundance indices would be derived from fisheries-independent surveys, such as those carried out on research vessels at sea. These are surveys that are scientifically designed to representatively sample across the geographical range of the fish population (typically referred to as *random* sampling), and are carried out in a way that consistently samples from year to year using a standardised procedure. This means that annual changes in the survey index (i.e. abundance index) can be interpreted as being directly proportional to changes in the underlying population. A good example of a fisheries-independent survey is the *Eastern Bering Sea Continental Shelf Bottom Trawl Survey of Groundfish and Invertebrate Resources* conducted by the National Oceanic and Atmospheric Administration Fisheries (Conner and Lauth 2017). This survey has consistently sampled 356 sampling stations spread evenly across the continental shelf in the eastern Bering Sea off the coast of Alaska since 1982 (except for a gap in 2020 caused by COVID-19). In addition to providing abundance data for a number of important commercial groundfish and crustaceans across a large extent of their range, this survey also serves as a vital platform for collecting length, age, stomach content, and other biological samples for these species.

Although fisheries-independent data provide the highest quality data for use in stock assessments, they are expensive and difficult to implement over large spatial scales. Within the Pacific Islands region, there are no large-scale, fisheries-independent surveys for highly migratory species such as tunas and billfishes, although such surveys exist for more sedentary species such as deepwater snappers in Hawai`i (Ault et al. 2018) and hoki, hake and ling in New Zealand (Marsh et al. 2018).

In many cases, due to cost or other logistical issues, fisheries-independent surveys are just not feasible and so fisheries-dependent, catch-rate data (CPUE) must be used to create an abundance index for stock assessments. CPUE data are typically already collected as a part of normal fishing operations and recorded as a part of the logbook or observer reports, making these data an inexpensive and convenient alternative to fisheries-independent survey data. Averaging the fisheries-dependent CPUE within years can produce an annual abundance index, and this is usually called the "nominal" index.

Effort creep and hyperstability

Unlike the abundance index from a fisheries-independent survey, the nominal index from fisheries-dependent CPUE cannot be assumed to change in a way that is directly proportional to abundance. There are a number of reasons for this, and two cases are described in further detail. In the first case, fishers may change their gear from year to year in an effort to catch fish more efficiently. For example, upgrading sonar can target fish schools more effectively and result in less wasted effort to produce the same amount of catch as in previous years, even if abundance does not change. This greater efficiency or "effort creep" may show up in the index as an increase in the nominal CPUE. This does not necessarily mean that the underlying population abundance has increased because the fishers became better at catching fish with less effort. In some fisheries, effort creep is estimated to increase the efficiency of fishing effort by at least 1–6% per year, depending on the length of the time period considered (Palomares and Pauly 2019). This may not seem like a lot but over time it can add up! Effort creep is generally defined as the gradual change in fishing effort efficiency (of the fleet or individual vessels) over time due to changes in

[1] NOAA National Marine Fisheries Service, Pacific Islands Fisheries Science Center, 1845 Wasp Boulevard, Building 176, Honolulu, Hawaii, USA 96818. Email: nicholas.ducharme-barth@noaa.gov

[*] Formerly: Fisheries Scientist (Stock Assessment), Oceanic Fisheries Programme, Fisheries, Aquaculture and Marine Ecosystems Division, SPC

gear, technological advancements, and/or knowledge acquisition by fishers. Effort creep can result in nominal CPUE remaining stable over time even as the underlying fish stock declines, referred to as "hyperstability".

The second case has to deal with where fishers choose to fish related to the distribution of their target stock. Fish are not distributed evenly in the ocean, and there are areas of high and low population densities. Fishers are naturally drawn to fish in areas where they have good catch rates, which are usually areas of higher fish population density. So compared to a scientific survey with *random* sampling, fishery-dependent data often involve targeted fishing referred to as *preferential* sampling. If a fisher fishes in a high-density area one year, and then moves to fish in a lower density area the next year, their catch rates could be expected to fall. This may show up in the index as a decrease in the nominal CPUE but this does not necessarily mean that the overall level of population abundance has changed.

Using nominal CPUE directly in a stock assessment as an abundance index can lead to biased estimates of stock status. If the nominal CPUE is stable or changes (declines) at a rate that is slower than the true rate of change of the population (hyperstability) then stock assessments will be overly optimistic and may result in managers not making the necessary decisions to prevent overfishing and the stock becoming overfished. If the nominal CPUE changes (declines) at a rate that is faster than the true rate of change of the population (hyperdepletion) then stock assessments will be overly pessimistic, and may result in managers unnecessarily restricting fishing effort or catch. Hyperdepletion could occur if gear becomes less efficient at catching fish over time, potentially due to fish learning to avoid the gear or other collective behavioural changes in the targeted population.

Standardising CPUE indices

Given that fisheries-dependent nominal CPUE indices may not accurately reflect changes in the underlying population abundance, and that fisheries-independent surveys are often unfeasible to implement, it is important to "standardise" fisheries-dependent CPUE indices before they are used in stock assessments. The process of standardising CPUE recognises that fishers may fish differently over time and among each other, and that these differences can affect catch rates independent of variation in fish abundance. CPUE standardisation aims to account for these differences by including identified variables that can influence catch rates, unrelated to fish abundance, as covariates in a statistical model. Using this statistical model, the goal is to remove the effects of these variables on CPUE, so that the *standardised* fisheries-dependent CPUE index is more closely related to the underlying fish abundance.

Considerable research has been devoted to the topic of CPUE standardisation over the years, with a large research focus on how to deal with spatial differences in catch rates and how to model areas that are not fished in all years (Campbell 2015; Walters 2003). If fishers do not fish in a given area, then we do not know how the abundance of that portion of the population may have changed. Ignoring these "unfished" areas in the CPUE standardisation makes the implicit assumption that unfished areas have the same abundance as the average of the fished areas. This assumption might be acceptable to make if fishers fish randomly with respect to fish density. However, as discussed before, fishers are more likely to follow the fish, so making this assumption in the analysis of fisheries-dependent data could lead to hyperstability in the abundance index.

Evaluating spatiotemporal modelling approaches using Pacific skipjack tuna as a case study

Recently, spatiotemporal approaches to traditional statistical models for standardising CPUE have become more popular. Spatiotemporal models explicitly account for the spatial and temporal relationships in data by taking advantage of the idea that "near things are more related than distant things" in space and time (Tobler 1970). These spatiotemporal models have been shown to outperform traditional statistical models (Grüss et al. 2019), and are well equipped to handle spatial variation in catch rates. Additionally, by explicitly modelling the spatiotemporal relationships in the data, scientists can make a more appropriate inference on what the catch rate would be in unfished areas when creating a standardised CPUE index. However, spatiotemporal models assume that data are collected from a *random* sampling process, which is not usually the case in fisheries-dependent data.

In our recently published study (Ducharme-Barth et al. 2022), we sought to evaluate the performance of spatiotemporal modelling approaches in situations where the underlying model assumptions are violated, such as when standardising fisheries-dependent CPUE. We also wanted to identify how well spatiotemporal modelling approaches handled changes in fishing location over time and their ability to account for effort creep. These investigations were done using a simulation framework so that we could compare our estimated standardised abundance indices with the simulated "true" population. Our simulation was constructed to be representative of the Japanese pole-and-line fishery for skipjack tuna[2] (*Katsuwonus pelamis*) in the western and central Pacific Ocean. We used output from the SEAPODYM spatial ecosystem and population dynamics model developed for skipjack tuna (Lehodey et al. 2008; Senina et al. 2020) as a realistic, simulated "true" population (Fig. 1). We then "fished" this population under

[2] See: https://www.youtube.com/watch?v=i5mMI8t7vV0

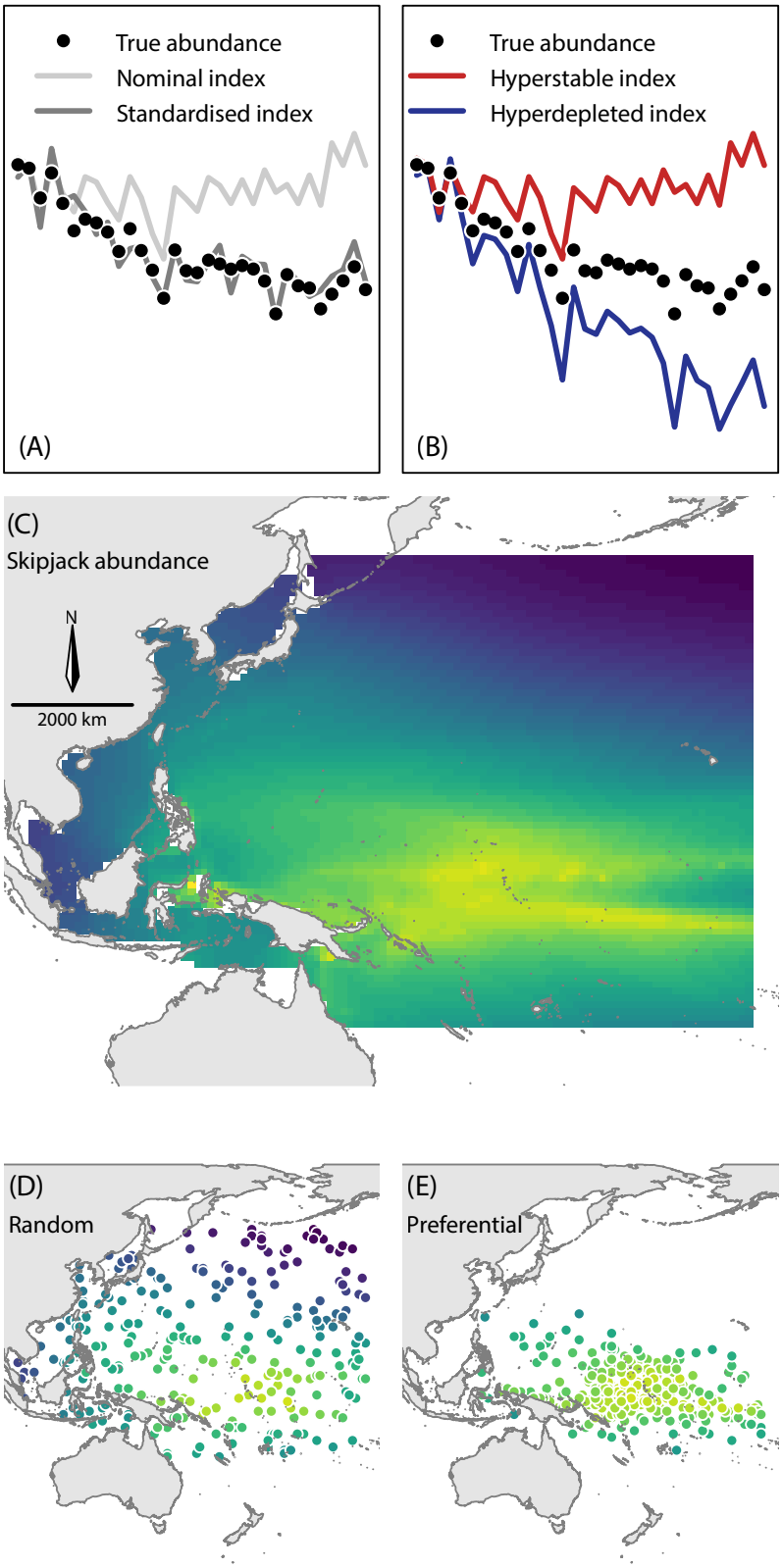

Figure 1. Panel A) A simulated time series of abundance (black points) with the nominal CPUE index (light grey) and the standardised CPUE index (dark grey). Panel B) A simulated time series of abundance with an example of a hyperstable nominal CPUE index (red) and a hyperdepleted nominal CPUE index (blue). Panel C) Simulated skipjack abundance distribution in the western and central Pacific Ocean from the SEAPODYM model. Darker colours indicate areas of lower abundance, and lighter colours indicate areas of higher abundance. Panel D) Example of random spatial sampling. All locations have an equal probability of being sampled, including areas of low abundance (darker colours). Panel E) Example of preferential spatial sampling. Areas of higher abundance (lighter colours) have a higher chance of being sampled resulting in few samples located outside of the core of the population distribution.

different fishing location scenarios, including *random* and *preferential* sampling types. Lastly, we fit spatiotemporal CPUE standardisation models to our simulated fisheries data to estimate abundance indices and obtain an understanding of the level of error and bias in our estimated indices across the different scenarios.

Skipjack tuna was selected as a relevant case study because of its cultural and economic importance to the Pacific Islands region – total western and central Pacific skipjack tuna catches in 2020 were valued at ~USD 2 billion (Williams and Ruaia 2021) – but also because of the unique challenges associated with assessing this species. Skipjack are caught across a huge area in the western and central Pacific, from as far south as the Tasman Sea to the Kuroshio Extension current off Japan, and extending within the tropics across the eastern Pacific. This enormous spatial extent makes developing a fisheries-independent survey of the population difficult from both financial and logistical standpoints. As a result, the stock assessment relies exclusively on fisheries-dependent data for its abundance index. Unfortunately, the two predominant sources of fisheries-dependent data, pole-and-line and the tropical purse-seine fisheries, have issues that may result in indices that do not change in proportion to skipjack population abundance. Historically, skipjack were primarily caught from pole-and-line vessels, and the Japanese pole-and-line fleet fished across a large portion of the assessment region. These data were used as the basis for the abundance index applied in the stock assessment. However, this fishery has greatly reduced its spatial extent such that it no longer samples the entire skipjack population distribution. More recently, skipjack catches have been dominated by the industrial purse-seine fishery, which primarily operates in tropical waters around the equator. The purse-seine fishery also has a limited geographical scope, although the bigger concern for this fishery is the ability to appropriately account for effort creep, which has been recently estimated at levels between 3% and 6% per year (Vidal et al. 2021). While data from the Japanese pole-and-line fishery may also contain the effects of effort creep, there exists a more robust record of gear and technological changes within this fishery that allow for some accounting of effort creep within the standardisation models.

Conclusions and considerations

Our research shows that spatiotemporal approaches are able to account for changes in the spatial location of fishing, provided that the shift in fishing was not too extreme of a departure from the underlying population distribution. Additionally, models were able to simultaneously account for minor changes in spatial location of fishing and effort creep, provided that all factors contributing to effort creep were included in the model. However, our results also confirmed that *random* sampling, as conducted in a fisheries-independent survey, performed as well or better than the different fishery-dependent scenarios in almost every situation.

So, what does this all mean, and in particular, what does this mean for upcoming assessments of western and central Pacific Ocean skipjack tuna? It is always important to consider how the data were collected in order to evaluate if there are potential issues with using them to develop an abundance index for a stock assessment. If you are able to account for all the factors leading to effort creep or other changes of capture efficiency in your standardisation model, then you may be able to create a viable abundance index. However, it is difficult to account for shifts in spatial sampling in a standardisation model, particularly if large shifts have occurred. More advanced modelling techniques applied to fisheries-dependent data are not a substitute for devising an index from data that are collected as a part of a well-designed fisheries-independent sampling study. With regards to western and central Pacific Ocean skipjack there is a real need to start thinking outside of the box, given that the Japanese pole-and-line fishery no longer sufficiently samples the total spatial extent of the skipjack population, and that effort creep remains challenging to model for the purse-seine fishery This means continuing to work with the industry to identify factors leading to effort creep (Wichman and Vidal 2021), and collecting the required data to effectively model these changes within the standardisation process. However, it also means exploring and investing in emerging technologies and techniques such as genetic analysis, including close kin mark recapture (Bravington et al. 2016), and/or acoustic data collected from autonomous platforms (De Robertis et al., 2021) in order to collect fisheries-independent data that can be used to reliably track abundance. Nevertheless, cost and logistics may continue to remain a challenge at the scales required.

The full study (Ducharme-Barth et al. 2022) is freely available at: https://doi.org/10.1016/j.fishres.2021.106169. The scientific results and conclusions, as well as any views or opinions expressed herein, are those of the author and do not necessarily reflect those of National Oceanic and Atmospheric Administration, the US Department of Commerce, or the Pacific Community.

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