SCIENTIFIC COMMITTEE
SEVENTEENTH REGULAR SESSION

Electronic Meeting
11-19 August 2021

Electronic monitoring for improved accountability in western Pacific tuna longline fisheries

WCPFC-SC17-2021/ST-IP-12

C.J. Brown, A. Desbiens, M.D. Campbell, E.T. Game, E. Gilman,
R.J. Hamilton, C. Heberer, D. Itano, K. Pollock

Marine Policy 132 (2021) 104664

Contents lists available at ScienceDirect

Marine Policy

journal homepage: www.elsevier.com/locate/marpol

Electronic monitoring for improved accountability in western Pacific tuna longline fisheries

Christopher J. Brown [a,*], Amelia Desbiens [a,1], Max D. Campbell [a], Edward T. Game [b], Eric Gilman [c], Richard J. Hamilton [b,d], Craig Heberer [e], David Itano [f], Kydd Pollock [g]

[a] Coastal and Marine Research Centre, Australian Rivers Institute – Coasts and Estuaries, School of Environment and Science, Griffith University, Gold Coast, Queensland 4222, Australia
[b] The Nature Conservancy, Asia Pacific Resource Centre, South Brisbane, Queensland 4101, Australia
[c] Pelagic Ecosystems Research Group and The Nature Conservancy, USA
[d] ARC Centre of Excellence for Coral Reef Studies, James Cook University, Townsville, Queensland 4811, Australia
[e] The Nature Conservancy, San Diego, CA, USA
[f] The Nature Conservancy, contractor, Honolulu, HI, USA
[g] The Nature Conservancy, Honolulu, HI, USA

ARTICLE INFO

Keywords:
Electronic monitoring
Longline fishery
Tuna
Bycatch
Elasmobranch
Joint species distribution model
Highly migratory species

ABSTRACT

The collection of accurate fisheries catch data is critical to ensuring sustainable management of tuna fisheries, mitigating their environmental impacts and for managing transboundary fish stocks. These challenges are exemplified by the western Pacific tuna longline fishery, who's management includes >26 nations, but is informed by critically low coverage of fishing activities by scientific observers. The gap in observer data could be filled by electronic monitoring (EM), but there are few trials that span multiple nations. A large-scale trial of EM systems on tuna longliners based in Palau, Federated States of Micronesia and the Republic of the Marshall Islands, is reported on. Comparisons are made of catch rates of market and bycatch species in corresponding EM, logbook and human observer data. Retained species were under-reported in logbooks by up to three times and discards of many species were not reported in logbooks. Discards identified in the EM data included threatened species such as marine turtles. Catch rate estimates from EM data were comparable to those estimated by human observers. EM data recorded a higher species diversity of catches than logbook data. Analysis of the EM data indicated clusters of bycatch that were associated with specific fishing practices. These results suggest further expansion of EM could inform improved management of both target and bycatch species. Ultimately greater coverage of EM data could contribute to reconciling debates in international stock allocation schemes and support actions to reduce the impacts of the fishery on threatened bycatch species.

1. Introduction

Fisheries management authorities rely on accurate catch records to determine controls on fishing effort, determine appropriate license fees, and to manage environmental impacts on bycatch species. Catch data recorded by scientific observers who are employed independent from the fishery operation provide more complete and accurate data than vessel-reported logsheet data [1–3]. Collecting accurate catch data for the highly migratory species caught in tuna fisheries poses additional challenges, because tuna fisheries operate over large areas, are at sea for long durations and often fish across multiple exclusive economic zones (EEZ). The multi-national longline fleet operating in the tropical waters of the western and central Pacific Ocean region exemplifies the complex catch monitoring issues: it has a footprint covering nearly half the Pacific Ocean, includes both local and distant water fleets, targets a diverse range of taxa with a multitude of fishing practices, and its management by the Western and Central Pacific Fisheries Commission (WCPFC) includes 26 jurisdictions as members and seven participating territories. Longline fleets typically have low observer coverage [4] and many fleets are not meeting the 5% minimum observer coverage rate recommended by the WCPFC [5,6]. There is therefore little fisheries independent data to validate self-reported logbook records. Consequently, regional

* Correspondence to: Griffith University, 170 Kessels Road, Nathan Queensland, 4111, Australia.
E-mail address: chris.brown@griffith.edu.au (C.J. Brown).
[1] Current address: School of Biological Sciences, The University of Queensland, Brisbane, Queensland 4072, Australia.

https://doi.org/10.1016/j.marpol.2021.104664
Received 3 February 2021; Received in revised form 9 June 2021; Accepted 21 June 2021
Available online 10 July 2021

assessments of endangered, threatened and protected species (e.g., [7,8]) are not representative of all fleets and geographies, so their findings may be misled by biased data inputs [9]. It is also unknown how much catch is discarded, whether the catch locations reported in logbooks are accurate, or how much catch is transhipped at sea [10]. Insufficient catch data is impeding environmentally sustainable management of the fishery and may compromise the management of stocks that are rapidly adapting their distributions in response to a changing climate [11].

Catch data for longline vessels is recorded in logbooks by ship captains, by human observers and recently by electronic monitoring (EM) systems. EM systems are increasingly being integrated into longline fishery monitoring [12], but there are few comparisons of their efficacy compared to other types of monitoring [13]. Evidence for their usefulness for science and compliance is needed to convince governments and regional fisheries management organisations to scale-up EM programs to cover entire fleets [10,12]. EM systems have been trialled in several locations [14], including on western Pacific tuna longline vessels [10,15,16]. Trials on tuna pelagic longliners suggest that EM is able to collect most data fields that are needed for fishery monitoring [10,15], but the cost of the systems and data review, the logistics of installation and remote diagnostics and maintenance have hindered further expansion of EM programs. Analysis of data from multiple fleets is needed to evaluate their usefulness to management and inform governments on whether these systems should be adopted for catch data collection. But to date, comparisons of EM and logbook data on Pacific longliners have been limited to a few trips, and cross-nation comparisons are lacking.

This study analysed data from a large-scale EM trial that commenced in 2016 and is ongoing: The Nature Conservancy-Pacific Islands Cooperative Longline EM trial [12]. The trial collected data from 98 longline fishing trips that ranged from weeks to months in length and across the EEZs of three Western-Pacific island nations: Republic of Palau, Republic of the Marshall Islands and the Federated States of Micronesia. Conventional human observer coverage rates on longline vessels licensed to fish in these countries are extremely low, and little is known about catches beyond what is recorded in mandatory self-reported logbooks and the sparse observer data collected to date [17]. Previous technical reports have indicated EM detects higher rates of discards, market species and greater species diversity than logbook data [18], but these trials were limited to a few trips. Further most longline trials in the Pacific have used <10 vessels and have not compared across different EEZs [13]. The new data analysed here includes 98 trips across 15 vessels and 3 EEZs. The aims were to (1) estimate differences between EM and logbook reporting rates for the main market tuna species (yellowfin, bigeye and albacore) and key bycatch groups (all species other than the main targeted tuna species, including sharks, turtles, billfish and other fish species), (2) compare catch rates in EM to human observer data, (3) compare EM and logbooks for species composition, (4) investigate whether EM can inform bycatch mitigation by looking at how fishing practices affect clustering of bycatch within sets, and (5) explore the representativeness of the current EM trials, to make suggestions for the utility of EM to improve monitoring coverage of different fleet components.

2. Methods

2.1. Data collection

Data were collected by EM analysts working for national fisheries agencies with funding support from the TNC Pacific Islands Cooperative Longline EM project. The TNC-Pacific Islands Cooperative Longline EM Project initiated in 2016 for pelagic tuna longline fisheries operating in the Republic of the Marshall Islands (RMI), Republic of Palau and the Federated States of Micronesia (FSM) exclusive economic zones (EEZ). Fleet characteristics varied across the EEZs. In Palau EM systems were deployed on Taiwanese flagged vessels based in Koror, Palau and on Japanese flagged vessels based in Naha, Japan. Both Palau EM fleets serviced the fresh fish market and fished in the Palau EEZ and adjacent high-seas zones. The Japanese data set only included information from fishing that occurred within the Palau EEZ per licensing agreement with Japan. In FSM, only large vessels with ultra-low temperature freezer capacity that were undertaking long trips had EM installed. Smaller locally based vessels operating in FSM that service fresh fish markets were not covered. In RMI, vessels were of similar capacity to FSM, but fishing for the fresh tuna market (generally making trips of ~2 weeks). The EM annotated data and the associated logbook data for the trips under review were authorized for release by the country's Fisheries Authorities. The Pacific Community (SPC) then provided data for EM, log sheet and observer data from their regional databases.

The EM equipment, supporting software, and remote diagnostics and maintenance were provided by Satlink LLC and consisted of their Sea Tube Lite EM system (Fig. 1) with central processing unit and monitor located in the vessel wheelhouse, 3–4 high resolution digital video cameras, and a standalone VMS/GPS antennae that provided independent watermarked stamps of date, time, and location on each video frame. The cameras were configured to cover the areas of normal fishing activities and record continuously (24/7) with fields of view including: (i) the setting station at the stern, (ii) the processing station in front of the wheelhouse looking towards the bow, and (iii) hauling station astern of the bow bulkhead. A fourth camera mounted at a high vantage point could capture transhipment and rendezvous events, though those data were not analysed here. The raw videos and associated meta-data files were stored on mechanical hard disk drives. Videos were converted to annotated data sheets in country by EM analysts. These EM analysts were experienced fisheries observers certified by the Pacific Islands Regional Fisheries Observer Programme and who were trained by the Digital Observer Service (a subsidiary of Satlink) in the Sat View Manager Review Software.

For each fishery, all available set-level EM data was matched to logbook data obtained from SPC using the vessel name, trip start date and set start time (Table 1). For RMI there were also human observer data, (566 sets, with 474 human observed sets matching logbooks data and 92 sets having EM, logbooks and human observer collected data). Fishing sets were matched by the commencement of the setting operation being initiated on the same day. Occasionally there were two sets which commenced on the same day, in this case they were matched using the time of day they were initiated. Sets that could not be reliably matched were excluded from the analysis that compared logbook, human observer and EM catch rates. All EM data were used in the analysis of bycatch species clusters.

Both the depth of sets and the time of day can influence catch rates of different taxa [17,19]. There were no data on fishing depth, however hooks between floats is often used as a proxy for depth. Only Palau showed variation in hooks between floats, having two clusters of sets with either <7 or >15 hooks between floats. Therefore, deep sets were defined in Palau as having more than 15 hooks between floats [17], though hooks between floats is an imperfect proxy of fishing depth (e.g., [20]). In Palau 33 of 110 sets had <7 hooks between floats, all other sets had more than 15 hooks between floats. In Palau, deep sets were generally initiated in daytime, shallow sets at night-time. Time of day of initiating the set varied across the other EEZs. The majority of sets were initiated in the early morning for vessels fishing in the FSM and Palau EEZs, and initiated in late afternoon for the RMI EEZ.

2.2. Aims 1 and 2: comparison of EM, human observer and logbook reporting rates

Differences in reporting of retained catch of target market tuna species (hereafter main target species) and differences in bycatch taxa for the matched logbook and EM data were analysed. The RMI comparisons, additionally included any sets that had matched logbook and human at-sea observations. The main tuna species retained were bigeye tuna, yellowfin tuna and albacore. Bycatch was aggregated into four

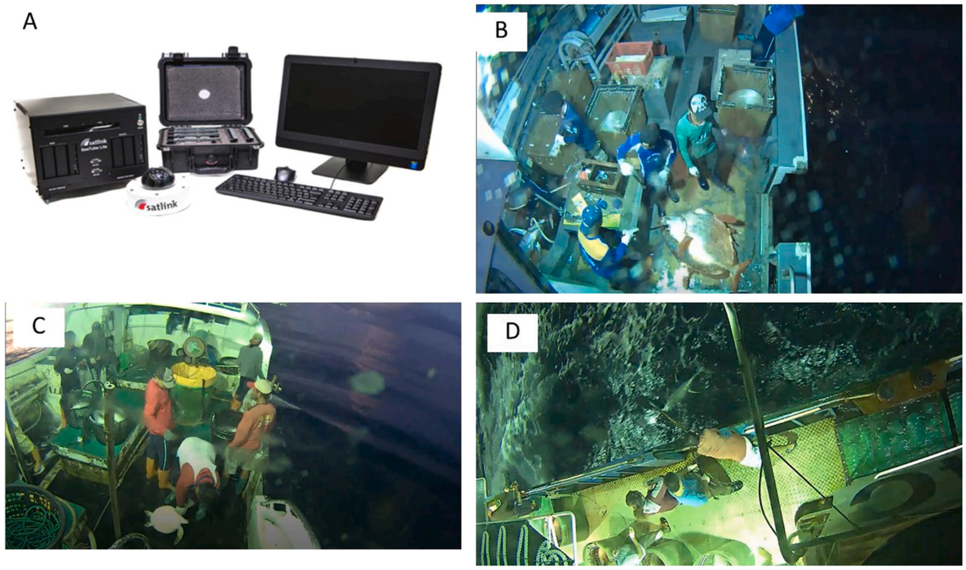


Fig. 1. The Satlink Seatube Lite EM System (A); example images of the EM system: Working deck camera, showing catch of opah (B); working deck camera showing catch of marine turtle (C); and catch of a yellowfin tuna (D).

Table 1
Sample sizes for matched logbook and EM sets. Values in brackets indicate total EM sample size, including sets that could not be matched to logbook records.

Exclusive economic zone	Vessels	Trips (total)	Sets (total)	Dates
Palau	5	13 (13)	108 (110)	Sep 2016 - Apr 2017
Federated States of Micronesia (FSM)	4	5 (8)	195 (363)	Nov 2016 - Apr 2017
Republic of the Marshall Islands (RMI)	6	73 (77)	749 (782)	Feb 2017 - Sep 2018

groups; billfish, sharks, turtles and other bycatch, because the sample size of the EM data was not sufficient to estimate species-specific differences in catch rates. For each bycatch group rates of retained and non-retained (escaped or discarded) catch were estimated.

Models for catch rates were estimated with Bayesian generalized linear mixed effects models fitted for each species and EEZ. The models had as a response the catch of each species group per set per observation method (EM, human or logbook). A fixed effect for observation method was included, to enable a direct estimate of the difference in reporting rate. For Palau, a fixed effect for set depth (deep versus shallow) was also included. The data were not balanced enough across times of day in any EEZ to include an effect of time of day.

The models had an offset for the number of hooks per set, so estimates were presented as catch rates (per 1000 hooks). Sets and trips were modelled as independent identically distributed random effects, to account for clusters of catch by sets and trips. The final model had the form:

$\ln(\text{Catch per set}) = \text{hooks} + b_1 * \text{method}[\text{EM or logbook}] + b_2 * \text{depth} + z_{set} + z_{trip}$.

The models used either Poisson or Negative Binomial error distributions for their residuals. Weakly informative priors for the fixed effects were used (normal mean 0, SD = 10). Student-t prior (with parameters 10, 0, 1) was used for the standard deviations of random effects. Model fits were verified with plots of Dunn-Smyth residuals [21] and empirical semi-variograms were used to verify there was no spatial autocorrelation. The best model for each taxa and EEZ was selected as the model with the lowest WAIC [22].

Models were fitted using the Bayesian Regression Models using Stan R package ('brms' [23]). Bayesian estimation was performed with the Hamiltonian Markov chain no U-turn sampler, fitting each model with four chains, performing 3000 samples as the burn-in and then 3000 samples for estimation. Convergence was checked using standard visual diagnostics and by confirming the Rhat statistic was <1.01 for all parameters.

2.3. Aim 3: species identification

Patterns in species level identifications were comparing graphically for matched logbook and EM sets. To summarize this analysis, graphs were made of the total number of species in logbooks and EM and also the difference in number of species seen on matched sets.

2.4. Aim 4: clustering of bycatch

The fourth aim sought to identify whether the EM data could support bycatch mitigation measures, like spatial or temporal closures or changes to fishing practices. Multivariate models were constructed to identify clusters of bycatch and market species catch. Ideally the modelling would include covariates relating to drivers of bycatch (e.g., [17,19]), however for most EEZs there was not sufficient data on fishing practices to do this. Therefore, correlations among catches of species groups were estimated, where strong positive correlations among groups indicate clustering of catches for those groups on particular sets. Such clustering may be indicative of fishing certain practices. All EM data were used in this analysis (Table 1), as opposed to Aim 1 where only matched sets were used. This larger sample size meant it was possible to model a finer taxonomic resolution than for Aims 1 and 2. Species level data were used where possible, but species were combined by higher order taxonomic groups if there were less than 20, 40 and 80 individuals for Palau, FSM and RMI respectively. This aggregation was done to ensure reliable model parameter estimates, but resulted in differences in species grouping among countries. The species or groups of discards were: blue shark (*Prionace glauca*), silky shark (*Carcharhinus falciformis*), thresher sharks (*Alopias* spp.), mako sharks (*Isurus* spp.), other sharks, marine turtles, billfish and other groups (whales, birds, fish, etc.). Included market catch consisted of yellowfin (*Thunnus albacares*), bigeye (*T. obesus*), skipjack (*Katsuwonus pelamis*), albacore (*T. alalunga*), oilfish (*Ruvettus pretiosus*), swordfish (*Xiphias gladius*), shortbill spearfish (*Tetrapturus angustirostris*), black marlin (*Makaira indica*), blue marlin (*Makaira nigricans*), striped marlin (*Kajikia audax*), wahoo

(*Acanthocybium solandri*), snake mackerel (*Gempylus serpens*), dolphin fish (*Coryphaena hippurus*), great barracuda (*Sphyraena barracuda*), Indo-Pacific sailfish (*Istiophorus platypterus*), Sickle pomfret (*Taractichthys steindachneri*), opah (*Lampris guttatus*) and escolar (*Lepidocybium flavobrunneum*). Marine turtles were grouped for analysis, rather than reporting individual species, because turtle catches were rare and it can be difficult to identify species if the shell is not presented to the camera.

Correlations among catch of taxa were estimated by fitting multivariate generalized linear models to all EM data for each country. Estimation was performed with Bayesian ordination and regression models [24]. These models construct multivariate ordinations that represent correlations among catch of different taxa. For each EEZ, multiple models were fitted with all combinations of 2–5 latent variables and Poisson and negative binomial distributions for the catch data. The Palau models also included fixed effects for set depth (77 deep versus 33 shallow sets) and initiating time, where time was classified into two categories: morning/daytime (5:00 – 15:00, 85 sets) versus afternoon/night (15:00 – 05:00, 25 sets). The set times were for initiation time only, and do not reflect different soak times, for which there was no data in the logbooks. Together, set times and depths may reflect different fishing practices, because most deep sets were in the morning/day category (69 sets) and most shallow sets were in the afternoon/night category (17 sets). For FSM and RMI the sets all had similar initiation times and hooks between floats, so there was not enough variation in the data to include fixed effects for fishing practices.

All models included trip as a random effect. Estimation was performed with a Gibbs Sampler [25], using a burn-in of 10,000 samples, followed by 80,000 iterations, thinning for every 30th sample. The optimal model for each EEZ was selected based on two considerations: (1) visual inspection of each model's Dunn-Smyth residuals to verify model fits; (2) model complexity, where simpler models were preferred to more complex models if the differences in Dunn-Smyth residuals were minor. Results for the correlations among catches not attributable to fixed effects were visualized with ordination plots [26]. The magnitude of the fixed effects was plotted with medians and 95% credible intervals.

2.5. Aim 5: representativeness of EM data

The catch rate estimates and bycatch estimates using EM were contingent on several assumptions. Importantly, they assume that the EM trials are a representative sample of all sets and trips. To check for representation bias, hooks and trip duration as reported in logbook data by trips with and without EM were compared. Vessel length was also compared between all logbook data and EM data, for vessels that had this data available, because vessel length is one indicator of fishing practices for which data are widely available [27].

3. Results

3.1. Aims 1 and 2: comparison of EM, human observer and logbook reporting rates

Overall catch rates for retained market species (albacore, bigeye and yellowfin tunas), and retained bycatch of billfishes and sharks were similar across the three EEZ's (Fig. S1). For all EEZ's the primary tuna species retained were yellowfin and bigeye, with 2–4 fish per 1000 hooks on average (Fig. S1). The higher catch rates of these tuna when compared to other species indicated that they were the main target species, for example, retained billfish catches were <1 fish per 1000 hooks and albacore catches were <1 fish per 10,000 hooks (Fig. S1).

Set-level analyses revealed considerable discrepancies between logbook and EM catch rates on a per-set basis (Fig. 2). The highest rate of under-reporting for the presumed target tuna was for yellowfin in Palau and RMI (up to 1.3 times higher in EM than logbooks). Reporting of retained billfish was generally close between logbooks and EM, except for Palau where EM had 2 times as much billfish as logbooks.

Discards of tuna, billfish and turtles were almost never reported in logbooks, though EM and human observers did observe discards for these taxa (Fig.S2). Discard rates were comparable to rates of retained catch, for instance rates of shark discards in the Palau fishery were up to 2 sharks per 1000 hooks on average. Turtle discards were also higher in Palau than the other EEZs (up to 0.5 turtles per 1000 hooks on average). When comparing Palau's EM and logbook data, the shark discard rate was estimated to be 7.7 times higher (Fig. 2). Shark discards were reported in the FSM and RMI logbooks, and the rates were not different from those estimated by EM. A single shark was reported retained by EM and human observers in RMI (Fig. S1).

Catch rates estimated from human observers in RMI were similar or slightly lower than estimates from EM data (Figs. 2, S1, S2). Human observers reported lower catch of yellowfin relative to logbooks (0.87 of logbook catch rates, compared to EM which reported higher catch at 1.22 times logbook catch rates). Human observers also had lower estimates of catch rates of the 'other' bycatch category compared to EM (Fig. 2).

3.2. Aim 3: species richness and diversity

Logbooks consistently reported fewer species and species groups than EM data (Fig. 3A). EM data averaged 8–10 species per set by EEZ,

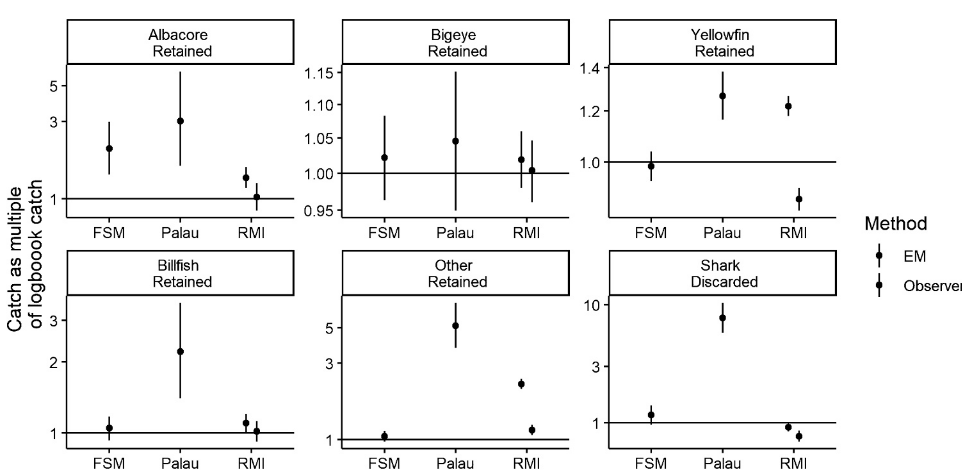


Fig. 2. Differences in catch rates of market and bycatch species groups for matched EM and logbook sets (multiples). Points show median, bars show 95% credible intervals. Note, y-axis changes between panels.

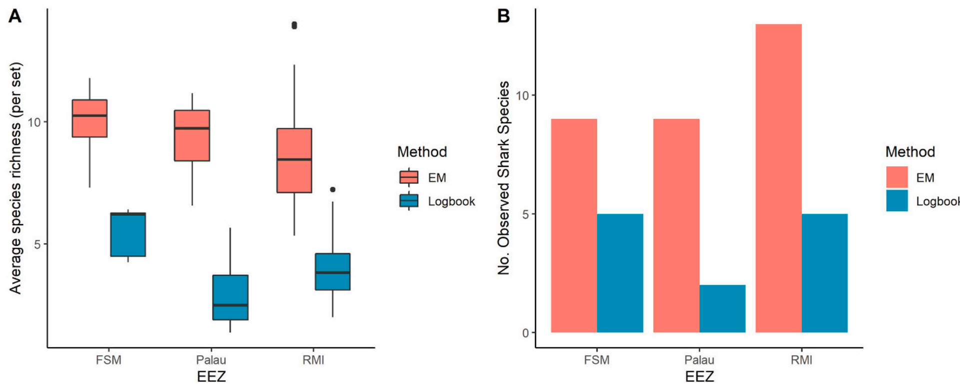


Fig. 3. Boxplot of average species richness per set (A) and total number of shark species per EEZ (B). In (A) boxes show median and interquartile range for average species richness across different sets within a trip.

whereas logbooks always reported less than eight species and typically reported only five species. Across the entire dataset for each EEZ, logbooks reported at most five different shark groups, whereas EM reported up to 12 (Fig. 3B). EM records included catches of oceanic whitetip shark that were not in the logbook data, though catches of this species were rare (Table S1). Counts of individuals per species suggested that logbooks were reporting most shark catch as blue shark and most billfish catch as blue marlin, because there were higher rates of catch of these species in logbooks than EM, but lower rates of other species in logbook than EM (Fig. S3). Logbooks generally did not report catches of lancetfish, pomfrets, escolar and pelagic stingray.

Turtle species observed in the EM data included leatherback, hawksbill, olive ridley and green turtles (Table S1). There were two recordings of false killer whale entanglement, both cut free and released alive (Table S1).

3.3. Aim 4: clustering of bycatch

The multivariate models selected for analysing patterns of EM catch had three latent variables in each of the EEZs (Table S1). Models for RMI and Palau included fixed effects for the initiation time of sets and the Palau model additionally included a fixed effect for set depth.

For Palau set depth and time of day together explained 33% of variation in catch patterns. Shallow sets had higher catch rates of turtles and escolar (LEC) (Fig. 4A). Deep sets had higher catch rates of blue shark, bigeye tuna and a weak trend towards catching more thresher sharks when compared to shallow sets. Time of day was less important for explaining differences in catch in Palau than set depth, but there were trends towards catching more skipjack and thresher sharks on sets initiated in the morning/daytime (which tended to be deeper) and more oilfish and silky sharks on sets initiated in the afternoon evening (which also tended to be shallower) (Fig. 4B).

For Palau, there were residual patterns in catch after the fixed effects were accounted for, with thresher sharks and swordfish clustering together, against skipjack, oilfish and escolar (Fig. 5A). Yellowfin catch had a weak negative correlation with blue shark and silky shark catch. Swordfish, bigeye tuna and thresher sharks tended to co-occur on the same sets. For RMI, there was clustering of albacore and bigeye on some sets versus silky and other shark catch on other sets (Fig. 5B). Blue shark and pomfret (TST) catch were strongly positively correlated, and negatively correlated with turtle catch. Turtle catch was not correlated with catch of the main target tuna species. FSM had highest catch rates of billfish when compared to the other EEZs (Figs. S1 and S2), enabling the model to distinguish a positive correlation between blue and black marlin catch rates and a negatively correlation with those groups and swordfish (Fig. 5C). Bigeye tuna catch rates were negatively correlated with silky shark catch rates.

3.4. Aim 5: representativeness of EM data

Trips with EM systems were broadly representative of all trips when comparing variables recorded in logbooks, including average hooks per set, hooks between floats and trip duration (Fig.S4–7). One exception was for FSM, where the duration of trips with EM was on average much longer than the 75th quantile for trip duration of non-EM trips. The EM trips were representative of the range of vessel lengths in all EEZs except for RMI. In RMI, EM trips were exclusively on large vessels, but all vessels were in the 20–30 m length range (Fig. S4).

4. Discussion

Large differences were identified in reporting of market species catch and bycatch between logbook and EM data. For example, estimates of yellowfin catches calculated from EM were up to 1.3 (30%) times higher

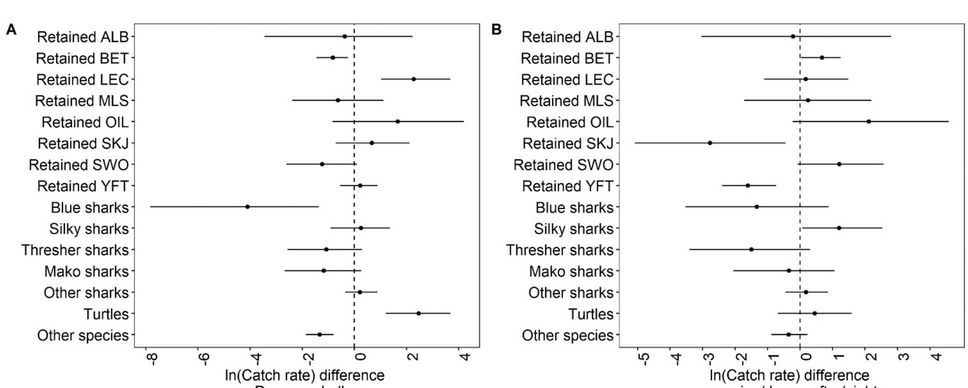
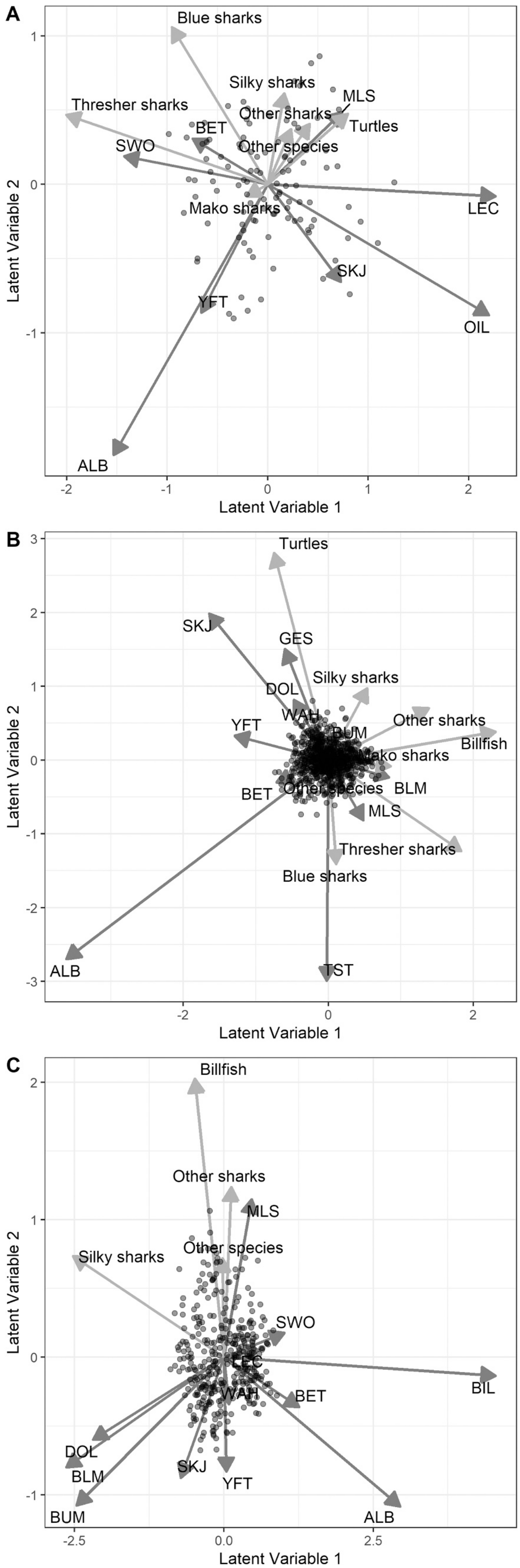


Fig. 4. Effect of set type on catch rates for Palau deep versus shallow sets (A) and time of the start of the set (B). Positive values indicate greater catch rates on shallow sets versus deep sets (A) and, afternoon/night versus morning (B). Points show median estimates and bars 95% C.I.s. Species codes: SKJ: skipjack tuna, ALB: albacore tuna, YFT: yellowfin tuna, BET: bigeye tuna, DOL: dolphinfish, SWO: swordfish, BUM: blue marlin, BLM: black marlin, BIL: other billfish, MLS: striped marlin, OIL: oilfish, LEC: escolar, TST: sickle pomfret, GES: snake mackerel.



(caption on next column)

Fig. 5. Ordinations showing residual correlations among of catch of taxa for Palau (A), RMI (B), FSM (C). Vectors pointing in the same direction indicate positive correlations between groups, orthogonal vectors have no correlation and vectors in opposite directions show negative correlation between groups. The length of the vector indicates the amount of variation in that direction. Dark grey arrows show retained catch, light grey arrows discarded catch. Species codes: SKJ: skipjack tuna, ALB: albacore, YFT: yellowfin, BET: bigeye tuna, DOL: dolphinfish, SWO: swordfish, BUM: blue marlin, BLM: black marlin, BIL: other billfish, MLS: striped marlin, OIL: oilfish, LEC: escolar, TST: sickle pomfret.

than catch estimates calculated from logbooks. This pattern was even more pronounced for discarded bycatch in some EEZs. In Palau estimates of shark discards calculated from EM were almost 8 times higher than estimates obtained from logbooks. EM observations from all EEZs also had much higher species diversity. These results are consistent with some earlier studies that found logbooks under-report discards and retained catch, relative to EM or human observer data [2,3,28].

The congruence between logbook and EM estimates of catch rates varied across species and geographies and notably, catch rates of sharks in FSM and RMI were similar between EM and logbooks. The higher congruence in FSM and RMI than Palau may reflect better attention paid to noting catch in the logbooks as part of the Marine Stewardship Council certification criteria for these fleets. Palau may also have lower rates of reporting sharks, because catch rates of sharks were much higher there (therefore it is more work for the fishing master to report the greater catch). Other EM studies have also reported variation in congruence between EM and logbooks across species. In Australia's Eastern Tuna and Billfish fishery, logbooks tended to report greater catches and interactions with threatened species than EM data, suggesting that logbook records were more accurate than EM [29]. The difference between the present study and the Australian case may relate to the auditing of logbook catches with EM data in Australia and strict penalties if reporting standards are not met. It could also relate to differences in training of vessel captains to properly complete logbooks. In Australia it was also found that changes to the positioning of cameras and the experience of EM analysts improved catch detection and species identification by EM over time [29]. As similar experience gains are made in the analysis of EM data from Palau, RMI and FSM one could therefore expect an increasingly large discrepancy between EM and logbook catch rates. The magnitude of underreporting reported here highlights existing knowledge gaps that may impact the sustainability and well-informed management of western pacific longline fisheries, and provides further support for increased electronic or human monitoring of longliner catch.

The extent of underreporting of the main target species landings has implication for stock assessments that use logbook data. The magnitude of underreporting in logbooks may be an issue if discards mean species managed with catch limits are underreported, in particular bigeye tuna which has a catch limit [30]. Under-reporting can also bias estimation of trends and stock status if certain conditions are met, in particular that there are temporal trends in the proportion of unreported catch [31]. The bigeye tuna stock assessment findings could be vulnerable to such trends if they exist, because it relies on fisheries-dependent datasets [32]. Stock assessments for shark species have also suffered from data quality constraints. For instance, a main finding from the Pacific-wide silky shark assessment was that the available data sources were too inconsistent for a complete assessment of stock status [33]. A standardized observer or EM data source could help overcome this issue. Expanding EM coverage across regions and importantly, across years, would enable more accurate estimation of multiyear trends in catch and CPUE. This could thus support more accurate reporting of catch against sustainable stock management targets and support more precise catch regulations. EM could also bring economic benefits to countries through more accurate charging of revenues for access rights, quotas and effort-based fees.

Global concern has been raised on impacts of longline tuna fisheries on vulnerable and threatened bycatch species [34]. In this study the EM data provided much more detailed information on species composition of bycatch than logbooks, and greater detail on species composition could be used to inform ecological risk assessments (e.g., [35]) and monitor regional conservation measures. For instance, discarded catch of oceanic whitetip shark and silky shark was observed. Oceanic whitetip sharks are critically endangered in the Pacific Ocean [7,36] and the WCPFC has declared a non-retention Conservation Management Measure for both species [6]. Further action to prevent catch of species of conservation concern requires detailed data on catch rates for different fishing practices, locations and times [35]. For instance, shallow sets in Palau were more likely to catch turtles, information that could be used to inform conservation management measures for turtles. Such analyses are supported in places with high observer coverage rates, but such high coverage is often difficult to achieve because of the programmatic and operational complexities of deploying scientific observers [37]. Thus, EM may be the only feasible way of obtaining more accurate bycatch estimates that can be used to inform mitigation and management measures.

This study can only provide limited information to inform catch mitigation measures, but these early results are encouraging. For instance, in RMI and FSM the EM data on hooks between floats did not suggest much variation in fishing depth, so we could not conduct comparisons of how fishing depth affected bycatch rates. The multivariate model used to analyse the EM data did allow detecting clustering of species catches on sets. This clustering indicated that there are environmental or fishery factors that could predict catch patterns. Future EM trials could be improved by expanding the fields collected by EM, for instance by collecting data on bait types [10,15], or through technology that measures additional environmental variables like sea temperature [38]. This would allow more precise estimation of how fishing practices affect catch rates and species compositions, such as how fishing daylight versus night-time hours affects shark catches.

Electronic monitoring data also enables more comprehensive monitoring of conservation actions within national waters. For example, in this study considerable discards of sharks were observed within the three EEZs, which are all shark sanctuary areas in which targeting and retention of sharks is prohibited [39]. Furthermore, retention bans have been shown to reduce catch rates of sharks but, as expected, increase discarding [40]. Greater EM coverage could provide the data needed to monitor the long term impacts of shark sanctuary policies in meeting the objective of reducing shark fishing mortality, and inform on further actions that could be taken, such as trade bans or prescribed use of fishing gear practices that reduce shark catch [39]. For example, the clustering of shark catches on some sets indicates that gear, spatial or temporal restrictions could prevent clusters of shark catch. The large area of Pacific Island Nation EEZs also means enforcement of sanctuaries is difficult. The granular level data that results from EM, when combined with new technologies, including broader based satellite monitoring data, could aid in more efficient enforcement of shark sanctuaries [41]. Longer term data could also be used to track repeat offenders, and perhaps consider exclusion of those vessels from future fishing opportunities in the EEZ [41], or to identify how handling practices could be improved to increase discard survival rates. Expanded coverage that is representative of fleet characteristics (particularly in FSM) and the spatial distribution of fishing is needed to investigate the effectiveness of alternative policy options for reducing shark capture.

The catch rates of key taxa were compared between human observers and EM data in RMI. It was found that EM tended to have much higher catch rates of yellowfin tuna than the human observer data. The reason for this difference is not clear. It may be that species identification of tuna was more accurate on EM than for observers, because the EM can review and re-review the image from multiple angles. Alternatively, EM analysts could be misidentifying small bigeye tuna as yellowfin, because the two species look similar as juveniles. Differences in the ease of counting hooks could also influence catch rate estimates. The misidentification of species that look similar has been an issue in other EM trials on longliners and it can be particularly difficult to identify species that are discarded from video images alone [29]. For instance, the EM data studied here reported hawksbill turtles. It is possible that the hawksbill observations are misidentification of juvenile green or olive ridley turtles. An advantage of the EM data over human observer data is that videos can be reviewed to check species identification and audited to standardize training of EM analysts. Future studies should prioritise the collection of paired EM-human observer data, so that biases in the two data sources can be more accurately characterized.

The presence of EM or human observers on vessels may modify fishers' behaviour [1,41,42], and bias EM catch records. It did not appear that vessel behaviour was significantly affected by the presence of cameras, because there was no evidence for any systematic patterns in comparisons of trip length and fishing practices across trips with and without EM systems. Further, in RMI and FSM, vessels already have CCTV cameras on-board, so crews are used to being recorded while working. Anecdotal evidence from the Nature Conservancy-Pacific Islands Cooperative Longline EM trial team suggests the crews change their behaviour for the first few weeks of EM deployment, then revert to 'normal' practices. However, the data available in this study cannot determine if crew behaviour was changed by the EM, for instance, crews may have been less likely to retain sharks when cameras were on board. Further, the agreements in trial meant there were no legal ramifications for non-compliance identified by the EM. Crew and fisher behaviour may change if there were legal ramifications. Issues with EM biasing behaviour could be overcome with 100% EM coverage and random sampling of EM imagery [15]. An advantage of EM over human observers is that it is feasible to reach 100% monitoring coverage and so overcome the bias that observer presence may have on fisher behaviour.

A primary impediment to expanding EM coverage in the Pacific is the cost of the system, its installation, maintenance and EM data review. Further, component failures can be challenging to repair in the western Pacific, because replacement parts or maintenance teams may not be available when and where vessels call to port. Thus, system failure can result in EM systems being non-operational for extended periods of time. Further work is needed to find ways to reduce the cost of EM data collection and analysis and streamline the logistics of system diagnostics and maintenance. For instance, maintaining high coverage would require local EM service providers to be stationed in key western Pacific ports. Cost savings can also be found in the review of EM data. Human observer coverage can be optimized to management objectives with the highest coverage levels required for detection and analysis of rare species catch rates [14,43]. Automated video analysis with machine learning tools can also reduce the cost of analysing EM video by selecting for catch or monitoring events of interest for careful video review and skipping imagery of no management interest [13].

The present study analysed EM data from three Pacific EEZs and found that EM systems have significant potential to improve monitoring and inform management of target and bycatch species on western Pacific longline vessels. The EM systems provided data that was complementary to human observers, had more detailed identification of species than logbook data and reported higher catch rates of market and bycatch species than logbook data. EM could support the enhanced observer coverage that is needed to inform international fishery agreements, especially as highly migratory fish stocks shift distribution under climate change [11]. Given the recognized constraints in substantially increasing current observer coverage rates, an increased use and reliance on EM seems like the prudent path to pursue.

Conflicts of interest

We confirm that we have not declarations of interest.

Acknowledgements

A grant from The Nature Conservancy supported CJB, MH and MC. We are grateful to the Republic of Palau Ministry of Natural Resources, the Marshall Islands Marine Resources Agency and the Federated States of Micronesia National Oceanic Resource Management Authority for granting permission to access the EM, logbook and observer data. The authors would like to recognize the Pacific Island EM Coordinators and the respective EM analysts who spent countless hours reviewing the video footage and annotating the data used in this study. Their work has been instrumental in paving the way for scaling up use of EM as a recognized and legitimate monitoring tool. The manuscript also benefited from a review by SPC staff for which we are very grateful.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.marpol.2021.104664.

References

[1] T.J. Emery, R. Noriega, A.J. Williams, J. Larcombe, Changes in logbook reporting by commercial fishers following the implementation of electronic monitoring in Australian Commonwealth fisheries, Mar. Policy 104 (2019) 135–145.
[2] W.A. Walsh, R.Y. Ito, K.E. Kawamoto, M. McCracken, Analysis of logbook accuracy for blue marlin (Makaira nigricans) in the Hawaii-based longline fishery with a generalized additive model and commercial sales data, Fish. Res. 75 (1–3) (2005) 175–192.
[3] W.A. Walsh, P. Kleiber, M. McCracken, Comparison of logbook reports of incidental blue shark catch rates by Hawaii-based longline vessels to fishery observer data by application of a generalized additive model, Fish. Res. 58 (1) (2002) 79–94.
[4] E. Gilman, K. Passfield, K. Nakamura, Performance of regional fisheries management organizations: ecosystem-based governance of bycatch and discards, Fish Fish. 15 (2) (2014) 327–351.
[5] T. Peatman, L. Bell, V. Allain, S. Caillot, P. Williams, I. Tuiloma, A. Panizza, L. Tremblay-Boyer, S. Fukofuka, N. Smith, Summary of longline fishery bycatch at a regional scale, 2003–2017, in: 14th Meeting of the Scientific Committee of the Western and Central Pacific Fisheries Commission, WCPFC-SC14, Busan, Republic of Korea, 2018, pp. 8–16.
[6] J. Rice, L. Tremblay-Boyer, R. Scott, S. Hare, A. Tidd, Analysis of stock statusand related indicators for key shark species of the Western Central Pacific Fisheries Commission, Western and Central Pacific Fisheries Commission 11th Regular Session, 2015, pp. 1-146.
[7] C.L. Rigby, R. Barreto, J. Carlson, D. Fernando, S. Fordham, M.P. Francis, K. Herman, R.W. Jabado, K.M. Liu, A. Marshall, N. Pacoureau, E. Romanov, R.B. Sherley, H. Winker, Carcharhinus longimanus. The IUCN Red List of Threatened Species, 2019.
[8] R.B. Sherley, H. Winker, C.L. Rigby, P.M. Kyne, R. Pollom, N. Pacoureau, K. Herman, J.K. Carlson, J.S. Yin, H.K. Kindsvater, Estimating IUCN Red List population reduction: JARA—A decision-support tool applied to pelagic sharks, Conserv. Lett. 13 (2) (2020), e12688.
[9] J.M. Molina, S.J. Cooke, Trends in shark bycatch research: current status and research needs, Rev. Fish. Biol. Fish. 22 (3) (2012) 719–737.
[10] T.J. Emery, R. Noriega, A.J. Williams, J. Larcombe, S. Nicol, P. Williams, N. Smith, G. Pilling, M. Hosken, S. Brouwer, The use of electronic monitoring within tuna longline fisheries: implications for international data collection, analysis and reporting, Rev. Fish Biol. Fish. 28 (4) (2018) 887–907.
[11] E. Mendenhall, C. Hendrix, E. Nyman, P.M. Roberts, J.R. Hoopes, J.R. Watson, V. W.Y. Lam, U.R. Sumaila, Climate change increases the risk of fisheries conflict, Mar. Policy 117 (2020), 103954.
[12] M. Michelin, M. Zimring, Catalyzing the Growth of Electronic Monitoring in Tuna Fisheries, CEA Consulting, The Nature Conservancy, San Francisco, 2020.
[13] A.T.M. van Helmond, L.O. Mortensen, K.S. Plet-Hansen, C. Ulrich, C.L. Needle, D. Oesterwind, L. Kindt-Larsen, T. Catchpole, S. Mangi, C. Zimmermann, H. J. Olesen, N. Bailey, H. Bergsson, J. Dalskov, J. Elson, M. Hosken, L. Peterson, H. McElderry, J. Ruiz, J.P. Pierre, C. Dykstra, J.J. Poos, Electronic monitoring in fisheries: lessons from global experiences and future opportunities, Fish Fish. 21 (1) (2020) 162–189.
[14] C.B. Wakefield, S.A. Hesp, S. Blight, B.W. Molony, S.J. Newman, N.G. Hall, Uncertainty associated with total bycatch estimates for rarely-encountered species varies substantially with observer coverage levels: Informing minimum requirements for statutory logbook validation, Mar. Policy 95 (2018) 273–282.
[15] E. Gilman, V.D.R. Castejón, E. Loganimoce, M. Chaloupka, Capability of a pilot fisheries electronic monitoring system to meet scientific and compliance monitoring objectives, Mar. Policy 113 (2020), 103792.
[16] M. Hosken, P. Williams, N. Smith, A brief update on ER and EM progress in theregion, WCPFC–Scientific committee thirteenth regular session, 9–17 August 2017, Rarotonga, Cook Islands, 2017.
[17] E. Gilman, M. Chaloupka, M. Merrifield, N.D. Malsol, C. Cook, Standardized catch and survival rates, and effect of a ban on shark retention, Palau pelagic longline fishery, Aquat. Conserv.: Mar. Freshw. Ecosyst. 26 (6) (2016) 1031–1062.
[18] M.H.V. Hosken, J. Agi, P. Williams, S. Mckechnie, D. Mallet, E. Honiwala, H. Walton, M. Owens, C. Wickham, E. Zaborovskiy, Report on the 2014 Solomon Islands Longline E-Monitoring Project, 2016. https://oceanfish.spc.int/.
[19] D. Bromhead, S. Clarke, S. Hoyle, B. Muller, P. Sharples, S. Harley, Identification of factors influencing shark catch and mortality in the Marshall Islands tuna longline fishery and management implications, J. Fish. Biol. 80 (5) (2012) 1870–1894.
[20] K. Bigelow, M.K. Musyl, F. Poisson, P. Kleiber, Pelagic longline gear depth and shoaling, Fish. Res. 77 (2) (2006) 173–183.
[21] P.K. Dunn, G.K. Smyth, Randomized quantile residuals, J. Comput. Graph. Stat. 5 (3) (1996) 236–244.
[22] A. Vehtari, A. Gelman, J. Gabry, Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC, Stat. Comput. 27 (5) (2017) 1413–1432.
[23] P.-C. Bürkner, Advanced Bayesian multilevel modeling with the R package brms, arXiv preprint arXiv:1705.11123, 2017.
[24] F.K. Hui, BORAL–Bayesian ordination and regression analysis of multivariate abundance data in R, Methods Ecol. Evol. 7 (6) (2016) 744–750.
[25] M. Plummer, JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling, in: Proceedings of the 3rd international workshop on distributed statistical computing, Vienna, Austria, 2003, pp. 1–10.
[26] F.K. Hui, BORAL–Bayesian ordination and regression analysis of multivariate abundance data in R, Methods Ecol. Evol. 7 (2016) 744–750.
[27] L. Campling, A. Lews, M. McCoy, The tuna longline industry in the Western and Central Pacific Ocean and its market dynamics, in: F.F. Agency (Ed.), Forum Fisheries Agency, Honiara, Solomon Islands, 2017.
[28] W.G. Macbeth, P.A. Butcher, D. Collins, S.P. McGrath, S.C. Provost, A.C. Bowling, P.T. Geraghty, V.M. Peddemors, Improving reliability of species identification and logbook catch reporting by commercial fishers in an Australian demersal shark longline fishery, Fish. Manag. Ecol. 25 (3) (2018) 186–202.
[29] T.J. Emery, R. Noriega, A.J. Williams, J. Larcombe, Measuring congruence between electronic monitoring and logbook data in Australian Commonwealth longline and gillnet fisheries, Ocean Coast. Manag. 168 (2019) 307–321.
[30] V. Post, D. Squires, Managing Bigeye Tuna in the Western and Central Pacific Ocean, Front. Mar. Sci. 7 (619) (2020).
[31] M.B. Rudd, T.A. Branch, Does unreported catch lead to overfishing? Fish Fish. 18 (2) (2017) 313–323.
[32] N. Ducharme Barth, M. Vincent, J. Hampton, P. Hamer, P. Williams, G. Pilling, Stock assessment of bigeye tuna in the western and central Pacific Ocean, Western and Central Pacific Fisheries Commission, 2020. 〈https://www.wcpfc.int/node/46610〉.
[33] S. Clarke, A. Langley, C. Lennert-Cody, A. Aires-da-Silva, M. Maunder, Pacific-wide Silky Shark (Carcharhinus falciformis) Stock Status Assessment, Western and Central Pacific Fisheries Commission, 2018. 〈https://www.wcpfc.int/node/31006〉.
[34] N. Queiroz, et al., Global spatial risk assessment of sharks under the footprint of fisheries, Nature 572 (7770) (2019) 461–466.
[35] E. Gilman, M. Owens, T. Kraft, Ecological risk assessment of the Marshall Islands longline tuna fishery, Mar. Policy 44 (2014) 239–255.
[36] WCPFC, Conservation and management measure for oceanic whitetip shark, Western Pacific Fisheries Commission, Tumon, Guam, USA, 2011.
[37] C.E. O'Keefe, S.X. Cadrin, K.D.E. Stokesbury, Evaluating effectiveness of time/area closures, quotas/caps, and fleet communications to reduce fisheries bycatch, ICES J. Mar. Sci. 71 (5) (2013) 1286–1297.
[38] E. Gilman, G. Legorburu, A. Fedoruk, C. Heberer, M. Zimring, A. Barkai, Increasing the functionalities and accuracy of fisheries electronic monitoring systems, Aquat. Conserv.: Mar. Freshw. Ecosyst. 29 (6) (2019) 901–926.
[39] C.A. Ward-Paige, A global overview of shark sanctuary regulations and their impact on shark fisheries, Mar. Policy 82 (2017) 87–97.
[40] E. Gilman, P. Suuronen, M. Chaloupka, Discards in global tuna fisheries, Mar. Ecol. Prog. Ser. 582 (2017) 231–252.
[41] D. Bradley, J. Mayorga, D.J. McCauley, R.B. Cabral, P. Douglas, S.D. Gaines, Leveraging satellite technology to create true shark sanctuaries, Conserv. Lett. 12 (2) (2019), e12610.
[42] H.P. Benoît, J. Allard, Can the data from at-sea observer surveys be used to make general inferences about catch composition and discards? Can. J. Fish. Aquat. Sci. 66 (12) (2009) 2025–2039.
[43] M. Bravington, C. Burridge, P. Toscas, Design of observer program to monitor bycatch species in the Eastern Tuna and Billfish Fishery, in: 16th Meeting of the Standing Committee on Tuna and Billfish, 2003, pp. 1–25.