Bayesian Skipjack and Yellowfin Tuna CPUE Standardisation Model for Maldives Pole and Line 1970-2016

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Abstract

An abundance index for skipjack and juvenile yellowfin tuna from 1970 to 2016 has been developed from Maldives pole and line catch and effort data. Solutions for missing data were a random effects component used to account for missing mechanization information on the fleet 1974-1979 (Medley et al. 2017a) and the reconstruction of vessel length information using a vessel survival regression (described in Medley et al. 2017c). Fishing power effects related to vessel length are explained using a segmented regression that accounts for different classes of vessel. Both skipjack and yellowfin are combined into a single multivariate model, with skipjack catch rates standardized through a log-normal regression and yellowfin through a delta-lognormal regression. Additional fishing power effects which have not been recorded in the data have been estimated using subjective priors based on an expert meeting, and these could be included in the model. The model was fitted obtaining a MCMC approximation to the Bayes posterior for the abundance indices using Stan software. Remaining issues include poor estimation of catch rates for the smallest vessels and unaccounted for differences among landing atolls, as the reasons for these differences are not understood. Also, recent declines in logbook reporting rates are a cause for concern. All raw anonymized data and analysis code have been provided for full review.

Introduction

The Indian Ocean skipjack stock assessments in 2014 and 2017 used the Maldives pole and line standardized CPUE as an abundance index. These data were only available from 2004 when information on each trip was recorded. Earlier data exist from 1970, but these were only available as monthly records by atoll and did not record individual trips. In addition, significant corollary information about the fleet operations was missing, making it difficult to use all data in a consistent index. Previous attempts have suggested that there was some potential in these earlier data, but abundance indices were not proposed because of the problems encountered (Kolody et al. 2010; Sharma et al. 2013).

Pole and line data have not previously been used for an abundance index for yellowfin tuna in the Indian Ocean. As well as being subject to the same issues as those affecting skipjack, pole and line yellowfin should also be considered an index of juvenile abundance since the catch is generally limited to fish weighing less than 5kg.

The primary reason for not using older data is because of the substantial changes in the fleet which have led to significant change in fishing power. While these changes have been noted qualitatively, they were at best only partially captured in the catch and effort data in quantitative form. The CPUE time series show an increasing trend which is thought primarily caused by increasing fishing power. For these data to be used as an abundance index, these changes in fishing power need to be accounted for.

In a preliminary evaluation of standardizing the catch and effort data, Medley et al. (2017a) suggested that a Bayesian approach could resolve the main problems encountered. It was proposed to combine the two main data sets into a single standardization model, include reconstructed fleet size composition from partial registry data (Medley et al. 2017c) and use a random effects model to bridge a gap 1974-1979 when information on motorization was missing.

Methods

Data

Catch and effort data collected by the Maldives Ministry of Fisheries and Agriculture extends back to 1959. From 1959 data were only recorded from masdhoni (pole and line) vessels. In 1966 the system was expanded to include the vadhu dhoni (trolling) fleet. At this time, numbers of tuna were only recorded in three categories: large skipjack; small skipjack and yellowfin; kawakawa and frigate tuna. The system was expanded again in 1970 to record five categories of tuna separately in addition to catches of reef fish. From 1970, with landings recorded by species, it should be possible to estimate a standardized CPUE index for each species.

The fishery and data collection have undergone significant changes over this time (Table 1). Fishery data collection began in 1959 using an enumeration system. Landings were reported in numbers of fish to the island offices, or collected by the office staff at the time of landing. These data were compiled and monthly reports sent to the Ministry of Fisheries.

Initially, the data collection system did not distinguish between gears. This was because traditionally, the Maldivian vessels would be gear specific to the type of fishing vessel (Adam, 2012):

- *Bokkuraa* (small wooden boats 3-5 m. originally powered with oars now mostly by outboard engines) used for trolling and handlining within atolls and on coral reefs. Currently they are used exclusively in the non-tuna fisheries.
- *Vadhu dhoni* (5–8m originally sail now motorized) used for troll fishing near the islands and within atoll lagoons as well as general coral reef fishing.
- *Masdhoni* (8-12m standard pole-and-line vessels), which used live bait to catch predominantly skipjack and yellowfin tuna.

For the IPTP/MOFA Merged data 1970-2007[1], individual trips were not recorded, but landings and effort are reported in aggregated form, missing information on vessels and their operations. In some cases, additional information was reported that tracked fleet changes. Notably, the Ministry required island office staff to report catches of sailing and mechanized *masdhonis* separately from 1979 after much of the fleet had already transitioned. Other changes to the fleet which may well have increased efficiency but have not been recorded include changes in fleet size composition, improved design and engine power, improved bait catching and storage techniques.

Table 1 A summary of the history of data collection and associated issues.

Year	*Notes*
1970	Reported catches may have been inflated particularly in 1970-71 because a number of fishermen reported grossly inflated catches in the hope of qualifying for a government prize. Although this incentive existed from mid 1950s to 1981, the problem was most apparent in 1970-1971 when cash prizes were given directly to top crews (Anderson, 1986).
1974	Vessel mechanisation starts, but is not recorded.
1979	Mechanized vessels begin to be recorded separate from sailing vessels.
1981	FAD installation begins. Prize money for high catches ceases.
1989	Vessel type and number of dhoni begin to be recorded, but mixed gear trips are not identified in data. Use of conversion factors for enumerated small and large skipjack were also questioned on the grounds that the “traditional size” of large and small skipjack may have been mis-reported due to an artificial cut off weight for commercial purchase (1.5kg).
2004	Trip landing data begins to be recorded.
2010	Log-book data begins, but does not cover the entire fleet. Landings begin to be reported as numbers and/or weight rather than numbers.
2014	Detailed log book data on trip begins to be recorded, including bait, set type, fishing times by gear and location. Weight rather numbers becomes commonest data to report landings.

In addition, during the latter years to the early 1980s, fishing vessels which completed a certain number of fishing days were exempt from annual registration fee. This may have prompted the over-reporting of effort to avoid the fee (Anderson et al. 2003). Further exploration of the details of the fee system will be sought to make a possible correction for this, if possible.

One of the largest potential source of errors for the catch weight data may be the conversion factors used to estimate the weight from recorded fish numbers (Anderson, 1986). Several factors have been derived over the years. For the standard data, mean weights have been estimated as 2.1kg for small skipjack and 5.7kg for large skipjack. There appears to be limited supporting evidence for these values and they are fixed over all years 1970-2016.

[1] These data were merged by Adam (1999) as part of his PhD research

Data were combined from five sources:

1. The vessel specific data 2004-2015 have already been used in CPUE indices (Sharma et al. 2013; Medley et al. 2017b)
2. The new 2016 logbook data were processed to be consistent with the 2004-2015 trip data and appended to the series.
3. The IPTP/MOFA Merged data 1970-2007 were drawn from previous work (Adam 1999) and represent the monthly catch and effort by vessel type. The structure of these data is different and the data set was organised separately. Only the pole and line data were used.
4. "New" vessel specific data were found in 2017 for the period 1995-2002 inclusive.
5. The reconstructed fleet size composition 1970-2007 was estimated from vessel register using a survival model (Medley et al. 2017c).

These vessel specific and logbook data are compatible as they have the same covariates. These have been combined into a single data set without adjustment. It should be noted however that there is some overlap between the logbook data and per-trip data collected by island staff.

Some of the problems with the data can be seen by plotting the CPUE (Figure 1). CPUE shows a positive trend most likely due to increasing fishing power. There are some differences between mean CPUE derived from the different data sources. The variance of the estimates, particularly in recent times, has increased.

Most of the data have the same underlying source 1970-2015, namely the island government staff who were required to collect these data. This system has now been replaced by the logbook data collection system. Although all the data 1970-2015 had the same source, they have been processed and maintained in different forms which have led to differences. The "new" data 1995-2002 discovered recently are important because they were in raw unprocessed form. This significantly increased the overlap between the vessel specific data and the IPTP/MOFA Merged data 1970-2007, which greatly improves the index as it crosses between data sets.

For the 1995-2016 data, records were filtered to remove all cases which were suspected as not being pure pole and line trips. This consisted of removing any data record where gear were not reported as pole and line, no skipjack were landed or "large" yellowfin were landed. This, as far as possible, created a relatively homogeneous data set of strict pole and line trips.

In preparatory analyses, it was found that vessels 7m or less in length had catch rates equivalent to much larger vessels and seemed to contradict the otherwise clear trend of catch rates declining with vessel size. It was suggested that the smallest vessels would not be pole and line because of the lack of space for live bait. However, this would still not explain the reported high catches from these vessels. This issue needs to be explored, but some response was necessary for the current analyses. It is important because although in recent times these vessels only make up a small proportion of the trips, in the older data they make up a much higher proportion so an incorrect interpretation of these data could bias results.

As an interim solution, it was proposed to remove data that were inconsistent with other information. Specifically, it was found that small vessels have a bi-modal catch rate distribution, and it was decided to remove the upper mode so as to reduce the impact of these suspect data. Therefore, data for vessels 7m or less with log catch rates above -1.5 were removed from the data (186 out of 11473 records).

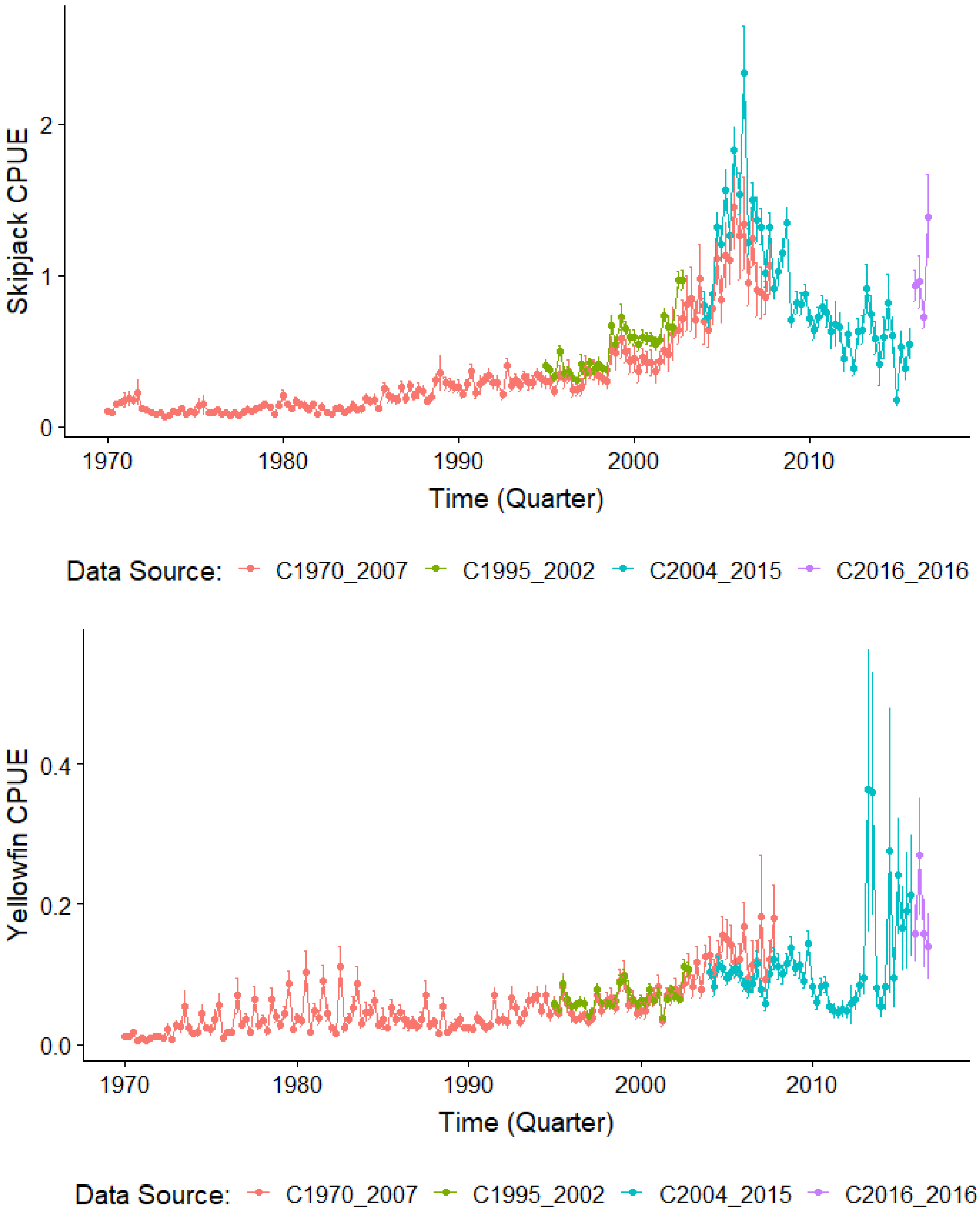


Figure 1 Nominal abundance indices for skipjack and yellowfin with standard errors.

Model Structure

Exploration of the model structure has not been exhaustive, but fairly wide exploration of the data suggested that the main factors have been captured.

The main effects were assumed to be linear in relation to log-catch. Log effort (trip length) was added as an offset (no parameter was fitted to it). This approach is identical to fitting to log-CPUE, but allowed greater flexibility during the exploration phase.

The model used the following data components:

- Atoll groups are treated as a categorical variable fitted as a simple main effect. Although there were significant differences between catch rates landed at different atolls, it was not clear how the atoll should affect the skipjack and yellowfin catch rates, so the current formulation may need to be revisited. Consistent with Sharma et al. (2013), atolls were grouped into North, Centre and South since this had the potential for having different catch rate time series. However, no further action was taken at this stage. Any further use of atolls in standardization will need to account for varying reporting rates among atolls.
- Vessel size classes were identified. The classes were based on exploratory GLM fits to the data and motivated by expert opinion which implied discrete changes in vessel upgrades reflected in the size classes.
- Vessel length is fitted as a covariate interacting with vessel size class.
- Vessel power for the early time series separates sail and motor vessels.

Other factors were identified in an expert meeting (MRC 2018) for which there is no quantitative data. These factors were included as an optional expert opinion offset for the model.

To deal with the various issues arising for the different data sources, it was decided to use a Bayesian approach as the only way to deal with the problems in a consistent and transparent manner.

The model included the following structures:

- Combining yellowfin and skipjack into a single model, where we expect fishing power effects to be the same for both species.
- Log-normal likelihood for skipjack CPUE observations and a delta-lognormal approach for yellowfin to explain inflated zero landings.
- Piece-wise regression on vessel length allowing for discrete vessel classes.
- Simple main effect adjustment for North and South regions relative to the Centre.
- Combining older IPTP/MOFA revised data (Adam 1999) with recent vessel specific reports (1995-2002, 2004-2015) and logbook data (2016).
- Estimating the unknown proportion of motorized vessel landings 1974-1979. The model estimates the proportion motorized fishing effort where they are missing using

the beta distribution with the same mean and variance as the binomial for the proportion motorized.

- The unknown fleet length composition for the IPTP/MOFA revised data 1970-2007 using a length probability matrix derived from the vessel register (Medley et al. 2017c).

Expert Opinion Offset

A small workshop was convened 26 June 2018 at the Marine Research Centre, Malé with seven invited experts, who have a long experience of the tuna fisheries in the Maldives to assimilate subjective information on the tuna fishery 1970-2018 on changes that have had an impact on the tuna fleet's fishing power (MRC 2018). The workshop consisted of two parts:

1. A scoping to identify relevant changes in the fisheries and a general discussion of their effects.
2. For each significant change identified within the scoping, an estimation of the period the change occurred and its impact on catch rates.

The identification of important changes in the fishery, and the period those changes were introduced were agreed by consensus. For estimating the impact of the change, a simple Delphi method was applied, where after initial discussion, each participant wrote down what they thought the percentage increase in catch rates would be for the change. To do this, participants had to imagine the only change that occurred was the one under discussion, so that it was separated from other changes. Once all participants had submitted an estimate, estimates were shared and discussed, with justifications given by participants for their own estimate. Once discussions were complete, the participants provided another estimate which could be the same, or adjusted with respect to justifications provided by other participants.

During the Delphi process, there was no encouragement to reach any consensus. Instead it was pointed out that the true answers were unknown and therefore these were subjective guesses, where the levels of difference between participants could indicate uncertainty. This was also used by participants, so that they agreed that their collective answers reflected appropriate uncertainty in the estimates.

While there was clear consensus over which factors had affected fishing power, opinions differed on the scale of the effects. It is clearly difficult to estimate in quantitative terms what effects have been, so any estimate will be highly uncertain.

Vessel length was identified as being a key determinant of vessel fishing power, and reasons were provided why this was the case. The effect of vessel length was estimated from the data, so there was no need to use expert judgement on this. However, six other effects not explained by vessel length were identified as important (Table 2).

All these additional effects except drifting FADs (dFADs) coming in from the Indian Ocean, were used to create a fixed offset combining each effect based on logistic model with 98% of the change occurring between Year 1 and Year 2 and the scale of the change set by the Mean in Table 2 (Figure 2). The scale of the estimated effects suggested an increase in fishing power by as much as 400% based on these five effects alone. However, it was noted that the combined effects may be exaggerated, as the overall view of the experts was the combined effects, including vessel size, have led to an overall increased efficiency of around 300%. Therefore, this offset should perhaps be taken as an upper limit for these five effects.

The fixed anchored FADs that have been placed around the islands are not included in the model. These were not included in the last skipjack indices because they did not explain catch rate changes (Medley et al. 2017b). At least some of the experts felt these FADs were not relevant to the commercial pole and line fleet, but are used by other fisheries.

The experts also provided insight on the effects of motorization among others. Early models seem to underestimate the motorization effect, and reasons were provided why this might be the case. These models were incorrect and recent assessments suggest the effect of motorization is in line with early observations (Anderson 1987). However, the experts noted, for example, that engines installed in the early vessel took away hold space for bait and tuna and reduced labour costs, which may not lead to a simple relationship with fishing power. They also identified vessel design as a key effect, and that vessel types could be identified from vessel length. This led to modelling separate vessel classes based on their length so the model would have flexibility to account for discrete changes in fishing power due to vessel design.

Table 2 Summary of expert assessment of changes in fishing not related to vessel size. Year 1 and Year 2 refer to the period when the change occurred, the mean is the group estimate of the final percentage increase in fishing power in year 2 and the final state indicates how much of the change has occurred in Year 2. Less than 100% for the final state indicates incomplete spread of the technology among fishing fleets. For dFADs, it is believed changes have been ongoing throughout the period and a simple logistic will probably not model this effect.

Effect	Year 1	Year 2	Mean	SD	Final State
Water sprays	1982	2000	48.6	21.7	100%
dFADs	1982	>2018	21.4	12.2	Linear
SCUBA baitfishing	2012	>2018	19.3	9.4	33%
Baitfishing lights	1990	2005	65.7	27.7	100%
Binoculars	1975	1990	39.3	10.2	100%
Ice availability	1995	>2018	12.9	5.2	70%

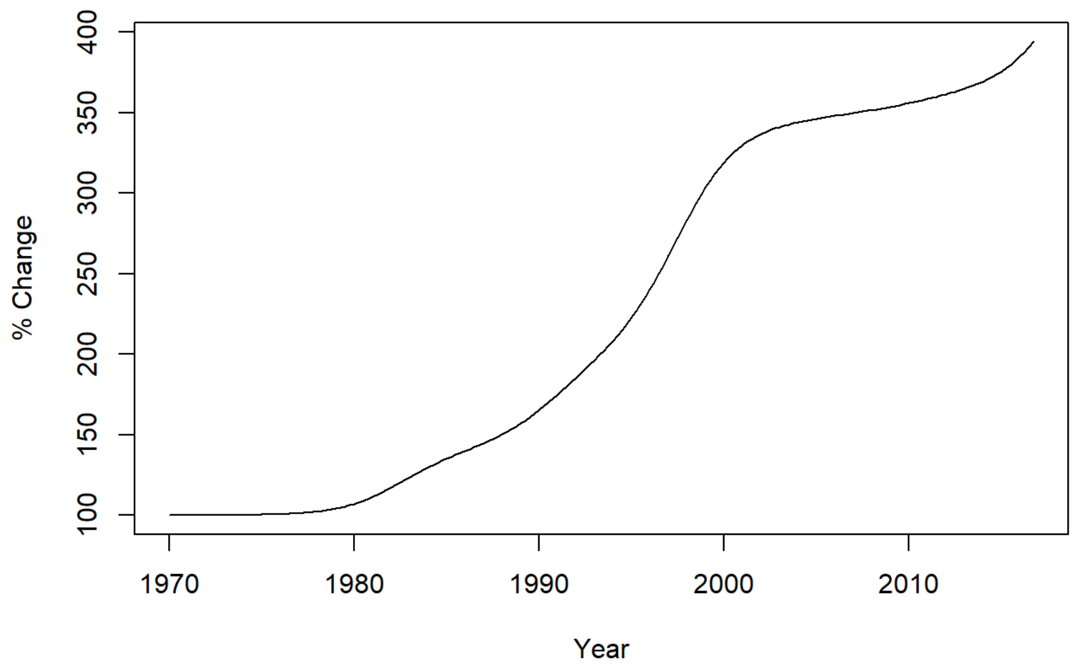


Figure 2 Fixed expert offset in fishing power accounting for five effects not recorded in the catch effort data set.

Motorization

The missing data (proportion motorized effort 1975-1978) were estimated as a latent variable ("random effect") within the model. The probability for the proportion was based on a binomial for the approximate number of vessels in the fishery. Although this was calculated from the effort, effort was not used to calculate the variance because clearly effort days were not independent. The number of vessels contributing to the observed effort was not known, so this was estimated as effort / 24 (assuming each vessel on average fishes 24 days in a month). Lower values for the number of trials were preferred to ensure precautionary variance estimates.

Some data on the number of motorized vessels in the fleet during this period was available. The following was obtained from Anderson (1987; Table 3). From 1979 onwards, motorized effort was recorded directly.

Table 3 Registered motorized vessels 1974-1978

Year	Motor Vessels	Sail Vessels
1974	1	2131
1975	42	2040
1976	218	1940
1977	413	1801
1978	548	1631

This suggests that mechanization began in 1974, so for 1974-1978 power is treated as "unknown". A posterior probability density function for the probability vessels were motorized was constructed based on these observations assuming uniform prior and binomial probability based on motor and sail vessels as "success" or "failures". The observations (Table 3) applied to whole years rather than quarters, so assuming vessel counts as independent trials will over-estimate the certainty. To reflect this, the effective number of trials was reduced to 12.5% of these totals.

It should be noted that the number of registered motorized vessels as a proportion of the whole fleet (~40%) was lower than the recorded motorized effort in 1979 (60-70%). This suggests that the most active vessels probably became motorized first. As such the register data above may underestimate the proportion of motorized effort. This may be another reason to reduce weight these data have in fitting.

The motorization rate appeared to have been too rapid for the standard logistic function, and therefore a 3 parameter generalized logistic was used to model the switch. It was necessary to fix one of the parameters (α) which could not be fitted separately. The final had the potential to fit observations well (Figure 3).

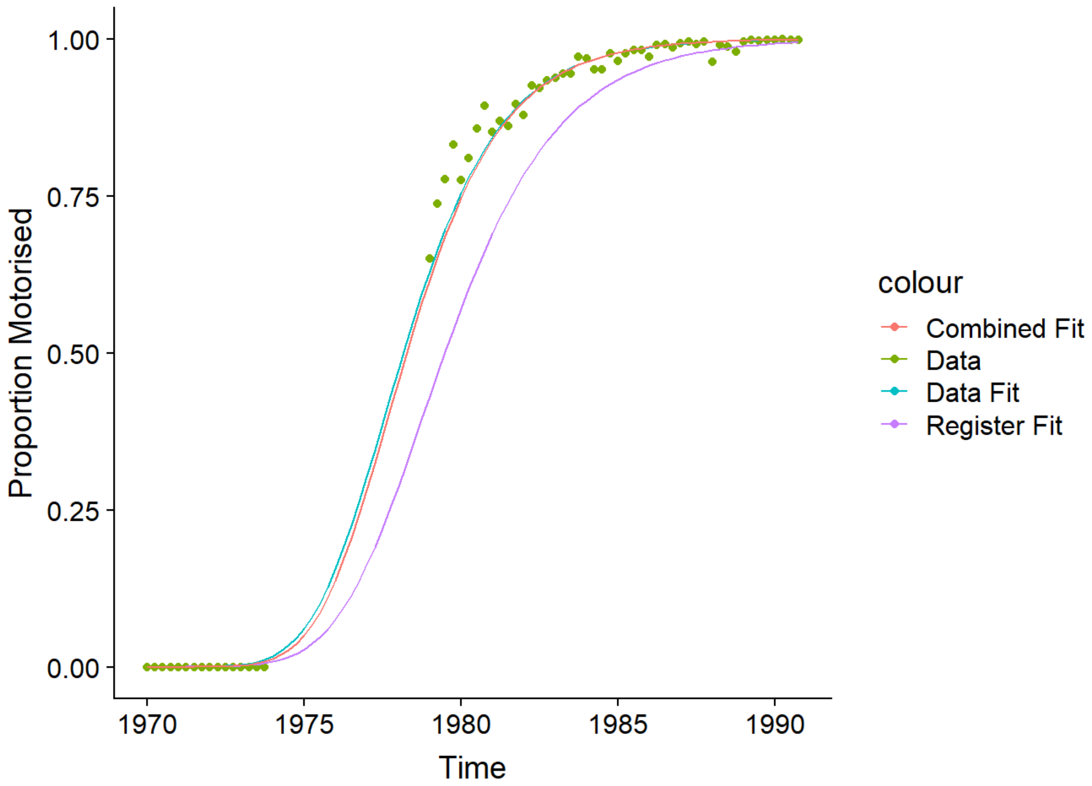


Figure 3 Exploratory fits of a generalized logistic model with fixed α parameter (-5.0).

Priors

Model parameters consist of the time series indices fitted to each quarter for skipjack and the yellowfin lognormal likelihood, a regional atoll effect (North, South and Centre), regression on vessel length with slopes and intercepts for each of the 6 vessel size classes and a motorization effect (Motor and Sail). A separate Bernoulli model was fitted for yellowfin presence/absence with the same parameters. For the two main data sources, the older IPTP-MOFA and the newer vessel specific data, an adjustment parameter was fitted to allow seamless transfer. This parameter should be close to zero, but differences, particularly in assumed mean weights, may have led to differences. The parameter was estimated from the common data for the period 1995-2007.

Very weak normal priors were provided for the abundance indices. These were set with a mean close to the mean of the raw data and large sigma (4.0). These priors should have little effect on the lognormal estimates, but prevented the yellowfin Bernoulli parameters failing to converge in the MCMC when a model category has no cases with no landings (zero "failures"). Any absolute effect on abundance indices of these priors should be negligible.

The lognormal and Bernoulli vessel length slope parameters for the first size class exhibited significant convergence problems during exploratory fits. In addition, the estimates of the regression slope for these vessels was negative, indicating increased catch rates for smaller vessels within this size class. This was already noted as a problem, and highly unlikely to be a real effect. Previous removal of some of these data only partially fixed this problem. Therefore, a highly informative prior was set on these parameters, effectively binding these slope parameters to zero. Therefore, effectively all vessels 2-7m length in this model have the same catch rates.

For the additional generalized logistic parameter (α), estimation was difficult because of the model form produced discontinuities during the fit, exacerbated by the lack of information on the parameter in the available data. This could be resolved by applying a very informative prior, but this would be little different to fixing the parameter at a reasonable level based on maximum likelihood fits. The remaining two parameters of the generalized logistic were fitted normally to allow for any error in the observations.

For the expert opinion offset, it was attempted to use the standard deviations from the differences in opinion to represent expert uncertainty by applying a normal prior and fitting these parameters. Balancing the statistical weight on aliased priors which have no independent information in the likelihood against other components in the model was difficult. Without arbitrary intervention, such as setting the prior sigma parameters very low, final estimates did not correspond to the original expert opinion. Therefore, the parameters were fixed so that including the offset would represent an alternative case for a sensitivity run as a worst case scenario for abundance decline.

Table 4 Fitted parameters and priors. Absence of priors implies a uniform distribution.

Parameter	**Number**	**Description**	**Prior**
Lognormal Model			
Itsj	188	Skipjack time series means	normal(-2, 4)
Ityf	188	Yellowfin time series means	normal(-3, 4)
so	1	Data source effect: old IPTP data vs new data	normal(0, 0.4)
at	2	Atoll effect by region	
vc	5	Vessel class intercept	
ve	6	Vessel length slopes for each class	ve[1] ~ normal(0, 0.01)
pw	1	Sail vessel effect	
sig	4	Residual sd	cauchy(0, 1)
Yellowfin Bernoulli Model			
Izyf	188	Binomial time series means	normal(3, 4)
soz	1	Data source effect: old IPTP data vs new data	normal(0, 0.4)

atz	2	Atoll effect	
vcz	5	Vessel class intercept	
vez	6	Vessel length slopes for each class	vez[1] ~ normal(0, 0.01)
pwz	1	Sail vessel effect	
efz	1	Effort effect	
Motorization Model			
lg_mot	3	Generalized logistic parameters for the motorised proportion	
		50% Motorized	uniform(1970, 1979)
		Steepness	gamma(1.0, 0.5)
		α	Fixed: -5.0
mot_p	20	Proportion motorised effort where unknown	
FPoffset	5	Expert opinion on percentage increase of 5 effects	
		Water sprays	Fixed: 0.486
		SCUBA baitfishing	Fixed: 0.193
		Baitfishing lights	Fixed: 0.657
		Binoculars	Fixed: 0.393
		Ice availability	Fixed: 0.129

Fitting the Model

The model was developed in Stan (Stan Development Team 2017), which provided a flexible, robust platform for fitting Bayesian models using MCMC. Stan is designed to improve MCMC performance by using Hamiltonian Monte Carlo (HMC) sampling. Among other things, it uses auto-differentiation to improve MCMC convergence and can cope with complex models which other software is unable to deal with.

For the vessel specific data, the main effects were fitted with a log-normal likelihood, with 4 separate scale parameters, for the two data sources and two species.

For the motorized random effects model, the proportion motorized was fitted through a beta-binomial (assuming a uniform prior) to the observed motorized / non-motorized trips for those quarters where the data exist with the expected proportion as a logistic function of time. The random effect variable was then estimated using the beta probability function consistent with a binomial having mean and variance taken from this logistic function and overall number of trips in that quarter.

For the vessel length model, the proportion of trips undertaken by vessels at each length was assumed to be proportional to the vessel fleet size composition estimated separately (Medley et al. 2017c). This proportion was multiplied by vessel length effect on the catch rate to generate the expected overall effect for each quarter.

The data were assembled as a list in R of simple vectors with the same names as data structures in the Stan model. The data were split as appropriate between skipjack and yellowfin, and the old IPTP data with known and unknown proportion of vessels motorized, and the new vessel specific data.

Standard generalized linear models were used to provide good first guesses for parameter estimates. These estimates were then adjusted towards the posterior mode using the Stan "optimizing" function. The output initial parameters were then checked by plotting and the optimizing function run as many times as necessary. Models with and without the expert opinion offset were fitted separately.

The Stan model was written in C++ modelling language and compiled using the Rtools C++ compiler in R. The Stan model was compiled and run in R (R Core Team, 2018) using the package "rstan" (Stan Development Team, 2018). In this case, 4 MCMC chains were run in parallel after 500 warm-up simulations to create 1000 random draws in total from the posterior. A MCMC test run was conducted to check the model was running correctly. Debug-printing was used to check calculations were as expected.

Results

MCMC Convergence

The Stan fit was reviewed and MCMC convergence confirmed. The ($\hat{R}$) statistic, which should be close to 1.0 and the effective sample size give a general indication of the convergence and how well they have been estimated. All parameters were reviewed, but the important parameters in this context are the time series indices which were reasonably well estimated (Table 5), although the simulations could be run for longer to improve the estimates.

Table 5 Summary worst MCMC diagnostics for time series parameters without (top) and with (bottom) expert opinion offset.

No Offset	**Minimum**	**Maximum**
SKJ Eff. N	82	1000
SKJ $\hat{R}$	0.997	1.012
YFT Eff. N	114	1000
YFT $\hat{R}$	0.996	1.016
YFT P/A Eff. N	276	1000
YFT P/A $\hat{R}$	0.997	1.021
Expert Offset	**Minimum**	**Maximum**
SKJ Eff. N	155	1000
SKJ $\hat{R}$	0.997	1.025
YFT Eff. N	216	1000
YFT $\hat{R}$	0.996	1.027
YFT P/A Eff. N	293	1000
YFT P/A $\hat{R}$	0.997	1.012

Abundance Indices

The quarterly indices are directly estimated as parameters in the model. The yellowfin abundance index is obtained by combining the lognormal and Bernoulli estimates.

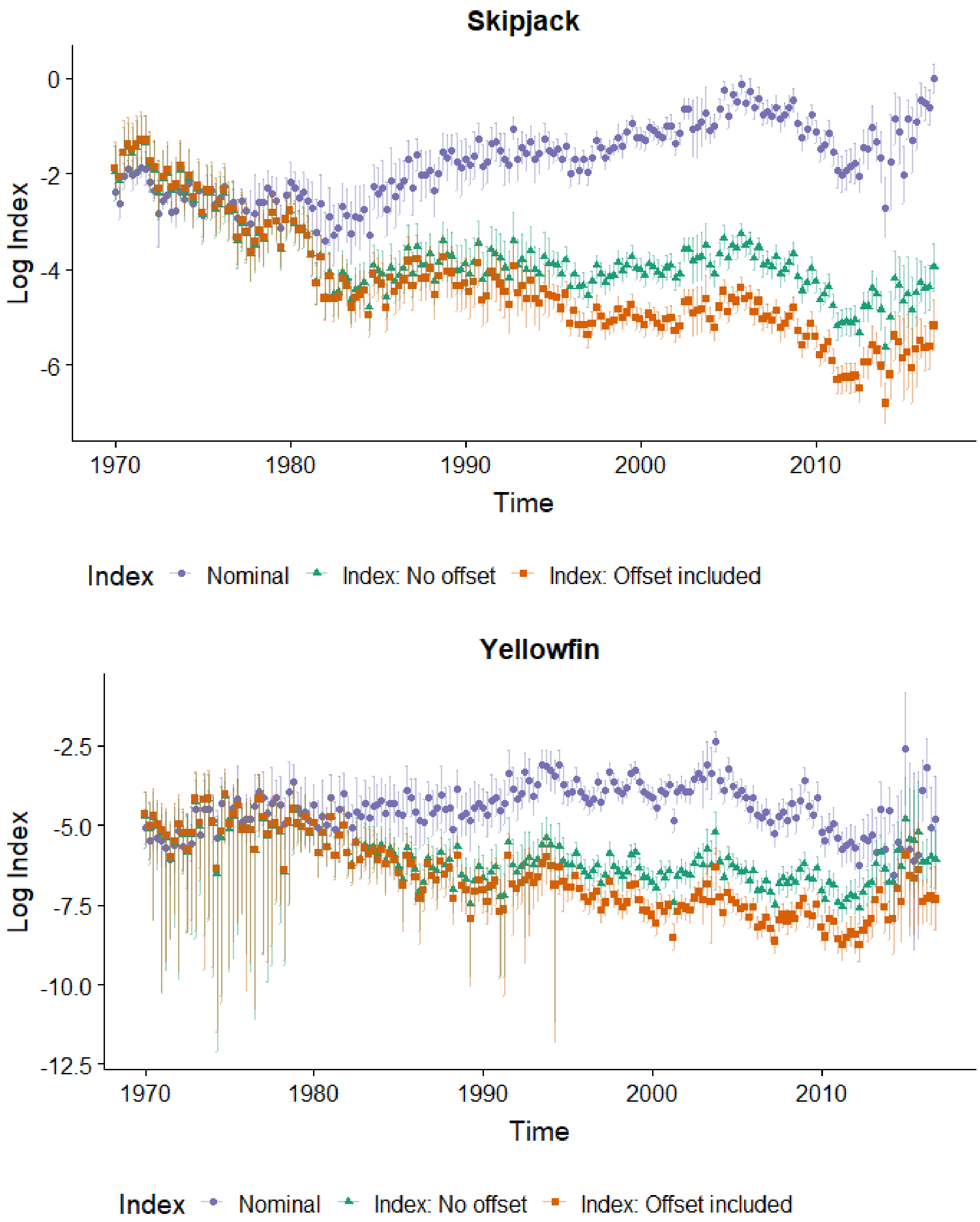


Figure 4 Log nominal CPUE and fitted abundance indices estimated from the model with and without the expert opinion offset for skipjack (top) and yellowfin (bottom). Error bars represent the 95% confidence interval for the estimates.

Vessel Size Effect

The vessel size category regression estimates are similar to the maximum likelihood estimates. Note that the negative slope regression estimate for the smallest size class has been forced through the prior to be relatively flat to avoid significant increasing catch rates with decreasing vessel length.

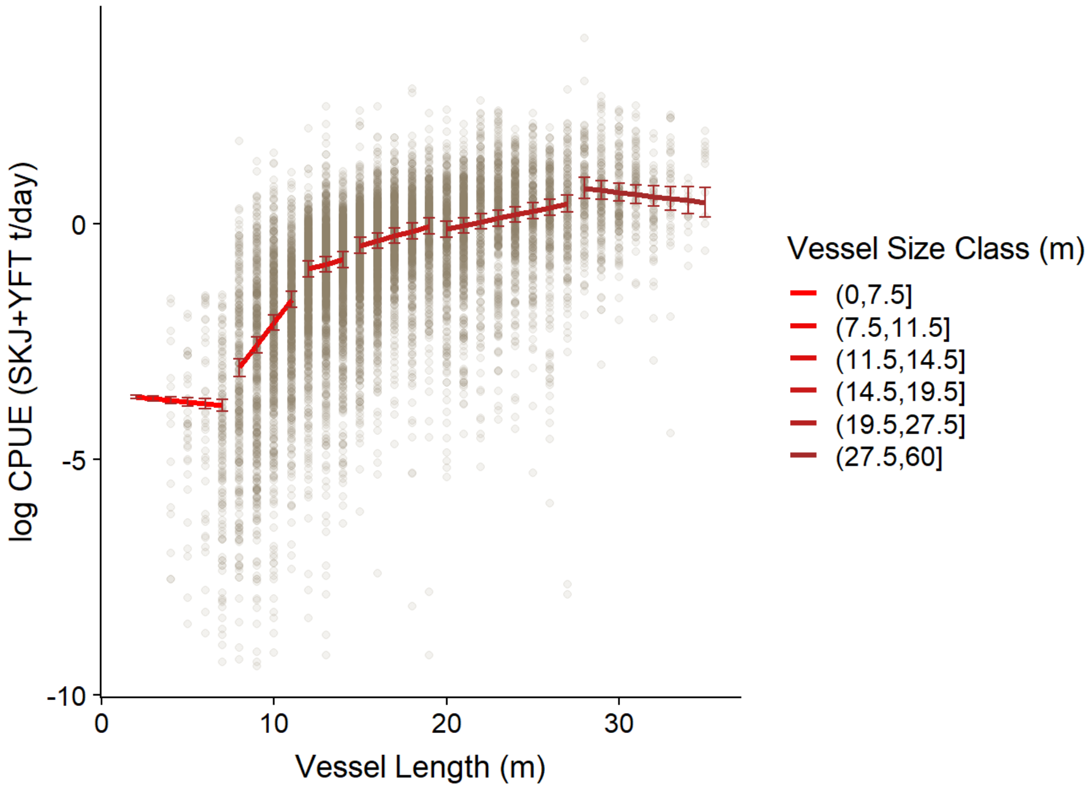
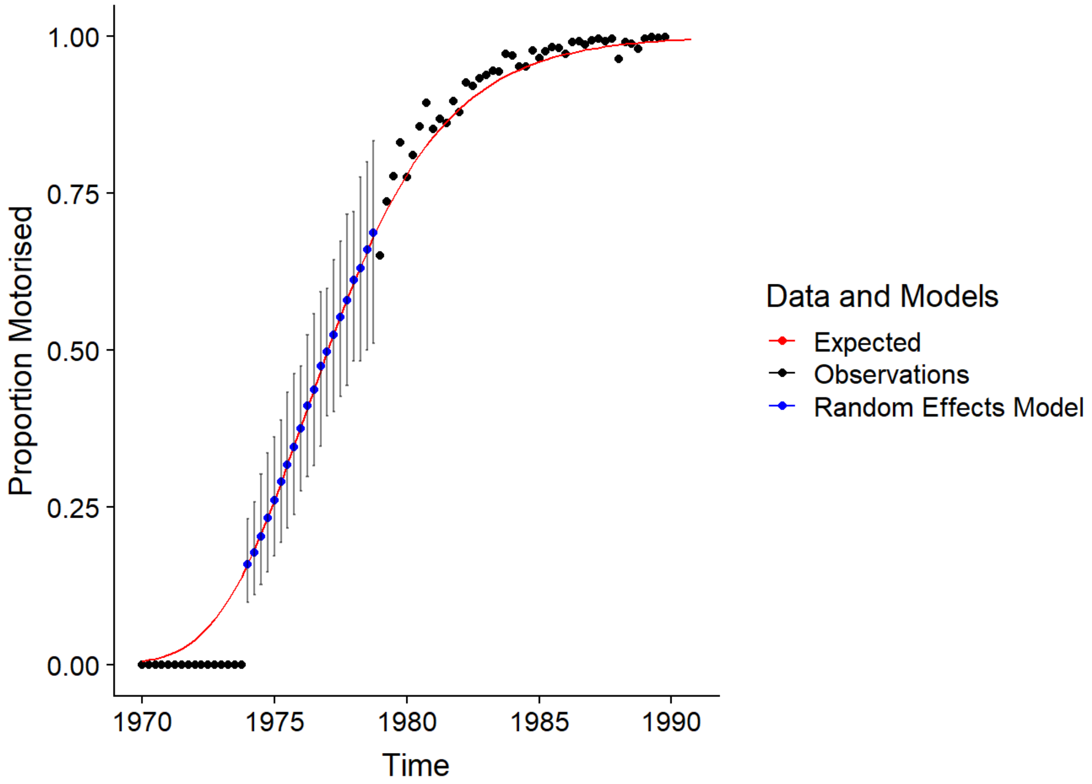


Figure 5 Median and 95% probability intervals for vessel size parameters, adjusted to plot over log-CPUE observations 1995-2016.

Motorization

The motorization model bridges the gap when motorization data does not exist (Figure 6



). The use of sail significantly reduced the catch rates for vessels and explains the early increasing catch rate trend in the 1970s as motors were installed. The results suggest sail boats had around 30% of the catch rates for motor vessels and were less likely to land yellowfin.

The random effects model fits observations well 1979 onwards, but the model may have a tendency to overestimate early motorization despite increasing the steepness in the generalized logistic model. There may be an argument to fix the random effects mean to a model that most agrees with available registry and effort data (Figure 5) rather than fit it in the final model.

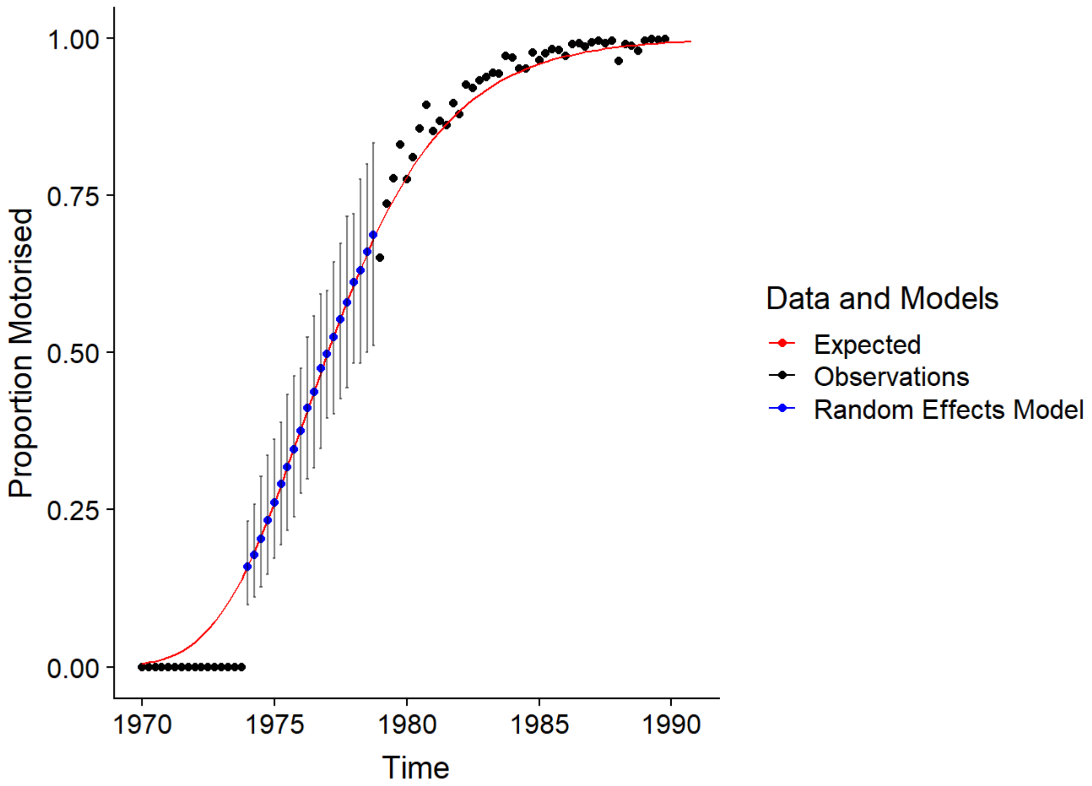


Figure 6 Proportion mechanized with observations, logistic curve defining expected proportion and “random effect” estimates with 90% confidence interval.

Conclusion

The primary objective of this exercise has been to estimate abundance indices suitable for use in stock assessments. The model has used all available information in 2018 to develop credible indices of abundance for skipjack and juvenile yellowfin caught on Maldives pole-and-line gear. Abundance indices show a clear decline consistent with possible population trends and in contrast to the nominal catch rates. The standardization process has been carefully documented and justified, providing full data and code so the process can be reproduced from raw data sets. This should allow independent review of the indices and the process applied to obtain them, to ensure they are correct and as far as possible reflect changes in abundance of these species.

Both skipjack and yellowfin show an upturn in abundance since 2010. For yellowfin, this could indicate a slight reversal of the long term downward trend in recruitment. However, the common pattern in both skipjack and yellowfin, and the fact that it coincides with the shift to the logbook system, suggests that the pattern requires independent support from other information before being treated as real population change.

Two types of indices were produced. The “no offset” model only used the available data, whereas the “expert opinion offset” model used subjective information on the likely impact of changes in fishing operations which have not been recorded. Including the “expert opinion offset" results unsurprisingly in lower abundance estimates for these species. These might be considered as best and worst case scenarios for tuna abundance.

Outstanding issues that may require further consideration and research include:

- The unrealistic increasing catch rates for small vessel less than 8m length.
- Mean fish weight has been included in the data as a mixture of observations and best guesses. This has added to the index errors in ways that are not fully understood. Further review of the use of fish mean weight to convert recorded fish numbers to estimated landings weight could improve the indices further.
- Government initiatives to encourage fish production may have affected data records in the past, but no clear pattern emerged. There could still be hidden biases and this adds to general uncertainty, but lack of a pattern suggests that any biases are most likely small compared to other effects. This management issue has been resolved and should not affect recent or future data.
- Current reporting rates have been declining while the government has switched to logbook system. Unfortunately the older system has been discontinued. It is recommended to 1) significantly improve reporting rates 2) analyse the data to provide a better bridge between the old and new data similar to that which has been done for the IPTP and vessel specific data.
- Some of the observed fluctuations in the abundance indices could be due to other unmeasured effects. Perhaps of most concern are drifting FADs, which are known to have increased use by purse seiners, but could also could increase through natural events (e.g. Tsunamis) and other human activities (e.g. lost fishing gear, floats, litter). Increased availability of floating FADs may not only add to the overall trend, but could raise the effective catchability over short term events producing fluctuations in catch rates.
- Likely past under-reporting of fishing effort (measured by number of days at sea). Vessels are likely to have carried out multi-day fishing but report this as a single trip recorded as 1 day of fishing. In this case their catch relative to effort would be over-estimated. This problem should now have been resolved through the logbook reporting, but the historical data may be improved by further investigation of this issue.

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