Effort creep in longline and purse seine CPUE and its application in tropical tuna assessments

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Abstract

This working paper investigates how catchability change may affect the indices of abundance used in Indian Ocean Tuna Commission (IOTC) stock assessments. This is an important issue for assessment outcomes and management advice. The paper begins with an overview of effort creep, placing it in context as a form of productivity increase, which allows us to learn from patterns of technological change in other industries. It considers methods for estimating effort creep, such as statistical analyses that compare catch rates between vessels with different characteristics, leading on to syntheses of analyses across multiple fisheries. For the particular case of tuna longline catch-per-unit-effort (CPUE), it examines previous work to explore factors that may affect catchability, demonstrating how the accumulation of changes in multiple areas can generate long-term growth in catchability. Syntheses of numerous effort creep studies indicate that technology creep should be assumed in all analyses involving time series of fishing effort, particularly if they exceed one decade of temporal coverage. Although index-specific estimates are often unavailable, ignoring effort creep will usually bias biomass estimates to be overly optimistic. Stock assessments should consider a range of scenarios regarding long-term catchability trends, from low to high but noting that 0% is rarely plausible. Finally, the paper proposes levels of effort creep to assume in both longline and purse seine CPUE indices.

1. Introduction

Increases in catch efficiency, or fishing power, have played a critical role in the history of fisheries (Gabriel et al., 2005; Scherrer and Galbraith, 2020; Squires and Vestergaard, 2013). Fishing power is a function of many components, including the skill and experience of the skipper and crew, and the technologies used to find and capture fish.

In the context of stock assessment, effort creep can be defined as an unquantified increase in the average fishing power over time that disturbs the relationship of proportionality between the index and the stock trajectory. These changes in catchability over time can substantially affect catch-per-unit-effort (CPUE) indices, and through them the outcomes of stock assessments. This is particularly important for assessments that lack abundance indices from fishery-independent surveys, which includes the majority of the fisheries managed by tuna regional fishery management organizations (RFMOs).

There is considerable uncertainty about how to estimate effort creep, and its importance for outcomes has led to ongoing debate. For example, at the 2020 Indian Ocean Tuna Commission (IOTC) Working Party on Tropical Tunas (IOTC, 2020), participants did not reach a consensus about how to represent

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effort creep in the skipjack stock assessment (Fu, 2020). Text was included in the meeting report that outlined the basis of the disagreement (see Appendix).

Other tuna RFMOs have similar concerns. WCPFC has recommended research into methods to account for effort creep in CPUE standardization and/or the assessment model, associated with the bigeye and yellowfin tuna assessments (WCPFC, 2023), and has commissioned a scoping study into longline effort creep. The WCPFC scientific services provider is currently undertaking research into development and modelling of defensible effort creep scenarios for the skipjack stock assessment.

This paper focuses on the implications of effort creep for stock assessment, but it also has implications for management, particularly associated with input controls (Kompas and Gooday, 2007; Squires et al., 2017). Both cases hinge upon how effort is defined, but the approaches and constraints for defining effort necessarily differ between effort definition for input controls and indices of abundance based on catch per unit of effort.

This working paper considers how cumulative fishing power has changed through time. It begins by taking a wider view, considering the characteristics, rates, and drivers of productivity improvements in a wide range of technological areas, before turning to focus on fishing. It then identifies methods used to estimate rates of change in fishing power. Next it considers syntheses of fishing power estimates from a range of fisheries. It then identifies individual factors associated with fishing power change in tuna fisheries, primarily focusing on longline fisheries. Finally, it looks at approaches that analysts have used in tuna stock assessments to address effort creep that is not included in their abundance indices.

2. Technological improvement

Productivity growth driven by technological progress is a key component of modern society, and various models have been developed to describe it. A well-known example is Moore’s law (Moore, 1965; Moore, 1975), which predicted that the number of components on a chip would double every one to two years – a rate that was maintained for 50 years (Leiserson et al., 2020). Across many domains, technological progress (improvement in a performance metric such as output per unit of input) is broadly predictable using exponential growth models. Nagy et al. (2013) used a database on the cost and production of 62 technologies to test the ability of alternative models to predict future costs, finding that Wright’s law (Wright, 1936) (based on cumulative production) performed similarly to Moore’s law (based on time).

Magee et al. (2016) examined 28 technological domains, found that the correlation of performance with time was strong in each one, and proposed that Moore’s law is fundamental to the dynamics of technological change.

Farmer and Lafond (2016) provided a statistical foundation, showing that long-term trends in progress are random walks around an exponential in time. They studied 53 technologies to explore the predictability of technological progress, and developed an approach for forecasting, including estimates of the distribution of uncertainty. These observations support the idea that, when comprehensive information is missing, it is reasonable to model technology-based progress such as increases in fishing power as a constant rate.

The rates of exponential improvement vary between technologies, and these characteristic differences tend to be maintained through time (Farmer and Lafond, 2016; Magee et al., 2016; Singh et al., 2021). Singh et al. (2021) used more exploratory methods to develop hypotheses about improvement rates across 1757 domains representing all patents in the US patent system. They found that improvement rates ranged from 2% to the domains with the fastest rates of improvement almost always centrally dependent on software. Modularity, or low interactions among components, is a major factor affecting performance improvement rates (Basnet and Magee, 2016). The other important factor is differences in scaling laws for different domains. Scaling refers to how change in a design parameter relates to relative change in performance.

Efficiency increases are also observed in industrial fisheries, and catchability change is a component of this increase. For our purposes, this suggests that fishing methods that are more technology-based are likely to maintain higher rates of improvement in fishing power, both because there are more independent areas in which improvements may occur, and because individual changes can have large scaling effects. One such fishing power component is the process of identifying where to fish, which increasingly involves high-tech methods such as remote sensing, sonar, statistical modeling, and communication networks.

The rate at which the performance of a technology improves is a useful indicator of how important that technology will be in future (Hoisl et al., 2015). In the context of tuna fishing, this is reflected in the more rapid improvement in catchability of purse seine fishing compared to longline (Kolody, 2018; Torres-Irineo et al., 2014), and the increasing relative importance and value of the purse seine fishery. Similarly, it reflects the increasing relative importance in the Indian Ocean of fishing on FADs associated with echo sounders compared to free school fishing (IOTC, 2023).

2.1. Effort creep

The term 'fishing power' describes the efficiency with which vessels catch fish, defined by Beverton and Holt (1957) as a vessel's effectiveness in catching animals relative to the effectiveness of a standard vessel.

Fishing power tends to increase through time due to a series of adjustments in fishing practices, materials, technologies, knowledge, and experience. These adjustments result in higher catch rates than would have otherwise occurred. Of course, fishing power changes are not always increases. For example, catchability for a bycatch species could decline if changes to the fishery are made to increase the catchability of the target species. However, this is special case. The incentive for fishers is to increase profit, rather than the catch of any individual species, and this is usually associated with targeting the most profitable species.

Effort creep is important for stock assessment because of the assumed relationship between catch rates (CPUE) and stock abundance. This relationship is based on the catch equation, which relates the number of fish in the catch, C, fishing effort, E, and the average fish population density, D, on the fishing grounds:

$$C = qED\text{, i.e., } CPUE = qD$$

where q is a fixed constant of proportionality known as the catchability coefficient and is related to the efficiency of the fishing gear (i.e., the proportion of the stock removed by one unit of effort). Effort creep progressively increases the value of q.

The concept of 'hyperstability' is sometimes linked with effort creep (e.g., Ward, 2008) since both can cause CPUE to remain high when abundance declines. However, hyperstability (like hyperdepletion) is best defined as a lack of proportionality between CPUE and abundance N, such that $CPUE = \alpha N^{\beta}$, (Hilborn and Walters, 1992), which can also be expressed in terms of density D: $CPUE = \alpha D^{\beta}$. Hyperstability is associated with the β parameter and occurs in a fishery when β is less than 1, whereas catchability increase is associated with changes in the α parameter. The form of a hyperstable relationship between abundance and CPUE depends on the distributions of fish and fishing effort in space and time, and the nature and definition of effort (Erisman et al., 2011; Harley et al., 2001; Ward et al., 2013). This paper focuses on effort creep, but effort creep and hyperstability can occur together.

Effort creep is affected by how the unit of effort is defined (Scherrer and Galbraith, 2020). For example, if the unit of effort is the fishing day, a vessel that increases the number of sets per day will increase its catchability, whereas that will not be the case if the effort unit is the set. Effort creep also depends on how the CPUE index is prepared. Standardization may adjust for some catchability changes through covariates such as the vessel identifier and the gear configuration.

2.2. The drivers of catchability increase

Industrial fisheries experience strong incentives to increase production, but these incentives are more complex than simply a drive to increase CPUE. In economic terms they can be summarized as incentives to increase the surplus in outputs, after subtracting inputs, i.e., to maximise profits. Productivity is an index of output divided by an index of total input usage (Grosskopf, 1993). For the fishing industry the relevant output is the value of the catch, and the relevant inputs are the total costs associated with fishing.

Economic incentives to increase productivity are therefore associated with more than just the CPUE. They are also linked to the abundances of the species caught, the values of those species, and costs of inputs such as fuel, crew, and interest payments. For example, despite technological advances and expansion of fishing throughout the world's oceans, global production efficiency in terms of the tonnage of wild marine catch per watt days of fishing effort was lower in 2012 than in 1950 (Bell et al., 2017). This was largely a consequence of stock reduction, because the increased efficiency was not enough to offset the global decline in fish stocks.

Productivity growth can be separated into technical change and efficiency change (Grosskopf, 1993), and the same considerations can be applied to fishing power change. Efficiency represents how far an observation is from the frontier of technical possibility, while technical change shifts this production frontier. A new technology such as bird radar or monofilament mainlines may shift the production frontier of potential catch rates, but a period of learning is required for individuals to apply the technology to full effect – i.e., for fishing efficiency to increase. For example, Robins et al. (1997) found that, in the Australian northern prawn fishery, "installation of a GPS without a plotter led to an increase of 4% in relative fishing power (over boats without a GPS). During the fisher's first year of using a plotter, fishing power increased by 7% over trawlers without a GPS or plotter; an additional year of experience with a plotter increased it to 9%; and a third year increased it to 12%."

One effect of this learning process is, to some extent, to smooth the rate of catchability increase and make it less episodic than it might otherwise be, given the intermittent nature of technology change.

Technologies are often trialled by part of the fleet before being taken up more broadly. For example, in 1995 in the Japanese southern bluefin longline tuna fishery, a small number of vessels were trialling the use of monofilament mainline material (Whitelaw and Baron, 1995), but their use soon spread to the whole fleet.

Regulation can affect technological change in fishing practices. In an extreme example of this, a study of the Dutch herring fisheries of the sixteenth to nineteenth centuries found almost no technological innovation for more than 300 years. Technical change was prevented by law (Poulsen, 2008).

2.3. Components of catchability increase

The effectiveness of a unit of effort in catching fish can change over time due to the adoption of new materials and technologies, gear modifications, fisher skill, enhanced communication / networking among skippers and/or access to other information such as oceanographic data that helps locate fish (Hamer and Teears, 2023). These factors vary by fishery. Although there are interactions between some factors, it is reasonable to assume that, in general, individual factors have multiplicative effects on fishing power.

Some factors are associated with equipment on vessels, such as the GPS systems, communication technology to share information between vessels and with fishing companies, and equipment that allows vessels to deploy fishing gear more rapidly and effectively (e.g., automatic baiting machines, more powerful winches).

Other technological factors are not directly related to equipment on board a vessel, such as increasingly informative environmental data from satellites and models, and scientific progress in understanding the factors that affect fish distribution, which may derive from public research or from fishers' interrogation of their own stored catch and effort data.

Squires (1992) found that the most important sources of technical progress in the Pacific coast trawl fishery were electronics and the application of scientific (rather than craft) principles to vessel and equipment design and to harvesting methods.

2.4. Implications of effort creep

Information that is unavailable to analysts cannot be included in CPUE standardization and accounted for in the index. These factors, when associated with increasing fishing power, lead to indices that increasingly overestimate abundance through time.

Since abundance indices are among the most important factors in determining assessment outcomes, effort creep can significantly affect assessment outcomes.

Similarly, simulations to optimise management strategies and determine harvest control rules generally assume that indices of abundance are unbiased. Effort creep breaks the assumptions used to design the harvest control rules, which will diminish the performance of the management system.

3. Methods for estimating catchability increase

One difficulty in estimating rates of fishing power change is obtaining the necessary data (Scherrer and Galbraith, 2020). The details of the equipment on a vessel are often unavailable to analysts, and factors unrelated to vessel equipment (such as details on the quality of information available to fishers) are almost never available and are very difficult to quantity. Thus, estimates of fishing power change using most methods are biased low because they omit important factors.

3.1. Summed contributions of individual components.

The introduction of new equipment and upgrades to improve technology can often increase vessel fishing power. These effects can be estimated using generalized linear or additive models. Technological creep is observed in almost all such analyses, particularly if the time series of fishing effort exceeds ten years (Palomares and Pauly, 2019). Analyses of equipment effects require reliable information about the timing of equipment change across the whole fleet, in a format that can be linked to logbook or observer data. They are therefore usually limited in their application to fleets with strong administrative oversight and documentation requirements. In most cases data are only available for major items of equipment and omit smaller, less obvious technological improvements. These analyses also require contrast between vessels in use of the technology, which can be limited when new approaches that confer an advantage are taken up rapidly across the fleet. This is a common problem with natural experiments, which is why randomised designed experiments are preferred.

When the data needed for statistical analysis is lacking, expert opinion can be used to elicit estimates of the impacts of changes in the fishery on catch rates (e.g., Medley et al., 2020).

3.2. Vessel effects

In the absence of data on equipment, catchability change associated with vessel turnover can be accounted for by including a vessel identifier (e.g., the callsign) in the model. This is essentially a special case of the individual component approach. Vessel effects are almost always statistically significant in CPUE analyses and represent consistent differences in catchability (Hoyle et al., 2024). The contribution of this component of catchability change can be estimated by comparing CPUE index trends with and without the vessel id in the model (e.g., Hoyle, 2009). Vessel turnover can proxy for various technological effects, since newer vessels tend to be equipped from the start with more recent technology. Vessels are also more likely to leave a fishery if they have lower catch rates. However, this method tends to underestimate effort creep because it omits the catchability change associated with equipment changes on an existing vessel, such as upgrading or installing new technology, learning to use it more effectively, or obtaining information from other sources. Estimates can also be affected by target change, since different vessels may have different targeting strategies, and these can change through time. In tuna fisheries targeting multiple species, effort creep estimates using this method can be positively or negatively biased by the targeting behaviours of individual vessels (Hoyle and Okamoto, 2013).

Operational data from Japanese longline vessels fishing in the waters of national jurisdiction of Pacific Island countries were analysed to estimate effort creep associated with vessel turnover for the period with sufficient data for reliable estimates, 1980-1998 (Hoyle, 2009). Results by 10° square were mostly positive, with median values of 0.72% per year for bigeye and 0.76% for yellowfin tuna. Combined results for the western equatorial region with the most data, from 10° S to 20° N, were 0.47% for bigeye and 1.4% for yellowfin.

Later analyses using a large database of operational data from the Japanese fleet (Hoyle and Okamoto, 2011) also provided estimates, though these were biased low because the 24 years from 1952 to 1975 did not include vessel effects. Nevertheless, estimates for the offshore fleet in western equatorial region were 0.38% and 0.98% per year for bigeye and yellowfin respectively from 10° S to 20° N, but higher at 0.62% and 1.3% per year when focusing on the core of the fishery between 5° S and 10° N. In central Pacific equatorial areas, the trends for the Japanese distant water fleet were 0.45% and 0.2% respectively, but showed signs of instability from the 1990s, possibly linked to a rapid transition within the distant water fleet to monofilament mainlines and larger HBF. This transition was more gradual for the Japanese offshore fleet in western areas (see figures 13 & 14 in Hoyle and Okamoto, 2011). Estimates for non-equatorial areas are considered unreliable due to low sample sizes and the likelihood of confounding with targeting strategies.

In Hoyle and Okamoto (2011), all increments due to vessel effects occurred in the period 1976 to 2010 but were averaged across 1952-2010. It is reasonable to adjust these from the longer to the shorter period using the equation $adj = (est^{58})^{\frac{1}{34}}$. The adjusted estimates are provided in Table 1.

Analyses for the Indian and Atlantic Oceans (Hoyle et al., 2019a; Hoyle et al., 2019b; Hoyle et al., 2019c) were not suitable for calculating trends in fishing power linked to vessel turnover, due to both confounding between the effects of vessel and cluster variables, and the effects of combining multiple fleets with various fishing strategies.

Note also that including vessel effects in analyses of Japanese longline catch and effort for southern bluefin tuna does not change the index trend (Itoh and Takahashi, 2022).

Table 1: Summary of estimates of catchability increase associated with vessel turnover, taken from Hoyle (2009) and Hoyle and Okamoto (2011).

Dataset	Area	Period	Species	Estimate	Adjusted
SPC-held	W Pacific, median of 10x10	1980-1998	BET	0.72%	
	W Pacific, median of 10x10	1980-1998	YFT	0.76%	
	W Pacific, 10S – 20N	1980-1998	BET	0.5%	
	W Pacific, 10S – 20N	1980-1998	YFT	1.4%	
Japanese	W Pacific, 10S-20N	1976-2010	BET	0.38%	0.65%
	W Pacific, 10S-20N	1976-2010	YFT	0.98%	1.68%
	W Pacific, 5S-20N	1976-2010	BET	0.62%	1.06%
	W Pacific, 5S-20N	1976-2010	YFT	1.3%	2.23%

3.3. Calibration against a baseline

Fishing power change can be estimated by comparing an index against a baseline, such as by comparing CPUE trends with biomass estimates from a survey or from mark-recapture experiments, by comparisons among gear types within a stock assessment, or by calibrating against abundance information from other sources such as mark-recapture experiments or composition data.

Comparisons with surveys have the advantage that they directly compare abundance indices from CPUE with a theoretically unbiased index of abundance, so can include all contributions to change in fishing power. There are a few examples of this approach, but difficulties include the high variability of both types of stock abundance indices (Marchal et al., 2002). Marchal et al. (2002) compared individual vessel catch rates with an external survey index. Damalas et al. (2014) compared CPUE indices from commercial landings with experimental survey indices by species group. Harley et al. (2001) and Dunn et al. (2000) compared CPUE and survey estimates but used them to characterise the relationship between abundance and catchability, rather than changes in catchability through time.

Relative change in fishing power between fisheries can be estimated by calibrating indices against one another within an integrated stock assessment. Comparing within the assessment adjusts for factors such as time-varying recruitment and differences in selectivity between fisheries.

This approach has been applied to tuna assessments (Kolody, 2018) to estimate the rate of increase in fishing power of purse seine fisheries. Kolody refitted both the bigeye (Langley, 2016a) and yellowfin (Langley, 2016b) tuna assessments from 2016, each with the addition of an associated purse seine (PSLS)-based CPUE index. Standardized PSLS effort for the bigeye and yellowfin time series was obtained from the standardized skipjack CPUE time series (Katara et al., 2017) by dividing skipjack PSLS catch by the CPUE. This represents effort adjusted for quarter, fleet, storage capacity class, and vessel. Bigeye and yellowfin CPUE indices were then developed by dividing PSLS bigeye and yellowfin catch by the standardized PSLS effort.

Prior to a change in methodology to a catch-conditioned approach (Davies et al., 2022), WCPO tuna stock assessments using MULTIFAN-CL estimated these fishing power changes implicitly for fleets other than the major longline fleets, by internally estimating a random walk in catchability (Kleiber et al., 2018).

Other sources of abundance information in integrated stock assessments are rarely sufficiently reliable to provide information about catchability change. Abundance information from conventional mark-recapture data for tunas is affected by uncertainty associated with incomplete mixing, release mortality, and reporting rate variation (Hoyle et al., 2015; Kolody and Hoyle, 2015; Leroy et al., 2013).

Information from composition data is affected by issues such as spatial size and growth variation, selectivity change, and sampling biases (Hoyle et al., 2021; Sampson and Scott, 2012). However, there is potential for data from close kin mark-recapture experiments to provide relevant information in future.

3.4. Syntheses

Comparing and combining results from multiple analyses can identify commonalities between fishing methods and gear effects, and permit inferences for fisheries where there are insufficient data to directly estimate fishing power changes. These analyses are generally based on data collected in logbooks or by observers.

Eigaard et al. (2014) estimated a mean rate of increase of 3.2% per year across a range of studies. Palomares and Pauly (2019) reviewed 51 estimates of trends in fishing power over time, with most in the range of 2-4% per year. They noted a negative relationship between the period of the study and the estimated rate of change: annual creep rate = 13.8 x (period in years)$^{-0.511}$. They suggest that this trend may occur because "creep factors are usually estimated and published to correct for the introduction of an effective new technology over a short period of time". The estimated relationship implies an expected rate of 1.3% per year for studies that cover a 100-year period. Conversely, however, this is likely to be an underestimate because the decline in the magnitude of estimates with time is likely also affected by negative biases in long-term estimates (Scherrer and Galbraith, 2020). Long-term analyses tend to omit some types of technological progress, particularly changes due to adding technology to existing vessels, and the accumulation of knowledge.

Galbraith et al. (2017) use hindcasting to show that a mean rate of technological progress across all fisheries at a rate of 5% per year best explains the 20th century pattern of change in fish harvest. Some of this increase is due to the displacement of less efficient fishing methods, rather than increased efficiency within individual fishing methods.

Wilberg et al. (2009) noted that time-varying catchability is common in most fisheries, and can be caused by environmental, biological, and management processes as well as technological factors.

4. Relevance for tuna fisheries

Here individual factors are discussed that may contribute to catchability change in tuna fisheries.

4.1. All fishing methods.

4.1.1. Navigation

Since the late 1970s, precise location fixes, initially from SatNav and subsequently from GPS, have allowed longliners to precisely locate bathymetric features such as seamounts (Ward and Hindmarsh, 2007), where catch rates can be higher (Morato et al., 2010a; Morato et al., 2010b). More generally, they also allow vessels to return to areas of historic and/or recent high catch rates. When combined with satellite imagery, they allow longliners to find promising oceanographic features. When combined with communication devices, they allow vessels to inform each other about where to fish, and where not to fish.

Whitelaw and Baron (1995) suggest that GPS had a major impact when introduced to the southern bluefin tuna fishery.

4.1.2. Fish finding

Japanese longliners have used echo-sounders since the early 1960s to detect the deep-scattering layer, tuna schools, current variation, and seamounts (Ward and Hindmarsh, 2007). Multi-directional sonar has been used since the mid-1980s to locate fish aggregations. Doppler current profiles have been used since the late 1980s to determine currents at various depths, which helps to optimise longline deployment. Remote sensing has been used to locate promising oceanographic features, including SST imagery since the 1970s, ocean colour and sea surface height imagery to identify areas of upwelling and current shear. These technologies have also changed and improved through time.

Over many decades there has been considerable public investment in understanding oceanography (Schwing, 2023), which has accelerated with the need to understand and predict climate change. Consequently, there is currently an explosion of new data about the ocean (Lubchenco and Haugan, 2023). Large-scale oceanographic models provide publicly available information about ocean dynamics at increasingly fine spatial and temporal scales. Catch rates of swordfish, yellowfin, and bigeye can be significantly correlated with fine-scale ocean colour, sea surface temperature and distance from temperature fronts (Lyne et al., 2000). Similarly, catch rates of predatory fish in the north Pacific have been found to be positively associated with anticyclonic eddies (Arostegui et al., 2022). The skill and specialised knowledge of experienced fishers is an important factor contributing to fish finding, and science is providing new information that skilled fishers can learn to take advantage of.

4.1.3. Communication

Communication is an essential tool for fishing vessels. It is important for safety, but also for sharing information a) between vessels, b) from shore to vessel, c) from remote sensing tools to the vessel. Information sharing is potentially very powerful for increasing catch rates. For example, improvements in communication via radio were estimated to double the fishing power of Japanese purse seine vessels during the 1950s (Inoue, 1961). Since 1959, all Japanese longline vessels have been required to carry radio transceivers (Ward and Hindmarsh, 2007). Weather data have been faxed to vessels since the early 1980s, with information on sea surface temperatures (SST), positions of other longliners, and areas of current and past catches (Ward and Hindmarsh, 2007; Yamaguchi, 1989). Since the 1980s, there has been increasing availability and use of satellite-based communication with a range of improvements in technology and cost reductions.

Communication networks increase search power, since vessels can search cooperatively and share information. Information sharing among vessels in the Japanese pole and line fleet used to be conducted by telephone, radio receiver, and fax, but smartphones are increasingly used due to the advance of communication networks (Wi-Fi is now available on many vessels) (Matsubara et al., 2022). Easy access to the fishermen's data network allows fishermen to use a wider range of data for searching fishery grounds. Internet access via satellite on the high seas is increasingly available, and its cost is declining, e.g., Starlink.

The Automatic Identification System (AIS) is an automated vessel tracking system, introduced in the 1990s as a safety feature to allow ships to view marine traffic in their area and avoid collisions. Initially the detection range of transponders was limited to the VHF range or line-of-sight, about 10-20 nautical miles. However, satellites are able to receive AIS signals (S-AIS) which has greatly increased their utility. Deployment of satellites with this capability began in 2009 and continues to expand. This has led to the public distribution of S-AIS data over the internet, resulting in global real-time position data being viewable from anywhere in the world, often for free (e.g., www.marinetraffic.com, www.globalfishingwatch.org) (McCauley et al., 2016). These datasets can be supplemented by remotely sensed satellite imagery, and in some cases by vessel monitoring systems (VMS).

The coverage of AIS has steadily increased, but some vessels turn off their transponders ('go dark'), falsify position data, or transmit incorrect identification data (McCauley et al., 2016). In 2014 about 71% of large fishing vessels used AIS (McCauley et al., 2016). Most Indian Ocean purse seine vessels are likely to go dark except when close to port (Nieblas et al., 2019), given the risk of piracy in the purse seine fishing area. Longline vessels are more likely to use AIS (Nieblas et al., 2019), although this varies by flag and location (Kroodsma et al., 2022). Kroodsma et al. (2022) estimated that, in an area to the north of Madagascar between September 2019 and January 2020, 65% of longline fishing vessels were broadcasting AIS.

A large component of fishing power is locating the fish. Vessels are increasingly able to track their colleagues and competitors, share information with other vessels, download remotely sensed data on ocean variables such as SST, ocean colour, sea surface height and ocean upwellings, obtain guidance from experts and modellers, and model predictions of ocean current and weather changes in the short and medium term. All of these factors are likely to increase fishing power.

Technological advances provide such a large volume of information that a lot of knowledge and experience is likely needed to make the best use of them. The impacts on catchability of current advances are therefore likely to increase as they spread through the fishery from the best-resourced to the less advanced fleets; and will be compounded by further advances in technology and scientific understanding.

4.2. Longline fishing

Indices of abundance based on longline CPUE are the key indices used in stock assessments for bigeye, yellowfin, albacore, and bluefin tunas, in all oceans. Trends in these indices are among the most important influences on stock assessment outcomes (Hoyle et al., 2024), and catchability changes associated with effort creep have the potential to change those outcomes. Indices used in stock assessment generally start in 1952 at the earliest, so this paper will focus on potential catchability changes during the period 1952 to the present.

The data used to develop longline CPUE indices come from large distant water tuna longline vessels. Longlines consist of a mainline carrying a series of branchlines (also called snoods or gangions) attached at 40–50 m intervals. Each branchline carries a baited hook. The mainline is suspended from buoys floating at the sea surface and carries 3000-4000 baited hooks. Longline effort is usually defined in terms of hooks set, so while increasing the number of hooks set is likely to increase catch per day, it will not itself affect the catch per hook. There may be some reduction in CPUE if only part of the longline occurs within a targeted feature, or if hook saturation occurs, but these are not thought to be important factors for tuna longline catch rates (Polacheck, 1991). The number of hooks set can also be associated with confounding factors such as targeting (Hoyle and Okamoto, 2013).

Ward and Hindmarsh (2007) noted that “Pelagic longline fishers have continuously modified their fishing gear and practices to improve fishing power and catchability, which has altered the relationship between catch rates and abundance”. Technological advances include electronic devices to help navigate, communicate, and find target species. Synthetic materials allowed fishers to improve hooks and lines which increased probabilities of both hooking and landing. Satellite imagery improved search efficiency. Freezers increased the proportion of time spent on fishing grounds. Equipment for faster longline retrieval increased hooks set without affecting soak time.

Table 1 of Ward and Hindmarsh (2007) summarises published studies that have measured variation in the catchability of longline fishing gear. Ward (2007) provides, in a WCPFC information paper, estimates of historical variation in the relative catchability and fishing power of pelagic longline fishing gear, applied mostly to bigeye and yellowfin tunas and blue marlin, but also considering mako shark, skipjack tuna, and some other species. He considers the following factors: body size (via animal movement), depth of gear, fishing master experience, period of hook availability, bait loss, gear saturation, gear detectability (branchline material), hunger, gear competition, bait type, bite off, and fish-finding equipment. The peer-reviewed version of this research (Ward, 2008) notes that although the effects on catchability of many of these factors appear large, they are also very uncertain. While this uncertainty may make it difficult to use the estimates directly to adjust CPUE trends, it also (and perhaps appropriately) reduces confidence in CPUE indices based on standardizing longline CPUE.

The views of Australian Fishing Zone observers working on Japanese longline vessels were canvassed via questionnaires and a series of discussions (Whitelaw and Baron, 1995), to help identify changes in equipment and fishing techniques from the 1970s to the 1990s. They investigated changes in fishing gear (lines, hooks, sinkers, bait throwers, radio beacons, baits), location finding techniques (electronics, visual observations), vessel and fleet structure (cooperation, crew, vessel design), and fishing practices (setting, hauling). These observations for the Japanese southern bluefin tuna longline fishery are also relevant for other Japanese tuna longline fisheries, in the Indian Ocean and elsewhere.

4.2.1. Materials

Longliners initially used natural fibres such as hemp. Synthetic materials such as kuralon were introduced for mainlines and branchlines in the 1960s, and began to be widely used in the 1980s (Ward and Hindmarsh, 2007). In some cases, wire branchlines were changed to stainless-steel, reducing breakage and rates of replacement. In the mid-1980s fishers began using monofilament branchlines, which have lower visibility to tunas than wire branchlines (Nakamura et al., 1999), and were said to increase catchability due to their low refractive index and high tensile strength (Kasuga, 1990; Ward and Hindmarsh, 2007).

For mainlines, monofilament largely replaced kuralon during the 1990s. Kuralon mainlines (diameter 7.9 mm) were too heavy to be sustained by a normal float when operating with more than 17 hooks between floats (HBF), and the change to monofilament was accompanied by a shift to higher numbers of HBF. The rapid increase of HBF which started around 1992 in the Indian Ocean seems to derive from the introduction of the new material (Okamoto et al., 2004).

Stone and Dixon (2001) found substantially higher catchability of multiple pelagic fish species for branchlines of monofilament nylon compared to tarred multifilament nylon. This was a small (10 sets) study with alternating branchline types, but other studies have obtained similar results suggesting that branchline visibility (monofilament versus multifilament or wire) affects catchability (e.g., Afonso et al., 2012; Kasuga, 1990; Vega and Licandeo, 2009; Ward et al., 2008). Lin et al. (1997) obtained higher catch rates with mainlines of monofilament versus kuralon.

The introduction of stainless-steel hooks in the 1980s increased fishing power by reducing breakage. In the early 1970s, Japanese tuna hooks replaced J hooks. Circle hooks were introduced in some fisheries in the 2000s.

4.2.2. Bait effects

Bait species and type can substantially affect catchability. Target species vary in their affinity for different baits. Japanese longliners initially used pilchard and saury, switched to frozen saury in the 1960s and 1970s, then other species such as mackerel in the late 1970. Squid bait has been widely used in many areas since the 1970s. Bait use has varied between areas, presumably due to a combination of availability and targeting.

Squid bait is believed to increase the catchability of bigeye tuna and swordfish. In the mid-1990s, some equatorial Taiwanese longliners used live milkfish, which increased catch rates of yellowfin tuna (Fitzgerald, 1996).

Loss rates vary among bait types, with higher loss rates for soft-bodied mackerel species compared to firmer squid, which are less likely to be removed from hooks (Ward and Myers, 2007). Bait loss also increases with soak time.

Tori lines and bait casting machines reduced bait loss to birds in some fisheries, and bait casting may also reduce tangles during setting (Whitelaw and Baron, 1995).

Changes in bait loss between the 1950s and 1990s have been estimated to multiply fishing power by up to 3 times, for all target species (Ward, 2008; Ward and Myers, 2007). Changes in the types of bait used by Japanese longliners may have approximately doubled bigeye catchability, while halving yellowfin tuna catchability (Ward, 2007).

4.2.3. Set time

Japanese longliners changed strategy from having all baits available at dawn, to having more available at dusk and at night (Ward and Hindmarsh, 2007). Expected catch rate for bigeye tuna for bait that is available at dawn and dusk is approximately twice that for bait available at dawn only (Ward et al., 2004).

4.2.4. Set depth

Before the 1970s, Japanese sets were relatively shallow (25-170m), but depths increased (25-300m) in the early 1970s in both the Pacific and Indian oceans (Suzuki et al., 1977) in order to target bigeye tunas. The number of HBF can be an indicator of set depth but other factors are also important, both in characteristics of the gear (mainline tension, weights on lines, and branchline and mainline material), and the environment (wind and current shear) (Bigelow et al., 2006; Rice et al., 2007). Catchability is affected by the overlap between stock and gear distribution (Boggs, 1992). These relationships have been explored in CPUE standardization (e.g., Forrestal et al., 2019; Goodyear, 2016; Hinton and Nakano, 1996) but the data available to analysts are insufficient to reliably estimate it for individual sets (Maunder et al., 2006a).

The depth distribution of bigeye tuna is affected by body size (Schaefer and Fuller, 2010), but it is not clear how much this pattern affects the size selectivity of different fishing gear configurations.

Based on a mixed model fitted to observer data, Ward and Myers (2005) inferred substantial (39%) increase in bigeye catchability from 1950 to 1990 based on increased set depth, and a non-significant (1%) increase for yellowfin tuna. Similarly, Bigelow et al. (2002) estimated an increase in effective longline effort in the WCPO from the late 1960s to the late 1980s, primarily due to increased effort effectiveness with deeper sets. It is unclear how successfully CPUE analyses account for these changes by including HBF in the analysis, given that HBF is an inconsistent proxy for set depth.

4.2.5. Fisher skill

In every area of human activity there is considerable skill variation between individuals, with contributions from factors like local knowledge, better use of available information, and stronger communication networks (Hilborn, 1985; Hilborn and Ledbetter, 1985).

Local knowledge and skill increase with time spent in an activity. Therefore, technological improvements that allow vessels to spend longer on the fishing grounds may have been important for improving catchability, by increasing fisher experience. Examples of such improvements include super cold freezers and transshipment.

User skill also affects the benefits obtained from each technological improvement, with greater skill improving efficiency, i.e., moving fishing power closer to the frontier of technical possibility (Grosskopf, 1993). This is likely to be particularly important for complex activities such as using remotely sensed data and developing collaborative arrangements between vessels.

Economic incentives can also reduce fisher skill through time which may reduce catch rates. If labour costs can be reduced by more than the value of the consequent loss of catch, skilled crew may be replaced by cheaper crew with less experience and training. In the early 1990s, fish price declines led vessel owners to reduce costs by replacing Japanese fishing crews with foreign crews (mostly Indonesians) who were considered to be less skilled (Miyake et al., 2010). Taiwanese distant water fleets rely largely on low-cost migrant labour, with the majority of workers from Indonesia, the Philippines, and Vietnam (Hung et al., 2022). However, this may not always be a disadvantage: Matsubara et al. (2022) commented that hiring foreign crews on Japanese pole and line vessels could improve searching and fishing efficiency, because they were more physically capable.

4.3. Purse seine CPUE

Purse seine CPUE is very susceptible to effort creep given the technology-linked basis of the search and capture processes. When there are more factors where efficiency can be improved, and efficiency is multiplicative, there is more potential to increase fishing power. The high value of the fishery also provides industry with both strong incentives to increase catchability, and the funding to invest in the necessary research and development. A scientific workshop held in 2012 explored some of the issues that make the use of purse seine CPUE in stock assessment difficult (ISSF, 2012).

For example, Fonteneau noted (ISSF, 2012) that “The 2 factors classified as being the most important ones in 2000 are the extensive use of FADs and the use of bird radars during searching. Other new factors are also considered as being very important to increase the efficiency of the vessels, including the use of supply vessels, improved echo sounders, improved sonar (e.g., increased range), intensive use of satellite imagery, deeper and faster nets, knowledge of underwater currents and of net depth, faster unloading, widespread use of computers, and technological improvements of FADs. Other changes may also be important to improve fishing power such as improved positioning of vessels, skippers' improved use of an increasing amount of information, higher crow’s nests, improved navigation radars, larger brail nets, and increased fish hold capacity. It was concluded that, as a result of these multiple changes, purse seiners are clearly much more efficient in 2001 (and today) than in 1980 (and before). This conclusion probably applies worldwide, although these improvements in fishing power were probably variable between flags and oceans. Unfortunately, the timing of changes in these factors is poorly documented by scientists and the exact effects of the interaction of these multiple factors producing the increase of purse seiner fishing power remain difficult or impossible to measure quantitatively.”

Note that most of Fonteneau’s efficiency factors are rarely or never available to analysts, and so they cannot be accounted for in a CPUE standardization.

Vessels can make multiple types of set on the same trip: associated with a floating object such as a FAD, unassociated, or (in the eastern Pacific) associated with dolphins. Each set type has different size selectivity, so is represented by a different fishery.

Purse seine fishing is complex, and purse seine CPUE is analysed via several different approaches. Most analyse free school fishing and associated fishing separately. Catch may be relatively easy to define based on logbook records, although it is complicated by uncertainty in estimates of species composition. The unit of effort, however, is challenging.

The search for fish is increasingly supported by technologies that reach beyond individual vessels. Fish aggregating devices incorporate GPS and echo-sounders that report to vessels via satellites, with regular upgrades in the technology, and increases through time in the proportions of FADs that are instrumented (Lopez et al., 2014). Echosounders were found to increase catch per set by an average of about 10% in a study of French purse seiners in the period 2012-2017 (Wain et al., 2021). They also reduce search time, which allows vessels to make more sets per day.

Vessels increasingly share FADs and the information they provide, allowing them to develop an understanding of the spatial distribution of tuna across the fishery (IOTC Secretariat, 2023). They may also use supply vessels to help with the search. Together, these factors make an individual vessel almost irrelevant as a unit of search effort. In the Indian Ocean vessels are limited to 300 active buoys per vessel under Resolution 19/02 (IOTC, 2019), reducing to 250 on 1 January 2026 and 225 on 1 January 2028 (Resolution 24/02).

A simple approach is to define effort as the set, which eliminates the search process. However, it is unclear what the relationship is between catch per associated set and the abundance of fish in an area. The abundance on a FAD is known to be affected by the characteristics of the FAD; the time since the FAD was released or last fished on; by the number of alternative aggregation sites available in the local area; by the time of day; and by other factors. The size of the catch on a FAD will be affected by the ability of the vessel to find aggregations of the preferred size, which will be affected by the quality of the information provided to the vessel via satellite from the echosounder on the FAD and from supply vessels. Vessels and groups of vessels may use software to predict FAD movements and likely fish association, and may optimise their path so as to maximise catch and minimise costs. Once found, catch size will be affected by the ability of the vessel to efficiently catch its preferred quantity of fish. These are affected by attributes of the vessel such as net size, depth and materials, the power and control of the winches, and the skill of the skipper and crew.

Many of these factors involve the use of technology, and technology can be improved.

Even without changes in catchability, catch per set may be hyperstable relative to abundance, due to upper and lower limits on the sizes of viable sets, and the ability of vessels to choose where to set.

4.3.1. Estimated rates of catchability change

Tidd et al. (2016) estimated an average increase in fishing power from 1993-2010 of 3.8% per year across the USA, Korean, Taiwanese, and Japanese purse seine fleets fishing in the Western and Central Pacific Ocean (WCPO). Estimates of between 3% and 6% per year were obtained for the exclusive economic zones (EEZs) of countries within the Parties to the Nauru Agreement (PNA) in the WCPO, for the period 2006-2018 (Vidal et al., 2021).

Studies on the French fleet indicate a 10% increase in catch per set associated with echosounder use, equivalent to about 1% per annum, and a 1.7 – 4.0 % increase in efficiency (stable across time) arising from fishing their own floating objects (IOTC, 2020; Wain et al., 2021).

5. Factors that may counterbalance effort creep

5.1. Reduced effort

There are fewer longliners in the tropical tuna fisheries now than there have been in the past, so it can be argued that each longliner will benefit less from the information sharing that increases their catchability. Industrial longline fishing effort in the Indian Ocean has declined by about 25% since the year 2000 (IOTC data, see https://iotc.org/data/browser). However, information sharing depends on the number of vessels with which each vessel collaborates, rather than the total number of vessels fishing. Interpretation requires knowledge of the trends in networks and group sizes through time. Catchability effects also depend on the quality of the information shared, and on the degree to which data from multiple vessels can be integrated to identify optimal strategies for each vessel in a group. Further research is needed, but on balance this factor appears unlikely to be an important factor in recent catchability changes.

5.2. Vessel deterioration

The use of vessel effects in CPUE standardization assumes that each vessel has constant catchability through time. However, wear across the lifetime of a vessel may lead to higher rates of equipment breakdown for older vessels, which may reduce their catchability. Vessel deterioration is not allowed for in CPUE standardization.

5.3. Arms race

There is likely to be an ‘arms race’ between fishers and fish, with the average catchability at the population level changing due to factors that include learning, selection, varying availability to fishing, and evolution. Such effects may have contributed to the early (1950s) declines of longline catch rates observed for tuna species in all oceans, which are considered too large to be due to biomass reduction given the relatively small catches at that time (Maunder et al., 2006b; Nakano and Bayliff, 1992; Polacheck, 2006). Similar declines in catchability on first exploitation have been seen in many fisheries (e.g., Askey et al., 2006; van Poorten and Post, 2005).

It has often been demonstrated that fish can learn how to avoid capture, particularly for passive gears such as longlines and recreational angling (Arlinghaus et al., 2017). Fish have well-developed cognitive abilities and learning skills (Brown et al., 2011). Learning can occur through encounters with gear, with long-lasting effects (Beukema, 1969; Fernö and Huse, 1983). The probability of fatal hooking at each encounter with a longline hook can be relatively low (Løkkeborg et al., 2010), which gives most fish one or more opportunities to learn. Learning would tend to reduce population-level catchability more with increasing exposure to fishing, which would lead to an inverse relationship between catchability and recent fishing effort. Since experience increases with age, learning will affect catchability more for older than for younger fish.

Fishing mortality will also result in short-term selection for lower catchability in the population. There is always behavioural variation among individual fish (Budaev and Brown, 2011; Evans et al., 2008), which will result in catchability variation (e.g., bold versus shy characteristics). Passive gears have been shown to preferentially catch bold, aggressive, or active individuals (Arlinghaus et al., 2017). Fish that are more catchable are more likely to be captured and removed, which will reduce population-level catchability. As for learning, this reduction will affect older fish more than younger fish. Similarly, the size of the selective effect on population-level catchability will be negatively correlated with recent fishing effort. Kleiber and Maunder (2008) demonstrated that aggregate CPUE for fish assemblages is likely to be hyper-responsive to changes in fishing effort, due to the variation in catchability between species. The same argument should apply to an individual species, to the extent that catchability varies among individuals. Thus, increases in longline fishing effort should reduce the average longline catchability, while reductions in longline fishing effort should increase longline catchability at the population level (Koeck et al., 2020).

The limited vulnerability model (Cox and Walters, 2002) “assumes that fish exchange between available and unavailable states and that fishery catches are taken only from the available pool. This limited vulnerability model exhibits a nonlinear, negative relationship between fishing effort and catch rate that manifests itself in the effort – exploitation relationship as an apparent decline in catchability with increasing effort”.

The fourth effect of fishing on catchability – evolution – will consistently tend to reduce it, and may act quite rapidly. Behavioural traits affecting catchability have heritable components (Dochtermann et al., 2015; Philipp et al., 2009), which implies that a fished population will evolve through time to have lower mean catchability to the fishing method applied (Monk et al., 2021). Heino et al. (2015) reviewed studies of fishing-induced evolution of behavioural traits and found limited evidence from the wild, but strong evidence from experimental studies. They suggest that such evolution is common but has so far been overlooked.

These factors may all affect population-level catchability to some degree. From the 1950s to 2000, industrial longline fishing effort in the Indian Ocean steadily increased from very low levels to reach 400,000,000 hooks per year (IOTC data – see https://iotc.org/data/browser). Since 2000, however, longline effort has declined by 25%, while catches in weight have declined by approximately 60% for yellowfin and 70% for bigeye tuna over the same period. Increases in longline fishing effort may have induced an initial rapid decline in catchability based on learning, selection, and availability, followed by smaller declines until the year 2000. Subsequent reductions in longline effort may have permitted some recovery of catchability due to learning, selection, and availability effects, while changes in the genetic make-up of the stock would have been retained.

5.4. Hunger

Ward (2008) notes that “if the historical removal of large pelagic predators has resulted in increased availability of food, then the remaining animals might be less attracted to longline bait. Competition for food would be more intense before exploitation, so more food is available per capita after stocks are reduced. However, analyses indicated a historical decline in the condition factor of Atlantic bluefin tuna (*Thunnus thynnus*), which is the opposite of what would be expected if food availability was increasing as stock size declined (Golet et al., 2007).” Long-term changes in fish condition have not been studied for other species of tuna, and may not be feasible given the sensitivity of fish condition estimates to covariates (Macdonald et al., 2023).

6. Stock assessment and effort creep

6.1. Purse seine CPUE

Some tuna RFMOs have begun to use purse seine CPUE in stock assessment. The 2022 WCPFC stock assessment for skipjack tuna (Castillo Jordan et al., 2022) included standardized purse seine CPUE indices in 4 of the 8 regions. No effort creep was included in this assessment.

In the Indian Ocean, the 2020 skipjack assessment (Fu, 2020; IOTC, 2020) included a standardized CPUE index based on catch rates in the European purse seine floating object fisheries (Guery et al., 2020). As noted in the introduction to this paper, there were differing views about the need to include effort creep. The model ensemble included alternative assumptions about effort creep in this fishery since 1995, with 0% and 1.25%. The estimate of 1.25% was the lowest of the values estimated by Kolody (2018).

The 2023 skipjack assessment (Fu, 2023) included an index based on standardized catch rates in purse seine floating object fisheries (Kaplan et al., 2023). The final model ensemble again included alternative assumptions about effort creep in this fishery, with 0% and 1.25%.

The 2021 Indian Ocean yellowfin tuna assessment included a purse seine CPUE index that was associated with the adult part of the stock. It was assigned an assumed rate of effort creep of 3.15% p.a., which resulted in a trend consistent with the longline CPUE. Nonetheless the independent review of the 2021 yellowfin tuna stock assessment recommended that purse seine CPUE should not be included in the assessment model (Maunder et al., 2023).

The 2022 Indian Ocean bigeye tuna stock assessment included a purse seine CPUE index associated with the juvenile part of the stock. It was included in every model in the final ensemble, but no effort creep was included.

IATTC yellowfin tuna assessments use an index based on the dolphin-associated purse seine fishery (Minte-Vera et al., 2020a). Various approaches to catchability are considered, including time blocks and density-dependent catchability. A review of the 2019 yellowfin assessment recommended that IATTC staff should prioritize investigating approaches to account for effort creep (Cass-Calay et al., 2019).

6.2. Longline CPUE

The CCSBT operating model for southern bluefin tuna assumes a continuous rate of effort creep of 0.5% for both conditioning and projections, and has done so since at least 2005 (CCSBT, 2005). The same rate is included in the management procedure (CCSBT, 2018).

Effort creep in longline CPUE indices is not currently used in the reference case or ensemble for any species of tropical tuna. It has mainly been used in sensitivity analyses.

- WCPO albacore tuna (Davies et al., 2009), 0.5% p.a.
- WCPO bigeye tuna (Hoyle et al., 2008), 0.5% p.a. 1952-1985, 2% p.a. 1985-2007
- WCPO yellowfin tuna (Harley et al., 2009) 0.5% p.a. 1952-1990, 2% p.a. 1990-2008
- Indian Ocean albacore tuna (Hoyle et al., 2014), 1% p.a. 1980-2012

In the 2021 Indian Ocean yellowfin tuna stock assessment (Fu et al., 2021), a sensitivity analysis was run during the WPTT meeting that included 1% effort creep per year for the entire period of the index (IOTC, 2021). This had the effect of decreasing the CPUE by 40-50% on average by the end of the time series, as well as increasing the biomass depletion level.

The 2022 Indian Ocean bigeye tuna assessment (Fu et al., 2022) reported the results of a sensitivity analysis which showed that the longline indices reduced by an additional 33% if a 1% annual rate of effort creep was assumed. This resulted in greater stock depletion to a level of 17%, compared to 27% for a model without effort creep.

6.3. Effort creep assumptions in final models and model ensembles

Rates of assumed effort creep were obtained for tuna stock assessments in all tuna RFMOs (Table 2). For the IOTC these were yellowfin 2021 (Fu et al., 2021), bigeye 2022 (Fu et al., 2022), and skipjack 2023 (Fu, 2023). For the IATTC these were yellowfin 2019 (Minte-Vera et al., 2020b), bigeye 2019 (Xu et al., 2020), and bigeye 2024 (Xu et al., 2024). For the WCPFC these were yellowfin 2023 (Magnusson et al., 2023), bigeye 2023 (Day et al., 2023), and skipjack 2022 (Castillo Jordan et al., 2022). For ICCAT these were yellowfin 2019 (ICCAT, 2020) and bigeye 2018 (ICCAT, 2019). Information for CCSBT was based on all approaches applied to southern bluefin tuna assessments and management procedures since 2005 (CCSBT, 2005), and the current approach to CPUE (Itoh and Takahashi, 2022).

Table 2: Rates of effort creep assumed in the final model ensembles used for management advice, in assessments presented to the tuna RFMOs for longline (LL), purse seine (PS), and pole-and-line (PL) series. The vessel ID column indicates whether this term is included in the longline CPUE standardization.

Ocean	Species	Year	LL	Vessel ID	PS	PL
Indian	SKJ	2020		Y	0%, 1.25%	0%
	YFT	2021	N	Y	3%	
	BET	2022	N	Y		
	SKJ	2023		Y	0%, 1.25%	0%, 1.25%
WCPO	SKJ	2022	N	N	N	N
	YFT	2023	N	N		
	BET	2023	N	N		
IATTC	BET	2019	N	Y		
	YFT	2019			complicated	
	BET[2]	2024	0%, 1%, 2%	Y		
ICCAT	BET	2018	N	Y	N	
	YFT	2019	N	Y	N	
CCSBT	SBT	2005-present	0.5%	N		

7. Recommendations for stock assessment

To avoid bias in depletion and stock status estimates (e.g., Han et al., 2023; Ye and Dennis, 2009), stock assessments need to adjust for effort creep in indices of abundance based on CPUE. Wilberg et al. (2009) recommend a default assumption that catchability varies over time. They also recommend that multiple methods of including time-varying catchability should be applied. Scherrer and Galbraith (2020) recommend that inclusion of technological creep in fisheries management is essential for long-term sustainability, since underestimating its long-term value will lead to underestimating fisheries impacts. Similarly, Palomares and Pauly (2019) state that technology creep must be included in all analyses involving time series of fishing effort, particularly if they exceed one decade of temporal coverage, since impacts are almost always significant at this time scale.

CPUE standardization can account for some effects on catchability, but it cannot account for every factor that improves fishing power. There is always likely to be effort creep due to unaccounted sources of increase in catchability. Hoyle et al. (2024) recommend that, to allow for uncertainty about fishing power, stock assessments (particularly for target species) should consider a range of scenarios regarding long-term catchability trends, from low to high but noting that 0% is rarely plausible. The 2023 review of the IATTC tropical tuna assessments recommended exploring the inclusion of longline effort creep at a rate of 1% per annum (Dickey-Collas et al., 2023).

Studies of technology change suggest that (in a well-developed fleet, all else being equal) fishing power can be assumed to follow a random walk around an exponential trend with a constant rate. This is consistent with the usual approach for applying effort creep via a constant multiplicative rate of change, i.e., for an index that begins in year *a* and ends in year *a+N*, for all years *n*=1:*N*, $\text{adjusted CPUE}_{\text{a+n}} = \text{original CPUE}_{\text{a+n}} \,/\, (1 + creep)^n$. An alternative and equivalent approach is to adjust the q parameter (e.g., Webber et al., 2023). If rates are relatively stable through time, it is reasonable to extrapolate beyond the period for which an estimate is available.

[2] Included in benchmark assessment presented to SAC meeting, 10-14 June 2024.

Over long periods, cumulative effort creep can substantially affect the index. For example, cumulative longline effort creep between 1953 and 1979 at a rate of 0.4% per year reaches an 11% increase in effective effort, but at the higher rate of 1.4% per year this reaches 44%. For the remaining period between 1979 and 2023, effort creep of 0.5% accumulates to 25%, while a rate of 1.5% accumulates to a 93% increase in effective effort.

7.1. What estimate of effort creep to use?

Proposals are needed for levels of effort creep to assume for indices of abundance based on longline, purse seine, and pole and line data.

Estimating individual components of the effort creep contributing to catchability change has several problems. First, it will omit sources of catchability change for which analysts lack data (Scherrer and Galbraith, 2020), so will tend to underestimate the total. Second, individual effort creep factors are usually estimated and published to correct for the introduction of an effective new technology over a short period of time, and are not representative of (tend to overestimate) long-term changes (Palomares and Pauly, 2019).

The best currently available approach for estimating effort creep is comparison against a baseline (see section 3.3). However, this approach is only available for comparing purse seine against longline indices. Without a time-series of independent biomass estimates from surveys, there is no base line against which to estimate longline effort creep.

If the rate of increase in a fleet's fishing power is constant, the amount of effort creep to add to an index will depend on how much fishing power change is already included in the index, via the effects included in a CPUE standardization. For example, analyses that include vessel effects implicitly account for a component of catchability change, which implies that these indices require less additional effort creep.

Although reliable estimates of effort creep are unavailable, dealing with uncertainty is one of the core functions of stock assessment. For example, similar effects of uncertainty are associated with our understanding of stock structure, movement dynamics, and estimates of natural mortality and the steepness parameter.

7.1.1. Longline

Investigation of individual factors demonstrates that there is considerable potential for longline fishing power to have increased through time.

Available estimates of longline effort creep associated with vessel turnover in the Japanese longline fleet in the western equatorial Pacific ranged from 0.5% to 2.2%. It is proposed that analysts apply alternative rates of 0.5% to 1.5% per year, representing effort creep associated with vessel turnover, to indices for tropical areas that do not include vessel effects, and for early periods when Japanese vessel identities are unavailable. The rate associated with vessel turnover is likely to represent less than half of the total improvement, particularly in recent years with rapid technological changes (communication, electronics, remote sensing) that support fish finding, as discussed in the earlier section on longline catchability. Scenarios are proposed of an additional 0.5% and 1.5% effort creep per year to all longline indices (beyond the rate associated with vessel turnover), to represent effort creep due to learning, equipment and communication technology upgrades on existing vessels, development of remote tools that are not tied to individual vessels, and increases in knowledge.

The longline indices used in tuna stock assessments are based on data from a variety of fleets. Effort creep is likely to vary between fleets, which will affect the indices used in many tuna assessments which are based on analyses of joint datasets. It is unclear how rates of longline effort creep in other fleets may differ from the rates in the Japanese fleet. However, the estimates above are recommended in all cases since they are currently the only ones available.

Appropriate longline fishing power trends for bigeye and yellowfin tuna outside tropical areas are less clear. The approach should be judged case-by-case based on the fisheries involved in the analysis and their preferred targets. Effort creep for all species can occur due to some types of technology change (e.g., monofilament leaders, targeting anticyclonic gyres), but not necessarily for others (e.g., hook and bait types).

7.1.2. Purse seine

For purse seine fisheries, estimates of purse seine effort creep can be obtained by measuring against baseline rates of longline CPUE inside a stock assessment. For purse seine associated indices measured against longline CPUE indices in the 2016 yellowfin and bigeye tuna assessments, estimates were 1.25% per year for yellowfin tuna and 4.1% per year for bigeye tuna (Kolody, 2018). These comparisons used the effort definition from a standardization of skipjack CPUE where the nominal and standardized indices had essentially identical trends (Katara et al., 2017). Comparisons of the standardized longline index and the purse seine free school index on adults in the western equatorial region of the yellowfin tuna assessment (Fu et al., 2021) provided an estimate of 3.15 % per year. The purse seine associated index in this case was also essentially unchanged between nominal and standardized (Guery et al., 2021).

For this paper, effort creep values by fishery in the 2019 skipjack stock assessment (Vincent et al., 2019) were calculated between 2000 and 2018 for WCPO purse seine CPUE against a baseline mainly provided by Japanese pole and line CPUE. This assessment constrains Japanese pole and line CPUE catchability to be seasonal but constant across years (except in region 6 where it is allowed to vary), but it estimates a constrained random walk for purse seine fishery catchability. Purse seine CPUE is unstandardized catch per set in region 7 and 8, and standardized in region 6 (Vidal et al., 2019). For equatorial model regions 6, 7, and 8, the average rate of catchability change determined by this random walk represents the difference between purse seine effort creep and pole and line effort creep. Quarterly catchability estimates were extracted from the model result files (https://fame.spc.int/resources/stockassessmentfiles). The mean estimates for associated purse seine were 2.7%, 2.1%, and 3.5% per year. For free school purse seine, they were 2.1%., 2.2%, and 1.3% per year. The free school estimates average 0.9% less than the associated fishery estimates.

Tidd et al. (2023) estimate an increase in production efficiency from 1992 to 2019 of 3.6% per year for Indian Ocean associated purse seine fisheries, and 2.1% per year for free school fisheries. These estimates of increasing efficiency use exploitation rates (catch / exploitable biomass) as the output variable. However, they are likely to underestimate increases in production efficiency, because they are conditioned on exploitation rates (and therefore biomass trends) estimated in the Indian Ocean skipjack and yellowfin stock assessments. This is particularly important for the skipjack component because its biomass is strongly influenced by purse seine CPUE. Production efficiency increases are somewhat different from catchability increases, because inputs include factors like vessel power and length, and the number of buoys deployed. Nevertheless, the estimated increases in efficiency are not inconsistent with the scale of effort creep estimates.

To obtain estimates of total effort creep for purse fisheries it is necessary to allow for unmodelled effort creep in the longline or pole and line fisheries that provide the baseline for these stock assessments. The longline indices in the analyses of Kolody (2018) and Fu et al. (2021) were based on joint analysis of data from multiple fleets (Hoyle et al., 2016; Kitakado et al., 2021). The analyses included vessel effects so had already allowed for vessel turnover, but the other variables only include HBF, cluster, and location. These could not be expected to explain much catchability change linked to technology. The preliminary recommendation is that analysts add another 0.25% to 0.75% to estimates of associated purse seine effort creep to allow for changes in the baseline biomass trend associated with longline effort creep. This is half of the rate assumed for longline effort creep, because fish caught in associated purse seine sets are younger than longline-caught fish, so the purse seine-vulnerable biomass trend would be less affected than the longline-vulnerable biomass. Free school yellowfin sets have similar selectivity to longlines, so the proposed additions are 0.5% and 1.5%. It is also recommended that the analyses of Kolody (2018) are updated to explore possible effects of longline effort creep and other uncertainties.

It is proposed that analysts trial alternative scenarios for effort creep of 1.5%, 2.0%, 4.35%, and 4.85% per year for associated purse seine indices. For free school fisheries alternative scenarios are proposed with rates 0.9% less than those for associated fisheries. These estimates of effort creep are based on abundance indices that do not effectively account for fishing power change, so lower rates should be used when standardizations include important factors linked to fishing power and significantly affect the index trend.

Nevertheless, there remains a very high risk that, in addition to effort creep, purse seine CPUE is both hyperstable and strongly affected by factors unrelated to abundance, such as environmental conditions. Such factors could also have biased the estimates of purse seine effort creep discussed above. When alternatives to purse seine CPUE are available, they should be preferred.

7.2. Research recommendations

These estimates are preliminary and based on very limited studies. There is an opportunity to develop better estimates of effort creep for purse seine fishery abundance indices, by applying the method of Kolody (2018) to available bigeye and yellowfin tuna stock assessments from all oceans. Using the same approach, estimates of long-term change in average catchability per vessel day or per set may be obtained by using nominal CPUE for purse seine fleets.

In addition, estimates of catchability change associated with vessel turnover could be obtained for all fleets, and for purse seine and pole-and-line vessels as well as longliners, by applying the methods of Hoyle (2009) to analyses of catch and effort data from individual fleets.

Applying the estimates developed by Ward (e.g., Ward, 2007; Ward, 2008; Ward and Hindmarsh, 2007; Ward and Myers, 2007) to the longline CPUE indices for the Indian Ocean would require information on changes in fishing practices through time by the fleets included in the indices. This information is mostly unavailable at the operational level. However, syntheses at a higher level should be sufficient to develop plausible hypotheses about likely rates of catchability change through time.

In addition, there is a need for experiments to estimate the species-specific catchability effects of individual changes in fishing practice. There is also potential for analyses of existing observer data to provide estimates of these effects.

In the longer term, estimates of effort creep in CPUE indices may be derived by comparing the indices with information from close-kin mark recapture experiments, a variation of the ‘comparison against a baseline’ method, though it will take some time to develop time series of CKMR estimates that are long enough for this purpose. The first such application to tuna longline CPUE may come from the southern bluefin tuna fishery (Bravington et al., 2016). A simulation study would be useful to support this approach, using the methods of Punt et al. (2024).

Other approaches may be considered and should be explored with simulation. For example, trends in recruitment deviates can be useful to indicate model misspecification (e.g., Merino et al., 2022), such as effects associated with inconsistency between the index and catches. In these cases, a hypothesis about effort creep can be developed by adjusting the index trend to remove the trend in recruitment deviates, along with consideration of alternative hypotheses such as productivity changes.

It may sometimes be impractical to simply include effort creep in an assessment without changing any other factor. If including effort creep pushes the model into an implausible parameter space, structural changes to the model may be needed. It would be a mistake to infer that this means the effort creep estimates are wrong. In fact, some other aspect of the model dynamics may be wrong, and inconsistent with the greater depletion implied by the effort creep. For example, the stock may have a more resilient stock recruitment relationship than assumed, some other density-dependent effect, or some other aspect such as the approach to modeling size data, tag mixing, or movement rates. Current multi-region assessment modeling approaches have been built up over years with careful adjustments to ensure that results are plausible. A major change to biomass trends may require various adjustments to reconcile this change with other assumptions in the model.

8. Conclusions

Cryptic increases in fishing power are an important source of uncertainty in stock assessments, with significant implications for management advice. Productivity growth is driven by technological change and increasing knowledge in almost all human enterprises. Rates of improvement in individual fields tend to be random walks with a relatively stable rate of exponential change through time. This result provides a sound justification for assuming constant rates of increase in fishing power through time. Rates of increase tend to be higher in fields where productivity is affected by more independent components that can be improved, particularly where improvements can occur rapidly. This is particularly true for fields that involve software. It is possible that the introduction of advanced communication technologies to fishing has led to an increase in rates of productivity change.

Studies of technology change in longline and purse seine fisheries provide examples of catchability change associated with multiple factors. These factors operate in combination as multiplicative changes to fishing power though time. However, data that permit analysts to estimate catchability change are unavailable for all but a few individual factors. One source of such information is vessel turnover, but this is likely to significantly underestimate fishing power change since it omits the effects of upgrades to existing vessels, or indeed any factor that is not permanently associated with individual vessels. We must therefore rely on syntheses and measurements against baselines to estimate total catchability change.

Ignoring effort creep would implicitly assume that a longline vessel from the 1970s, fishing in the present using 1970s techniques, would obtain the same catch rates as a modern vessel, despite all the developments of the last 50 years.

Effort creep in longline fisheries is particularly important for tuna stock assessment, with long CPUE time series that provide the foundation for assessment outcomes. Although index-specific estimates are often unavailable, ignoring effort creep will usually bias biomass estimates towards more optimistic levels of depletion, and higher status. Syntheses of numerous effort creep studies indicate that technology creep should be assumed in all analyses involving time series of fishing effort, particularly if they exceed one decade of temporal coverage. Stock assessments should consider a range of scenarios regarding long-term catchability trends, from low to high but noting that 0% is rarely part of the plausible range, particularly for the tropical fisheries targeting bigeye, yellowfin, and skipjack tunas.

Including effort creep in stock assessments will result in significantly lower estimates of stock status, and greater levels of depletion. Although these estimates are likely to be more realistic, awareness of the implications is a barrier to implementing effort creep in stock assessments.

For Indian Ocean stock assessments, this paper proposes rates of effort creep for both longline and purse seine indices, each with alternatives to apply as part of the model ensemble to represent uncertainty.

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Appendix:

Text included in the report of the 22nd session of the IOTC Working Party on Tropical Tunas, stock assessment meeting (IOTC 2020, references added).

● Some participants felt that the 0% per year PSLS catchability option was sufficient because:
- The floating object (PSLS) CPUE standardization analysis (Guery et al., 2020) should have removed the catchability trend;
- Acoustic fish aggregating device (FAD) uptake was very rapid in the Spanish fleet with almost 100% usage since 2013;
- The acoustic FAD technology has not improved since ~2014;
- The number of FADs deployed per vessel has been decreasing in recent years as has the use of support vessels;
- The independent echosounder indices (Santiago et al., 2020) in the most recent years resemble the large PSLS CPUE increase, and should be given additional consideration in the future, as they operate consistently over time.

● The opposing participants thought that the 1.25% per year catchability trend should have been adopted as a minimum, because:
- The PSLS standardized CPUE (Guery et al., 2020) series closely resembles the nominal CPUE series, despite decades of technological development in the fishery. Furthermore, it is not theoretically clear why catch per set should be interpreted analogously to catch per unit effort, since there is no link to search effort, and a set would not be undertaken without prior acoustic evidence of the presence of fish;
- Studies on the French fleet (Kaplan et al., 2020; Wain et al., 2021) indicate a 10% increase in catch per set associated with echosounder use, and 1.7 – 4.0 % increase in efficiency arising from fishing owned FOBs (and this practice has increased in recent years);
- The 2018 analysis (Kolody, 2018, IOTC-2018-WPTT20-32) confirmed that the standardized 2018 PSLS CPUE (Katara et al., 2018) (which closely resembles the most recent series) must have long-term increasing catchability trends to be internally consistent with the bigeye and yellowfin tuna assessments at the time. 1.25% per year was an initial estimate derived from yellowfin, while the equivalent estimate for bigeye was 4.1%. These increasing catchability trends are qualitatively consistent with similar results from the Pacific Ocean;
- If one accepts the BET and YFT assessments and the analysis outlined in IOTC-2018-WPTT20-32 (Kolody, 2018), but assumes that standardized PSLS catchability has not changed, it implies that the LL fisheries must have become increasingly less effective over the past several decades. The WPTT and WPM have endorsed 1% per year increasing catchability trends in the LL fisheries as plausible assumptions in bigeye and yellowfin MSE Operating Models, due to factors that the standardization is not expected to be able to address. If correct, this would imply an even greater catchability trend in the PSLS fishery;
- The catchability trend should have been introduced from the start of the time series (~1990), rather than 1995 as was requested from the WPTT in 2017 and repeated in 2020.