



# IOTC-2019-WPNT-17 CPUE Standardisations for Neritic Tuna Speices Using Iranian Gillnet Data 2008-2017

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#### SUMMARY

We analysed the catch effort data from the Iranian gillnet fishery in the coastal waters of Persian Gulf and Oman sea, and applied statistical models to obtain abundance indices from nominal catch per unit effort (CPUE) for the main neritic tuna species captured in the fishery. The spatial and temporal trend of catch and effort was characterised, and standardisation analysis using GLM models was conducted for longtail tuna (*Thunnus tonggol*), narrow-barred Spanish mackerel (*Scomberomorus commerson*), kawakawa (*Euthynnis affinis*), and frigate tuna (*Auxis thazard*), using trip-level catch effort data collected from the port-sampling program from 2008 to 2017. Additional analyses using Bayesian MCMC and mixed effects models were also investigated. The analyses showed that the standardised catch rates have declined for the longtail tuna and has been increasing for the narrow-barred Spanish mackerel in recent years, and standardised catch rates for kawakawa and frigate tuna showed a slight increasing, but overall stable trend. The caveats of the data used for CPUE standardisations were discussed. This analysis represents the first attempt to estimate a relative abundance index from the Iranian gillnet fishery for potential use in stock assessments of IOTC neritic tuna stocks.





### 1. BACKGROUND

Neritic tuna is of great commercial values to many Indian Ocean coastal states and support important artisanal and semi-industrial fisheries across the Indian Ocean. Neritic tuna species accounted for approximately 40% of total catches of commercial species under IOTC mandate in recent years (IOTC–WPNT07 2017). However, due to poor availability of data, so far IOTC neritic tuna stocks have been assessed using data limited method (Zhou & Sharma 2013, Fu & Martin 2017, Martin & Fu 2017). These assessments are associated with very large uncertainty because of highly uncertain catch history, and particularly the lack of catch-and-effort and indices of abundance, limiting their usefulness in the provision of sound management advice. The lack of detailed information about catch and effort of the large gillnet fleet is a critical issue for the assessment and management of stocks of tunas and of many other species in the Indian Ocean (Andrade 2017).

For most of the important fisheries catching neritic species in the Indian Ocean, catch-and-effort is either not available, or only partially reported. To date, there are only a few standardised CPUE analysis ever performed for IOTC neritic tuna species, including the attempt to standardise the catch effort data from the Maldives Pole and Line fishery for Kawakawa (Sharma, et al. 2015) and for longtail tuna from the gillnet fishery in Sultanate of Oman (Al-Siyabi et al. 2014). In this context, capacity building activities, through data compliance and support missions, aiming at improving the availability of catch effort data and developing standardised CPUE series for fleets which account for the largest catches of neritic tuna and tuna-like specie, have been considered as a high priority by IOTC Working Party on Neritic Tuna, Working Party on Data and Statistics, and Scientific Committee (IOTC–SC20 2017).

I.R. Iran accounts for the second largest catches of neritic species in the Indian Ocean but had only reported partial catch-and-effort according to the IOTC standards in the past. A data compliance and support mission were conducted by the IOTC Secretariat in 2017 to evaluate the status of data collection and reporting of Iranian fisheries data to the IOTC. Discussions were also held regarding the possibility of developing standardized CPUE series for the Iranian gillnet fleet, given that Iran Fisheries Organization (SHILAT) has collected catches and fishing effort for around 15 years, in addition to information on vessel and fishing characteristics. Following that mission, the SC requested that the IOTC Secretariat collaborate with I.R. Iran to explore options for developing standardized CPUE indices from its coastal gillnetters targeting neritic tunas for use in future stock assessments. In response to that request, a second data support mission to I.R. Iran was conducted 8-12 June 2019 by the IOTC Secretariat to collaborate with SHILAT to analyse the drift gillnet data for the main neritic tuna species. This report summarised the results of the analysis performed.

#### 2. OVERIEW OF IRANIAN FISHERIES IN THE SOUTHERN WATERS

The southern waters of Iran (Figure 1) support important fisheries of large pelagic species, accounting for over 50% of the country's aquatic production (Rajaei 2017). Over 12 thousand vessels consisting of fishing boat, dhows and ships are engaged in fishing in the Persian Gulf and Oman Sea (Naderi 2017). A range of fishing methods are employed to target tuna and tuna-like species in the coastal and offshore waters, including gillnet, purse seine, longline, and trolling. Gillnet is the dominant fishing gear targeting large pelagic species (especially tuna and tuna-like), and majority of the catches comes from the gillnet vessels operating within EEZ of Iran as well as offshore waters (Rajaei 2017).

The neritic tuna is major component of the pelagic fisheries in the coastal waters and approximately a third of the catches were attributed to neritic tunas, which included longtail tuna (*Thunnus tonggol*), narrow-barred Spanish mackerel (*Scomberomorus commerson*), kawakawa (*Euthynnis affinis*), Frigate





tuna (*Auxis thazard*), and Indo-Pacific king mackerel (*Scomberomorus guttatus*) (Naderi 2017). In 2014, the total catches were around 65610 t for longtail, 29400 t for narrow- barred Spanish mackerel, 23640 t for kawakawa, and 13490 t for frigate tuna (Naderi 2016). The longtail tuna accounted for approximately 40% of all tuna catches.

Over the last decade, the Iranian gillnet fishery have been characterised by changes in fleet dynamics with varying targeting on neritic and tropical species (IOTC–WPNT07 2017). Catches of tropical tunas declined with the onset of the threat of piracy in the late-2000s, and during this period the catches of neritic tunas increased due to changes in targeting and relocation of fishing effort. Since 2011, large declines in catches of longtail tuna have been reported by I.R. Iran. The reasons are unclear, but possibly related to the establishment of management measures for downsizing the fishing effort (Naderi 2016). Catches of tropical tuna are increasing again in more recent years but the catches of neritic tuna species have not decreased by the same magnitude, with the exception of longtail tuna (IOTC–WPNT07 2017).



Figure 1: A map showing the coastal fishing grounds in Iranian southern waters (Persian Gulf and Oman Sea). The fishing grounds are designated in Iran Fishery Data Collection System as areas 1-3 (Khozestan), 3-9 (Busherhr), 10-17 (Hormozgan), 18, 19-181 (Sistanan baluchestan)





### 3. DATA

Fishing statistics from the Iranian coastal and offshore fisheries in the southern waters (Persian Gulf & Oman Sea) since 2005 have been collected and managed under the Iran Fishery Data Collection System (IFDCS). The IFDCS collects catch and effort data through a port sampling regime that covers approximated 10% of the vessels. The sampling scheme has adopted a stratified random design to ensure representative coverage of fleet size and capacity. The data are stored and managed in a SQL-Server database (SIMAB) which are comprised of a series of inter-linking tables containing information on vessel characteristics, fishing gear, catch and effort. The database covers a range of fishing methods including trawl (bottom, Midwater, and shrimp), Gillnet (Bottom, Drift, Encircle), Trap/Cage, Longline, Hook, Trolling and boat Purse-since. Catches have been reported at species level covering over 40 species (including IOTC species). The following data from the database were considered for the CPUE standardisations.

**Vessel registry** (*Mojavez*) – All vessels are required to obtain permission or a licence before the start of fishing. The *Mojavez* table contains vessel number, permit number, vessel capacity (GT), trip start/end dates, active days at sea, fishing gear, and fishing ground. A permit is issued for a duration for up to a month during which period multiple trips are usually conducted. Thus, the registered trip start/end dates in Mojavez table covers the duration of all trips under the same permit number (sometimes these dates are not accurate as local regulations or sea conditions resulted in delay in departure and return), and consequently, 'active days at sea' is an aggregated number of multiple trips (unless there is only one trip under the permit). Vessels are classified into four size categories: 0–3t (boats), 3–20t (dhows); 20–50t, and 50–200t or larger. A target species is recorded but it is understood that this seldom represents the true fishing strategy employed by the fisher.

**Trip effort** (*Por*) – The *Por* table contains information on a subset of completed fishing trips collected by enumerators through the port-sampling scheme which covers approximately 10% vessels. Each record in the table correspond to an individual fishing trip under a permit number (there could be multiple records/trips under the same permit). The data includes the permit number, start/end dates of the fishing trip, fishing duration at sea (in hours), and fishing ground. The fishing grounds consist of twenty-five coastal zones (Figure 1), and one offshore area which refers to areas 24-nautical miles offshore including high seas.

Catch (*Por\_fish*) – The table contains catch weight by species for fishing trips sampled by enumerators.

A CPUE dataset was extracted from the database for the standardisation analysis. The dataset was restricted to the drift gillnet fishery and covers four neritic tuna species –longtail (LOT), narrow-barred Spanish mackerel (COM), kawakawa (KAW), and frigate tuna (FRI). Trip effort were extracted from the *Por* Table, and were linked to the *Mojavez* Table (for vessel information) and the *Por\_fish* table (for catch information). Each record in this dataset represents a trip-level, aggregated fishing event with following variables: *vessel\_no*, *vessel\_tonnage*, *trip\_start\_date*, *trip\_end\_date*, *fishing\_ground*, *panel\_number gear\_duration\_at\_sea*, *lot*, *com*, *kaw*, and *fri* (catch weight in Kg). The catch of a species is set to zero if it was not reported for the trip. Over 2000 gillnet vessels were sampled annually from 2008 to 2017 (Table 1). The sampled catch and number of trip days are shown in Table 2.

Some grooming was conducted to remove erroneous data including duplicated /mismatched records, and potential outliers. We have focused only on obvious errors and a more thorough checking routine needs to be developed to resolve some of the inconsistency in the database in future analyses. The threshold values chosen for identifying outliers were based on discussions with SHILAT officers.





### 3.1 Further notes on fishing effort

CPUE standardisation requires a robust measure of fishing effort. For a passive fishing method such as drifting gillnet, the fishing effort should be quantified as the time between the deployment and hauling of a set. The port-sampling collates information at the trip level and therefore the fishing effort are available only in aggregated form. There sampling questionnaire records fishing effort in several fields – *trip start/end dates, active\_days\_at\_sea,* and *gear\_duration\_at\_sea.* The duration based on *trip start/end dates* includes sailing time to and from the fishing ground and is not appropriate for measuring effort for longer trips (e.g. A 40-day fishing trip could include up to 15 days of sailing time). *active\_days\_at\_sea* is recorded for each permit and is aggregated over multiple trips. It is also not entirely clear what 'active days' means (whether not it is always associated with fishing). *gear\_duration\_at\_sea* (hours) is understood to provide the best estimates of fishing duration for a trip.

The number of panels is also an important indicator of fishing effort. However, discussions with SHILAT officers revealed that the *panel\_number* does not always indicate the actual numbers used for fishing and it may have included all the panels on-board (including spare ones). It has been suggested that panel number over 100 should be reduced by 20% if they are to be included in the standardisations.

Year	0-3t	3-20t	20-50t	50-200t	Total
2008	870	330	297	145	1 642
2009	1 142	340	386	350	2 218
2010	1 183	339	408	316	2 246
2011	1 242	311	429	333	2 315
2012	1 093	277	436	295	2 101
2013	1 112	269	420	281	2 082
2014	1 210	273	495	358	2 336
2015	1 162	243	554	324	2 283
2016	1 022	233	591	316	2 162
2017	1 034	221	644	323	2 222

Table 1: Number of sampled drift gillnet vessels by size category in the SIMAB database 2008 to 2017.

 Table 2:
 Sampled catch weight (t) for the four neritic tuna (LOT, longtail; COM, narrow barred Spanish mackerel; FRI, frigate tuna), and trip days from the drift gillnet fishery 2008–2017.

Year	LOT	COM	KAW	FRI	Trip days
2008	1 921	419	819	443	76 956
2009	3 952	694	1 279	470	136 819
2010	5 199	1 027	1 420	572	130 394
2011	6 848	1 144	1 844	886	128 160
2012	7 501	1 359	2 396	831	146 405
2013	6 879	1 389	2 086	675	130 525
2014	7 793	1 877	2 863	1 425	155 438
2015	7 305	1 666	2 610	1 075	133 869
2016	6 461	1 517	2 764	1 000	125 406
2017	7 411	1 859	3 208	1 190	121 237
2013 2014 2015 2016	6 879 7 793 7 305 6 461	1 389 1 877 1 666 1 517	2 086 2 863 2 610 2 764	675 1 425 1 075 1 000	130 525 155 438 133 869 125 406





### 4. DESCRIPTIVE ANALYSIS OF DATA

The groomed data included 185, 065 trip records from 2008 to 2017 and retained approximately 80% of sampled catches for each of the four neritic tuna species.

The sample data showed a rapid increase of longtail tuna catch between 2006 and 2012 (Figure 2), largely a result of the shift of fishing effort into coastal areas due to the threat of piracy. The catches for the other three species also increased, albeit at a slower rate. Fishing effort appeared to be stable with a peak in 2014 and a decline in the last few years (Figure 2).

Most fishing trips were less than 20 days (Figure 3 - left). Small boats (< 3 t) normally conducted daily trips whereas dhows and larger vessels conducted longer trips. There is generally a good correspondence between the total gear duration and trip days although some longer trips had low gear duration (Figure 3 - right), presumably because they had longer sailing time.

Most longtail catches were attributed to fishing ground 9–21 off the Hormozgan and Sistanan baluchestan Provinces (Figure 4-left), and there also appeared to be significant catches of longtail tuna from high seas (fishing ground 25, label as '20' in Figure 4). However, this could be misleading as the sampling questionnaire only requires the fishers to report one fishing ground per trip (only one fishing ground is registered with a permit number) whereas the vessel could fish a much larger area during the trip especially for larger vessels taking longer trips. This could potentially undermine the CPUE analysis as the *fishing ground* is an important standardisation variable. However, it is understood that the fishers would normally fish in adjacent areas due to cost constraints.

Catches of the four neritic tuna species were generally taken all year round but the longtail catch was low in winter and the catch of narrow-barred Spanish mackerel was small in summer (Figure 4-right). Overall the catches would decline in June and July as many fishing crafts cease their fishing activities due to poor weather conditions in the Oman Sea.

The plot of the catch rates (kg / hour) and vessel tonnage showed a positive relationship (Figure 4Figure 5). The strongest effect occurs between 3 and 20t of vessel size and the relationship appears to be weak at larger sizes. Most of neritic tuna catch by the gillnet fishery was attributed to the traditional fishing boats and wooden-hull vessels less than 50 t as larger vessels are primarily fishing in offshore waters.







Figure 2: Sampled catches (t) for longtail, narrow-bared Spanish mackerel, kawakawa, and frigate tuna, and trip days from 2008–2017 in the drift gillnet CPUE dataset.



Figure 3: Distribution of trip days (left) and trip days vs. gear duration (hours) for individual trips (right) for the drift gillnet CPUE dataset. The colours indicate four different vessel size classes.







Figure 4: Sampled catches for longtail, narrow-bared Spanish mackerel, kawakawa, and frigate tuna by fishing ground and year (left) and by month and year (right) in the drift gillnet CPUE dataset. Note that the scale is not comparable between the two plots.



Figure 5: The relationship of (log) catch (the total of the four neritic tuna) per hour and vessel tonnage, as derived from simple GLM models: dots represent individual observations; triangles represent estimated individual tonnage effects (log(CPUE) ~ factor(vtonnage)); the blue line represents an overall non-linear effect (log(CPUE) ~ log(vtonnage)). The coloured lines represent estimated linear effects within each of the four vessel size classes.





### 5. CPUE STANDARDISATIONS

The primary goal of CPUE standardization is to estimate a time series of relative abundance, and this is accomplished by identifying and removing the effects of various sources of CPUE variation that are attributable to causes other than changing abundance (e.g. changes in efficiency of the fleet due to improvements in technology). The analysis involves estimation annual time series of relative abundance using Generalized Linear Models (GLMs). The GLMs estimate the effects of independent variables which are expected to influence catchability, such that the effect of these variables can be removed to estimate a time series in which (ideally) the main source of variability is changing abundance.

We used the delta-lognormal approach to the standardize the catch rates for each of the four neritic tuna species. The process involves fitting two separate models to the CPUE dataset (for each species): a binomial model for the probability of obtaining a nonzero catch for individual fishing trips and a lognormal model for the positive catch rates. An annual/quarter index was derived from both models and then combined to provide an overall standardised index.

For the binomial model, the response variable is the presence/absence of the catch (e.g. longtail), and explanatory variables include *gear\_duration*, *year*, *quarter*, *fishing\_ground*, and *vessel\_vtonnage*. The model links the probability of obtaining a positive catch to the set of explanatory variables through a logit link function. Year/quarter was included as a single variable (or alternatively as an interaction term). *vtonnage* is included as a category variable with four levels (0–3t, 3–20t, 20–50t, 50–100 t).

For the lognormal model, the response variable is the log transformed catches, the explanatory variables are essentially the same as the binomial model, except that (a) the *gear\_duration* was as an offset term (it means the effect is not estimated but assumed known); (b) vessel tonnage effects (including an intercept and a slope) were estimated separately within each vessel size category.

The models were implemented using the *glm* function in R (R Core team 2019). To obtain the annual index, the *predict* function was used to predict the probability of obtaining a positive catch (binomial) and the catch rate (lognormal) for each year/quarter, with other variables fixed at median or most common values (e.g. *gear\_duration* = 6 hours). The combined index is obtained by multiplying the binomial indices by the exponentially-transformed lognormal index. The resulting indices are shown in Figures Figure 6–Figure 9 for each for the four species. A selection of model diagnostics is given in Appendix A.

Two alternative modelling approaches were also experimented: Bayesian MCMC modelling and mixed effects models. Both models are based on the binomial-lognormal framework and were applied to the longtail tuna. The Bayesian model aims to obtain a MCMC approximation to the Bayes posterior of effects assuming to affect catchability and is presumably better to capture the variance/uncertainty of the abundance index (Medley et al. 2017). The Bayesian model was implemented using Stan software (Stan Development Team 2017). The resulting index for the longtail tuna is given in Appendix B.

The mixed effects model incorporated individual vessel effects as random effects (i.e. the effect of a vessel is equal to the sum of a fixed vessel size effect and a random effect). This is perhaps a more appropriate approach as the vessels in the CPUE dataset could be considered as a random sample of the 'vessel' population (the port sampling covered about 10% of vessels in the fishery). For the analysis, the CPUE dataset was reduced to include only vessels that that is above 3t (vessel size category 0-3t was dropped) and had conducted more than 10 fishing trips with at least one trip of positive longtail catches. The data was further restricted to the main fishing ground for longtail tuna (Hormozgan and Sistanan baluchestan Provinces). The model was implemented in Template Model Builder (Kristensen et al. 2016). The resulting index for the longtail tuna is given in Appendix C.





### 5.1 Longtail tuna



Figure 6: Standardised CPUE indices (year-quarter) for longtail tuna using the GLM Binomial-Lognormal models: (a) index from the binomial model on the presence/non-presence of longtail catch; (b) index from the lognormal model on the positive longtail catch rates; (c) combined index (over-laid with lognormal index).







# 5.2 Narrow barred Spanish Mackerel

0

Index (binomial)

0.2

Figure 7: Standardised CPUE indices (year-quarter) for narrow-barred Spanish mackerel using the GLM Binomial-Lognormal models: (a) index from the binomial model on the presence/non-presence of narrow-barred Spanish mackerel catch; (b) index from the lognormal model on the positive narrow-barred Spanish mackerel catch rates; (c) combined index (over-laid with lognormal index).





### 5.3 Kawakawa



Figure 8: Standardised CPUE indices (year-quarter) for kawakawa using the GLM Binomial-Lognormal models: (a) index from the binomial model on the presence/non-presence of kawakawa catch; (b) index from the lognormal model on the positive kawakawa catch rates; (c) combined index (over-laid with lognormal index).



5.4 Frigate





Figure 9: Standardised CPUE indices (year-quarter) for frigate tuna using the GLM Binomial-Lognormal models: (a) index from the binomial model on the presence/non-presence of frigate tuna catch; (b) index from the lognormal model on the positive frigate tuna catch rates; (c) combined index (over-laid with lognormal index).





### 6. DISCUSSIONS

The analysis represents the first attempt to explore options of standardising the catch effort data from Iranian coastal gillnet fishery to provide time series of abundance for neritic tuna species. The data collected from the port-sampling program provides ample information on vessel characteristics, gear effort, and spatial and temporal distribution of catches, which potentially allow abundance indices to be examined in a standardisation framework. The analysis indicated that standardised catch rates have distinctive trends over the time-period examined for the major neritic tuna species targeted by the Iranian drifting gillnet fishery: the index has declined for the longtail but has been increasing for the narrow-barred Spanish mackerel in recent years, and the index for kawakawa and frigate tuna showed a slight increasing, but overall stable trend. However, like most CPUE standardisations, it is difficult to verify whether the resulting time series can index the underlying stock without alternative, independent source of abundance information. The reliability of these indices depends mostly on whether various sources of variation in the catchability have been captured and correctly accounted for in the standardisation process. Below we briefly discussed some of the caveats of the data and analysis that might influence the interpretation of the resulting CPUE indices.

The analysis was based on data collected from the port-sampling program which adopted a stratifiedrandom design to ensure that the sampling covers approximately 10% of the vessels in each size category. As neritic tuna is migratory, and catches are seasonal, it would be useful to conduct a more detailed analysis on whether the data is representative of the fishery with respect to its spatial and temporal distribution. This would increase the confidence of using the data as a monitoring tool, in addition to deriving catch effort statistics for the fishery.

Limited data grooming was performed as part of the analysis, but more robust criteria need to be developed to remove and/or correct for inconsistency in the data. For example, the average daily gear duration for some trips are suspiciously low (even if the sailing time is considered), considering that the normal set time (between the deployment and hauling) is approximately 6 hours. There are some issues related to the fact that information is collated at trip level rather than for individual fishing events. For example, the information on fishing ground is known not to be very precise (and no location information if fishing offshore). With the introduction and implementation of VMS, the accuracy and availability of finer scale spatial information is expected to improve. Another complication arises from vessels fitted with multiple gears (e.g. gillnet and trap), and such vessels could register for one gear, but report catch effort under the other gear. It is understood that multi-gear vessels are not encouraged (or even permitted in some provinces) but they were very common, therefore some revisions to the data reporting system is perhaps needed to accommodate this. The panel number is another important effort variable, but the reported panel number may not have reflected what's used. Preliminary modelling of longtail tuna suggested there was almost no relationship between catch and panel number. This might be because the panel number is positively related to the vessel size which has been accounted for in the model.

Changes in targeting strategy attributes greatly to variations in CPUE and most standardisation analyses invested greatly in identifying targeting strategy. For the drifting gillnet fishery, in addition to the inshore-offshore fleet dynamics there is also differential targeting among the neritic tuna. Longtail tuna and Spanish mackerel are caught by the drift gillnet with different mesh sizes and the other species (frigate, kawakawa, king mackerel) are largely considered as bycatch. Different net materials (e.g. Monofilament vs. multifilament) are also used to target different neritic tuna species in different seasons. However, the effort data specific to the different types of gear configurations are not available so expert knowledge on possible changes in targeting will need to be explored to be fully understand the dataset.

The delta approach is used to explicitly account for the encounter probability of the species in the catch. This type of modeling generally requires a clear definition of the fishery sector that has a close





association of the species. For example, vessels or areas by which the species was seldomly caught may be considered as being irrelevant to the fishery. Given the time constraint, the GLM standardizations used all the data, and as a result, the binomial models estimated a very proportion of zero catches for each of the four neritic tuna species (up to 80, 90%, see Figures Figure 6–Figure 9). Clearly many of the 'zero' catches are 'false' zeros (if the fishers are targeting the species or regularly taking it as bycatch, it might be expected that they could at least caught a few fish during a fishing trip). The standardizations of longtail tuna using the mixed effects models provided a useful exploration of defining fishery that is more relevant to the species (by restricting to te Hormozgan and Sistanan baluchestan Provinces and to vessels larger than 3t).

The standardised index for longtail tuna showed a large decline since 2012. Discussions with fishers suggested a number of alternative interpretations on this trend. One relates to the market condition: the recent increase in demand and price for hairtail has prompted many fishers to switch from longtail tuna to hairtail fishing (using hooks). The other relates to fish behaviour: longtail tuna dwell both at the surface and the bottom and overtime they have adapted to the fishing strategy and some are able to swim under the gillnet panel to dodge the gear (as a result it has become more and more difficult to catch them). This behaviour (bottom-dwelling) also means it is difficult for smaller boats to catch longtail tuna as they usually deploy shallower net panels than large vessels.

There is a very strong seasonal pattern in the catch rates of Spanish mackerel, with the CPUE being high in winter, and low in summer (see Figure 7). Grandcourt (2011) suggested that there is a seasonal productivity cycle in the southern gulf which sees a reduction in the abundance of zooplankton and small pelagic species during the warm summer months, and the high CPUE coincided with reduced water temperatures and an increase in the abundance of the fish in winter. There maybe market factors too as it was suggested that fishermen were trying to avoid Spanish mackerel during summer because the meat quality was not good due to high sea temperature. The recruitment variability is also likely to be very high as the fishery is mainly based on the first two cohorts (Grandcourt 2011).

As a final point, the standardized indices derived from the Iranian coastal drift gillnet fishery are very unlikely to represent the abundance for the entire Indian ocean. Effort should also be made to develop indices for fisheries in other regions where suitable data are available (e.g. the Pakistan drift gillnet fishery). Nonetheless indices developed in this analysis could be incorporated in a biomass dynamic model or an integrated assessment model to further evaluate its utility as relative abundance indices for neritic tuna populations.

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Appendix A: Selected diagnostics from the GLM CPUE standardisation models

Figure A1: distribution of normalised residuals (left) and normal QQ plot (right) from the lognormal model for the longtail tuna.





Figure A2: distribution of residuals by year quarter, vessel size class, and fishing ground from the lognormal model for the longtail tuna.







Figure A3: Influence plots shows the annual distribution of number of trips by fishing ground (top) and vessel size class (bottom), as well as their influence on the predicted years effects from the lognormal model for longtail tuna.







Figure A4: Estimated vessel effects by vessel size class for the binomial model (left) and lognormal model (right) for the longtail tuna. The dots represent the proportion of longtail tuna in the catch (among four neritic tuna species) for individual trips (left), and the log catch rate (kg per hour) of longtail tuna (right).



Figure A5: distribution of normalised residuals (left) and normal QQ plot (right) from the lognormal model for the narrow barred Spanish mackerel.







Figure A6: distribution of normalised residuals (left) and normal QQ plot (right) from the lognormal model for the kawakawa.



Figure A7: distribution of normalised residuals (left) and normal QQ plot (right) from the lognormal model the frigate tuna.







Appendix B: CPUE standardisation using Bayesian MCMC modelling for longtail

Figure B1: Standardised CPUE indices (year-quarter) for longtail tuna using the Bayesian MCMC: (a) index from the binomial model on the presence/non-presence of longtail catch; (b) index from the lognormal model on the positive catch rates of longtail tuna.







## Appendix C: CPUE standardisation using random effects models for longtail

Figure C1: Standardised CPUE indices (year-quarter) for longtail tuna using the random effects model: (a) index from the binomial model on the presence/non-presence of longtail catch; (b) index from the lognormal model on the positive catch rates of longtail tuna.







Figure C2: Maximum likelihood estimates of individual vessels effects (modelled as random effects) from the mix effects models for the longtail tuna: (a) from the binomial model on the presence/non-presence of longtail catch; (b) from the lognormal model on the positive catch rates of longtail tuna.