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A comparative analysis of the ecological impacts of Chinese tuna longline fishery on the Eastern Pacific Ocean

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ABSTRACT

Ecological Risk Assessment (ERA) has been widely applied in data-poor fisheries to identify potentially vulnerable species and prioritize future research. We performed an ERA study using semi-quantitative Productivity-Susceptibility Analysis (PSA) to analyze the relative vulnerability of 24 species caught by the Chinese tuna longline fishery operating in the Eastern Pacific Ocean (EPO). The PSA results in our study were compared with those of all longline fisheries in the EPO and validated by the quantitative vulnerability assessment (EASI) applied to EPO longline and purse-seine fisheries. We conducted a sensitivity analysis of the attributes used in the PSA. Of the 24 species assessed, five species were classified as highly vulnerable, including the target species of Bigeye tuna (*Thunnus obesus*) and four shark species, with the remaining species being moderately vulnerable. Our findings revealed good concurrence with the PSA study considering all longline fisheries but differed significantly from EASI. There were seven medium vulnerability species in our assessment corresponding to low vulnerability in the EASI study, which is largely attributed to the precautionary attribute scoring and vulnerability classification criteria used in PSA. The sensitivity analysis suggested that species vulnerability was more likely to be influenced by susceptibility attributes than productivity attributes, especially Areal Overlap with RMSE value of 0.146. Given these findings, while it is reasonable to adopt the PSA approach until we have more reliable data, there is a need to move further toward quantitative assessment.

1. Introduction

Traditional stock assessments and fisheries management tend to be more focused on the sustainability of economically target species. However, there is growing evidence that fishing activities have direct and indirect negative impacts on non-targeted species and disrupt ecosystem structures (Myers et al., 2007; Griffiths et al., 2019). Over the past decades, many researchers have advocated for an ecosystem-based fisheries management (EBFM) approach to better explain the ecological impacts of fisheries (Pikitch et al., 2004; Jacobsen et al., 2016; Bauer et al., 2019). A major challenge in the implementation is the lack of reliable biological and catch information for non-target species with low economic value, especially in pelagic waters (Zhou and Griffiths, 2008; Williams et al., 2011; Gilman et al., 2014).

Ecological risk assessment (ERA) was developed as an effective alternative to assess the ecological effects of fishing on data-limited species (Milton, 2001; Stobutzki et al., 2001). Unlike traditional stock assessments designed to precisely determine the status of a population, the primary goal of ERA is to rapidly identify potentially vulnerable species and prioritize them for further data collection, assessment and management (Patrick et al., 2010; Hobday et al., 2011). The ERA approach provides a hierarchical framework based on data availability, including qualitative risk analysis (level 1) driven by stakeholder involvement, semi-quantitative analysis (level 2) and fully quantitative assessment models (level 3). Due to its flexibility, ERA tools have been increasingly used to assess the ecological sustainability of data-limited fisheries worldwide (Zhou et al., 2012; Griffiths et al., 2017; Lin et al., 2020).

Currently, semi-quantitative Productivity-Susceptibility Analysis (PSA) is the most commonly applied ERA method (Patrick et al., 2010; Hobday et al., 2011; Lin et al., 2020). A variety of data types can be used in PSA to generate vulnerability (v) measures for the species being assessed, and the results can be easily interpreted by researchers and fisheries managers (Griffiths et al., 2017). Kirby (2006) applied the PSA

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method to assess the vulnerability of sea turtles, seabirds, and marine mammals in tuna fisheries in the western and central Pacific Ocean. The effects of purse seine and longline fisheries on bycatch species were analyzed using PSA throughout the Eastern Pacific Ocean (EPO) (Griffiths et al., 2017; Duffy et al., 2019). In the Atlantic Ocean, PSA has also been applied to species caught by different gears in tuna fisheries (Arrizabalaga et al., 2011; Lucena-Frédou et al., 2017). The PSA method has become the most recommended ERA method in recent decades, especially for different Regional Tuna Fishery Management Organizations (RFMOs) (MSC, 2010; Duffy et al., 2019).

Longline is the only fishing gear for the Chinese tuna fishery in the EPO, targeting Albacore tuna (*Thunnus alalunga*) and Bigeye tuna (*Thunnus obesus*). It is inevitable that many non-target species are caught during the fishing. In the 21st century, the concept of EBFM has gradually started to be implemented and applied by the Inter-American Tropical Tuna Commission (IATTC). Fisheries operating in the EPO are becoming increasingly aware of the need to demonstrate to IATTC that their fishing does not negatively impact the supporting ecosystem (Griffiths et al., 2021). Thus, we applied PSA to conduct an ecological risk assessment of the Chinese tuna longline fishery in the EPO. This paper aims to 1) evaluate the vulnerability of species caught by the Chinese longline fishery and prioritize species that would require specific research; 2) validate the PSA approach by comparison with two other ERA assessment outcomes for EPO; and 3) identify attributes with high impacts on species vulnerability through sensitivity analyses.

2. Materials and methods

2.1. Data sources

The study area was defined as the average historical distribution of Chinese tuna longline fisheries operating in the EPO from 2015 to 2019 as shown in Fig. 1. A total of 24 species were assessed in this study, including 15 commonly caught species recorded in Chinese logbooks and additional 9 species recorded in observer data. The catch of these 24 species accounted for over 90 % of the total catch of all species in the Chinese tuna longline fishery. Seabirds, sea turtles, and marine mammals have already been regarded as species of priority concern and conservation by IATTC, but data on their interactions and mortalities in the EPO longline fishery are not yet available (Griffiths and Duffy, 2017). Therefore, we did not include these species in our ecological risk assessment of Chinese longline fishery but instead aligned with the PSA study of all large-scale longline fisheries conducted by IATTC staff (we call it IATTC study below), which focused on teleost and elasmobranch species (Griffiths et al., 2017). All 24 species interacting with the Chinese longline fishery were included in the IATTC study.

2.2. Productivity and susceptibility attributes

In this study, six susceptibility (s) attributes and five productivity (p) attributes were used to determine species vulnerability caught in the Chinese tuna longline fishery following Griffiths et al. (2017). This was done to make our results comparable with the IATTC study. For individual species, all 11 attributes used in this study were scored on a rank of 1 to 3, where 1–3 indicates low to high productivity and low to high susceptibility, respectively. Productivity and susceptibility attributes and scoring thresholds were derived from Duffy et al. (2019) and Griffiths et al. (2017) and modified to be relevant to EPO longline fishery, as outlined in Table 1.

Stock productivity indicates the ability of a stock to recover from depletion and is closely related to the species' life history characteristics (Stobutzki et al., 2001; Patrick et al., 2010). The five productivity attributes in Table 1 include maximum size (L_{max}), Growth coefficient (K_{vb}), fecundity (F), reproductive strategy (RS) and age at first maturity

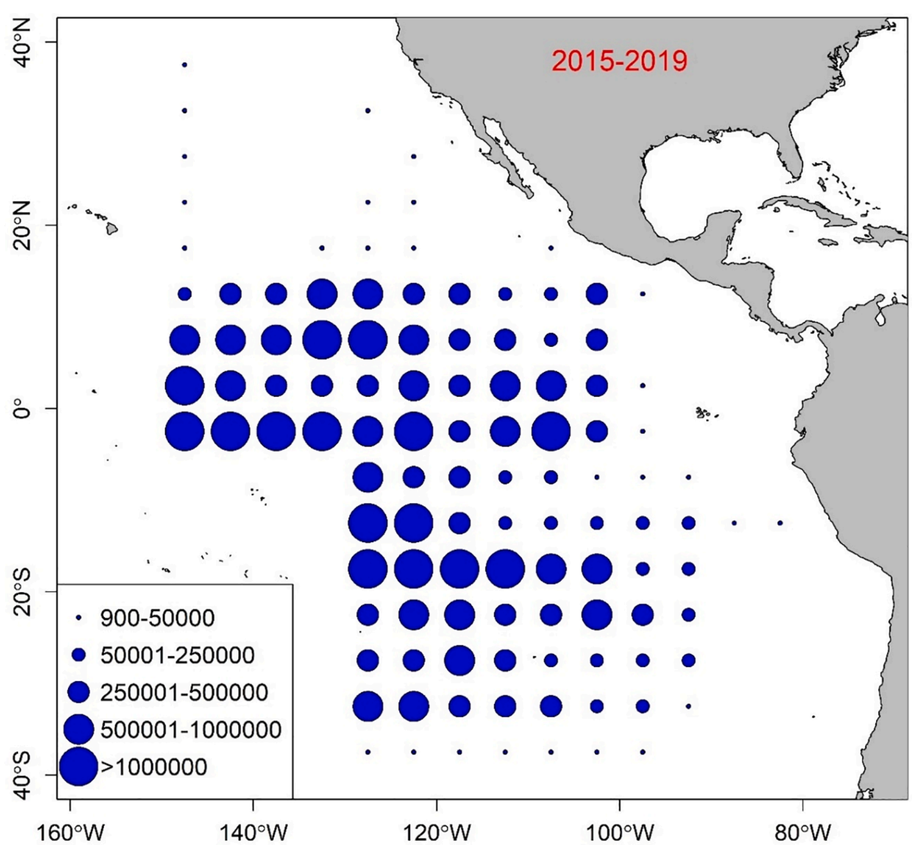

Fig. 1. Average distribution of total effort, in number of hooks by 5°x 5°grid, by the Chinese tuna longline fishery in the eastern Pacific Ocean from 2015 to 2019. The number of the largest blue dot occurrences indicates the number of high-effort areas.

Table 1
Attributes and corresponding scoring thresholds used in the Productivity-Susceptibility Analysis for the Chinese tuna longline fishery in the eastern Pacific Ocean (adapted from Duffy et al., 2019; Griffiths et al., 2017).

Productivity attribute	Low Productivity (high risk, score = 1)	Medium Productivity (medium risk, score = 2)	High Productivity (low risk, score = 3)
Maximum size (cm, L_{max})	> 350	> 200, ≤ 350	≤ 200
Growth coefficient (K_{vb})	< 0.1	0.1–0.3	> 0.3
Fecundity (F)	< 10 eggs per year	10–200,000 eggs per year	> 200,000 eggs per year
Reproductive Strategy (RS)	Live bearer	Demersal egg layer	Broadcast spawner
Age at first maturity (years, tm)	≥ 7.0	≥ 2.7, < 7.0	< 2.7
Susceptibility attribute	**Low susceptibility (low risk, score = 1)**	**Medium susceptibility (medium risk, score = 2)**	**High susceptibility (high risk, score = 3)**
Areal Overlap (AO)	Overlaps between high-catch and high-effort areas < 2	Overlaps between high-catch and high-effort areas are 2–3	Overlaps between high-catch and high-effort areas > 3
Seasonal Availability (SA)	<3 months	3–6 months	>6 months
Aggregation Behavior (AB)	Solitary species, and/or not attracted to baits on longlines	Normally found in loose aggregations, and/or has some attraction to baits on longlines	Normally schooling species, and/or highly attracted to baits on longlines
Encounterability (E)	Low overlap with fishing gear (<25 %)	Medium overlap with fishing gear (25–50 %)	High overlap with fishing gear (>50 %)*
Gear Selectivity (GS)	Small proportion of the stock that encounters the gear is hooked (<25 %)	Medium proportion of the stock that encounters the gear is hooked (25–50 %)	Large proportion of the stock that encounters the gear is hooked (>50 %)*
Post-capture Survival (PCS)	Evidence of post-capture release and survival	Bycatch species (discarded) or limited evidence of survival	Retained species, or majority dead when released*

Note: * indicates the default score of target species.

(tm), which have been proven to be reliable and useful in PSA studies by IATTC staff (Duffy and Griffiths, 2019). These biological data were compiled using a hierarchical method, first attempting to obtain them from the IATTC reports and existing studies in the Pacific Ocean. For bycatch species where detailed biological studies are lacking, data from FishBase or similar species were used. The specific values, scoring criteria and sources of these five productivity attributes used in the study were listed in Supplementary material Table S1.

Stock susceptibility is the extent to which a fishery negatively affects a stock, i.e., the propensity of a species to be caught by a fishery and cause mortality (Stobutzki et al., 2001; Patrick et al., 2010). The six susceptibility attributes in Table 1 include Areal Overlap (AO), Seasonal Availability (SA), Aggregation Behavior (AB), Encounterability (E), Gear Selectivity (GS) and Post-capture Survival (PCS). Like the productivity attributes, we first obtained the susceptibility value from the Chinese catch data and IATTC related studies, and refer to other sources if not available. AO describes fishing effort overlapping with the geographic distribution of a species, and it is one of the most critical attributes reflecting species susceptibility. The species' distribution caught by the Chinese tuna longline fishery was defined in terms of catch number. Supplementary material Fig. S1-4 demonstrated the average catch distribution of main caught species by the Chinese tuna longline fishery in the Eastern Pacific Ocean from 2015 to 2019. The AO value of a species was determined by the number of overlap areas between the high-effort of the fishery and the high-catch of the species. For attribute SA, we assumed that species in our study were available for capture by the longline fishery for>6 months of a year, as most species are highly migratory in the EPO. Encounterability denotes the degree of overlap between species' depth preferences and fishing gear. The distribution of Chinese tuna longline gear ranges from 100 to 300 m. Reliable GS is available for species that stock assessments have been undertaken. However, the knife-edge selectivity was assumed for some bycatch species based on Chinese observer length-frequency data. PCS depends on species' economic value and the tolerance of the species to longline fishing gear. Still, there are many problems remaining to be solved in the estimation of PCS, and relevant studies conducted in the EPO are limited (Musyl et al. 2011; Griffiths et al., 2019). Hence, we made simple assumptions about the attributes of a species based on whether it was discarded or retained after capture. The specific values, scoring criteria and sources of these six susceptibility attributes used in the study were listed in Supplementary material Table S2.

Vulnerability is defined here as the likelihood that a stock's productivity is reduced by direct and indirect fishing pressure (Stobutzki et al., 2001; Patrick et al., 2010). The 11 attributes were weighted equally, and then the averaged productivity and susceptibility scores were combined to give an overall vulnerability score for the 24 species following the equation (Patrick et al., 2010):

$$v = \sqrt{(p-3)^2 + (s-1)^2} \tag{1}$$

The v score ranges from 0 to 3, with higher values indicating higher species risk. In order to be comparable with the PSA study in the EPO, we defined species vulnerability according to the same criteria, i.e., species with v scores of <1, 1–2 and >2 were categorized as low, medium and high vulnerability species, respectively (Griffiths et al., 2017). In addition, the vulnerability status of most species was verified by comparison with the outcomes of the quantitative vulnerability assessment approach (EASI) applied to EPO longline and purse-seine fisheries (Griffiths et al., 2019). EASI uses the similar method that is used in stock assessments to identify species vulnerability, namely based on the biological references (fishing mortality and spawning stock biomass) of species (Griffiths et al., 2019).

2.3. Sensitivity analysis of productivity and susceptibility attributes

After the vulnerability scores for the 24 species were determined, we conducted a sensitivity analysis on productivity and susceptibility attributes. The 11 attributes were removed in turn, and the following equation (Chai and Draxler, 2014) was used to calculate the Root mean squared error (RMSE) of each attribute after removal:

$$RMSE_j = \sqrt{\frac{\sum (v_{ij} - v_i)^2}{24}} \tag{2}$$

where i is species, j represents different attributes, v_{ij} denotes the species' vulnerability score after the removal of attribute j, and v_{ij}-v_i is the relative error between vulnerability scores (Lin et al., 2020). The higher the RMSE value, the greater the impact of this attribute on the overall vulnerability score of species.

Additionally, we analyzed the changes in each species' vulnerability by varying the averaged susceptibility scores by ± 10 %, ±20 % and ± 30 %. We then compared changes in species vulnerability category of these six scenarios. The fishing effort of Chinese tuna longline fishery in the EPO has remained relatively stable for the last decade under IATTC's fisheries management. The above sensitivity analysis can serve as a meaningful reference for us to identify management measures that can effectively mitigate the impact of fisheries.

3. Results

3.1. Species vulnerability and comparison with other assessments

The six susceptibility attribute scores and their average scores of 24 species were shown in Table 2. Tunas had the highest susceptibility scores, with Bigeye tuna at 3, Albacore tuna and Yellowfin tuna both at 2.83, followed by several billfishes and sharks. In contrast, Pelagic Stingray (*Dasyatis violacea*) and Escolar (*Lepidocybium flavobrunneum*) had a low susceptibility score of 1.83, suggesting that these species are likely to be less vulnerable to the Chinese longline fishing pressure.

The five productivity attribute scores and their average scores of 24 species were listed in Table 3. The vulnerability of each species is visualized on an X-Y scatter plot in Fig. 2. We also presented the vulnerability results of IATTC and EASI studies in Table 3 for comparison with our assessment (Griffiths et al., 2017; Griffiths et al., 2019). Of the 24 species assessed in this study, five species were classified as highly vulnerable and the others as moderately vulnerable. Among the five species with high vulnerability, in addition to Bigeye tuna as a target species, four shark species were included, namely Longfin mako (*Isurus paucus*), Bigeye thresher (*Alopias superciliosus*), Shortfin mako (*Isurus oxyrinchus*) and Scalloped hammerhead (*Sphyrna lewini*). BTH had the highest vulnerability score (2.4), and all four sharks exceeded the vulnerability score of BET (2.01). All nine shark species in this study had productivity scores <2, with the smallest scores of 1 for BTH and LMA, meaning that their high vulnerability was driven by low productivity rather than susceptibility to the fishery.

Among the moderately vulnerable group of the assessment, the vulnerability scores of Oceanic whitetip shark (*Carcharhinus longimanus*), BSH and ALB were 1.98, 1.92 and 1.88, respectively, making them the three species approaching high risk. Furthermore, Wahoo (*Acanthocybium solandri)*and Shortbill spearfish (*Tetrapturus angustirostris*) shared the lowest vulnerability score (1.02) in this study because of their low susceptibility and high productivity.

In the PSA results of IATTC study, there are 10 highly vulnerable species, twice as many as when only the Chinese longline fishery had been considered. The five high vulnerability species in our study were also at high risk in the IATTC study, except for BET. Besides, the vulnerability scores of BTH and Blue shark (*Prionace glauca*) in the IATTC study were the highest, both at 2.33. Thus, BTH has been considered as a highly vulnerable species in both studies. Of the 14 species with moderate vulnerability, 13 species were the same between the two studies.

The difference between EASI and our findings was also obvious. Seven species were identified as highly vulnerable in the EASI study, two of which were identical to the present assessment, namely SMA and BTH. In addition to four shark species and Pelagic stingray (*Dasyatis violacea*), the high vulnerability species included two billfishes, Blue marlin (*Makaira nigricans*) and Striped marlin (*Kajikia audax*). Both target species in the Chinese tuna longline fishery were considered as having low vulnerability in the EASI study. Surprisingly, seven of the eight low-risk species in the EASI study were classified as having medium vulnerability in our PSA assessment.

3.2. Sensitivity analysis of attributes

After excluding the 11 attributes in turn, we found that the top three attributes that had a greater impact on the vulnerability scores were AO, SA and AB, with RMSE values of 0.146, 0.119 and 0.110, respectively (Table 4). In particular, the average relative error of 24 species increased by 10.9 % when AB was removed as demonstrated in Fig. 3. Besides, the relative errors of all five productivity attributes reflected only slight fluctuations. The above results suggested that species' overall vulnerability was strongly influenced by susceptibility attributes rather than productivity attributes.

The vulnerability scores of all 24 species in the assessment changed significantly (Table 5). The overall trend of the six scenarios was that as susceptibility score increased, the number of high-risk species increased, and conversely, as susceptibility score decreased, more species changed from higher risk to lower risk category. When the susceptibility scores increased from 10 % to 30 %, the vulnerability categories changed for 4, 6 and 10 species, respectively. Whereas, 6, 11 and 12 species changed their vulnerability categories after a 10 %, 20 % and 30 % reduction in susceptibility scores, respectively. Besides, nine species were classified as having low vulnerability under the scenario with a 30 % reduction of susceptibility score. Another interesting phenomenon is that the vulnerability scores of Black marlin (*Istiompax indica*, 1.08–1.89), PLS (1.23–1.83), BTH (2.10–2.85) and LMA (2.04–2.56) changed considerably under six scenarios, but their vulnerability categories remained the same.

Table 2
The scores of susceptibility attributes for 24 species caught by Chinese tuna longline fishery in the eastern Pacific Ocean.

Code	Common name	Scientific name	AO	SA	AB	E	GS	PCS	Susceptibility
BET	Bigeye tuna	*Thunnus obesus*	3	3	3	3	3	3	3.00
YFT	Yellowfin tuna	*Thunnus albacares*	3	3	3	3	2	3	2.83
ALB	Albacore	*Thunnus alalunga*	3	3	3	3	2	3	2.83
SWO	Swordfish	*Xiphias gladius*	3	3	2	2	2	3	2.50
BUM	Blue marlin	*Makaira nigricans*	2	3	1	2	2	3	2.17
MLS	Striped marlin	*Kajikia audax*	2	3	1	1	3	3	2.17
BLM	Black marlin	*Istiompax indica*	1	3	1	2	2	3	2.00
BSH	Blue shark	*Prionace glauca*	2	3	2	2	3	3	2.50
SMA	Shortfin mako	*Isurus oxyrinchus*	1	3	2	2	3	3	2.33
OCS	Oceanic whitetip shark	*Carcharhinus longimanus*	2	3	2	1	3	2	2.17
BTH	Bigeye thresher	*Alopias superciliosus*	2	3	2	2	3	2	2.33
FAL	Silky shark	*Carcharhinus falciformis*	1	3	2	2	2	2	2.00
LMA	Longfin mako	*Isurus paucus*	1	3	1	3	2	2	2.00
SPL	Scalloped hammerhead	*Sphyrna lewini*	1	3	2	1	3	2	2.00
SKJ	Skipjack	*Katsuwonus pelamis*	1	3	3	3	2	3	2.50
SSP	Shortbill spearfish	*Tetrapturus angustirostris*	1	3	1	3	2	2	2.00
WAH	Wahoo	*Acanthocybium solandri*	1	3	3	1	2	2	2.00
LEC	Escolar	*Lepidocybium flavobrunneum*	1	3	1	1	3	2	1.83
ALX	Longnose lancetfish	*Alepisaurus ferox*	1	3	2	2	3	2	2.17
DOL	Dorado	*Coryphaena hippurus*	1	3	3	1	3	2	2.17
GES	Snake mackerel	*Gempylus serpens*	1	3	3	2	3	2	2.33
PLS	Pelagic stingray	*Dasyatis violacea*	1	3	2	1	2	2	1.83
PSK	Crocodile shark	*Pseudocarcharias kamoharai*	1	3	2	2	3	2	2.17
PTH	Pelagic thresher	*Alopias pelagicus*	1	3	2	2	2	2	2.00

Table 3
The scores of productivity attributes and vulnerability for species caught by Chinese tuna longline fishery in the eastern Pacific Ocean. IATTC denotes the PSA results for all large-scale longline fishery (Griffiths et al., 2017), and EASI indicates the quantitative vulnerability assessment results for all large-scale longline and purse-seine fisheries (Griffiths et al., 2019). The red, yellow and green shadings indicate high, medium and low vulnerability species in the three studies, respectively.

Code	L_{max}	K	F	RS	tm	Productivity	Vulnerability	IATTC	EASI
BET	2	3	3	3	3	2.8	2.01	1.90	Low
YFT	2	3	3	3	3	2.8	1.84	2.00	Low
ALB	3	2	3	3	2	2.6	1.88	2.01	Low
SWO	1	2	3	3	2	2.2	1.70	2.06	Low
BUM	1	2	3	3	3	2.4	1.31	1.79	High
MLS	1	3	3	3	3	2.6	1.23	2.04	High
BLM	1	1	3	3	2	2.0	1.41	1.89	-
BSH	1	2	2	1	3	1.8	1.92	2.33	Medium
SMA	1	2	1	1	2	1.4	2.08	2.26	High
OCS	1	2	1	1	2	1.4	1.98	1.98	High
BTH	1	1	1	1	1	1.0	2.40	2.33	High
FAL	2	2	1	1	2	1.6	1.72	1.98	High
LMA	1	1	1	1	1	1.0	2.24	2.28	-
SPL	1	1	2	1	1	1.2	2.06	2.26	-
SKJ	3	3	3	3	3	3.0	1.50	1.60	Low
SSP	2	3	3	3	3	2.8	1.02	1.71	-
WAH	2	3	3	3	3	2.8	1.02	1.81	Low
LEC	3	1	3	3	1	2.2	1.16	1.44	Low
ALX	2	2	3	3	3	2.6	1.23	1.60	-
DOL	2	3	3	3	3	2.8	1.18	1.80	Low
GES	3	2	3	3	2	2.6	1.39	1.84	-
PLS	3	2	1	1	2	1.8	1.46	1.56	High
PSK	3	2	1	1	2	1.8	1.67	1.71	-
PTH	1	2	1	1	2	1.4	1.89	2.24	-

4. Discussion

4.1. Comparison and analysis of species vulnerability

In this study, we applied the PSA method to assess the potential vulnerability of species documented to interact with the Chinese tuna longline fishery operating in the EPO. PSA proved to be an effective method, even though most of the species were bycatch with limited available data. The present assessment categorized five species as highly vulnerable species, including one tuna and four shark species, meaning that these species are likely to become unsustainable under current fishing intensity. Bigeye tuna had a vulnerability score of 2.01, which is close to medium risk species, while all four shark species had higher vulnerability scores than BET. The high vulnerability of BET is not surprising, as it is the target species of Chinese tuna longline fishery, and it is susceptible to longline gear. However, BET was assessed as having low vulnerability in the EASI study and the recent stock assessment results of BET in the EPO revealed an unreasonable bimodal probability distribution of its stock status (Xu et al., 2020). Consequently, these findings above were a reflection of the great uncertainty in the status of BET stock, and further research is needed to address this issue. For shark species, the high vulnerability is largely attributed to their life history traits resulting in limited productivity. For example, LMA and BTH, the most vulnerable species in this assessment, produce only 2–3 pups a year (Frisk et al., 2005; Compagno, 1984) and take approximately 8 years to reach maturity (Parsons and Peters, 1989; White et al., 2006).

The high risk of shark species has long been an issue of particular concern to the IATTC (Fu et al., 2016). We noted that, in addition to the four sharks mentioned above, OCS and BSH in the moderately vulnerable species group also had vulnerability scores close to those of highly vulnerable species (Fig. 2). Six shark species were classified as highly vulnerable in the IATTC study, four of which were consistent with our assessment (Griffiths et al., 2017). BTH, in particular, was assessed as the species with the highest vulnerability score in both studies. Similarly, PSA studies undertaken in the western and central Pacific Ocean (Kirby, 2006) and the Atlantic Ocean (Cortés et al., 2010) identified SPL and BTH as highly vulnerable. Additionally, the findings of EASI, a method that can provide quantitative measurements for species, validated the high vulnerability of BTH and SMA. However, for shark species without a quantitative assessment, it remains difficult to determine whether their stock status is truly at high risk. Dulvy et al. (2021) presented the first global reassessment of 536 shark species, of which 167 (31.2 %) species were placed in the threatened category. As we mentioned above, the life history characteristics of sharks, such as slow growth, long life span and low fecundity, making them less resilient to fishing. Even under relatively low fishing intensity, sharks are also

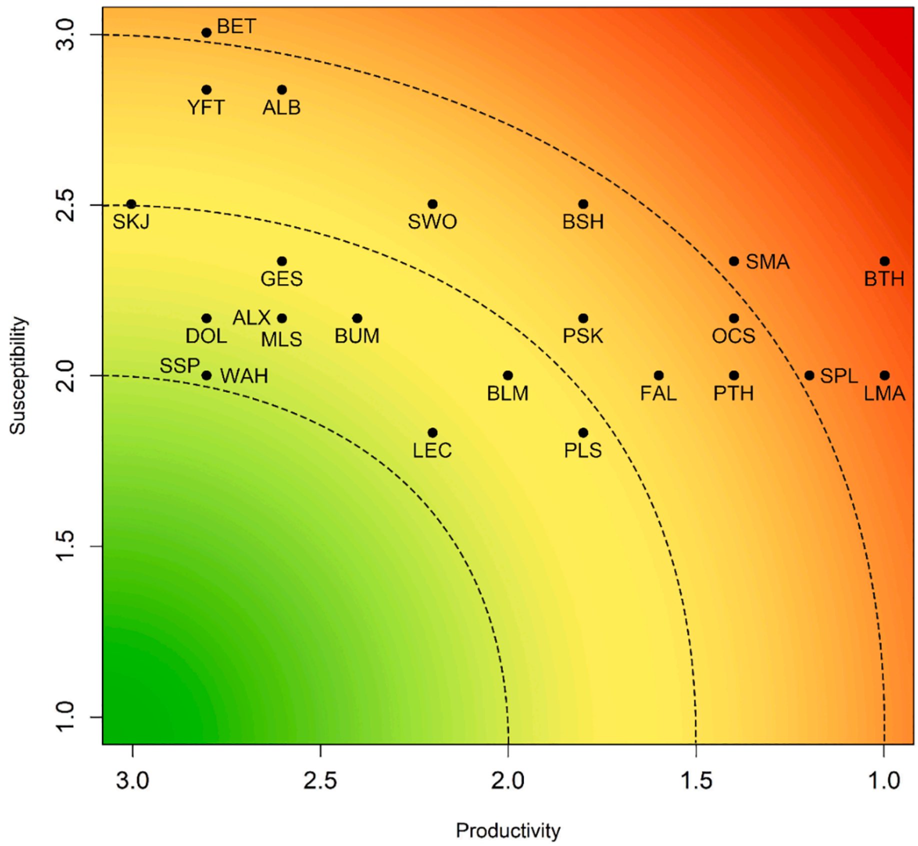

Fig. 2. Productivity-susceptibility plot of 24 species caught by Chinese tuna longline fishery in the eastern Pacific Ocean. Species in the yellow and red zones are considered to be moderately and highly vulnerable, respectively. See Table 2 for species codes.

Table 4
Root mean squared error (RMSE) between vulnerability scores when removing 11 attributes sequentially from PSA of Chinese tuna longline fishery in the eastern Pacific Ocean.

Attribute removed	L_{max}	K	F	RS	tm	AO	SA	AB	E	GS	PCS
RMSE	0.101	0.073	0.088	0.084	0.077	0.146	0.119	0.110	0.108	0.099	0.066

vulnerable to exploitation (Kirby, 2006; Fu et al., 2016). Therefore, such evidence clearly suggested that shark species require additional management attention, despite the fact that relevant resolutions about several sharks have been adopted by IATTC.

The absence of low-risk species in the assessment is related to the precautionary classification categories we used. We defined species with vulnerability scores < 1 as low vulnerability species following the IATTC PSA study. In contrast, many PSA studies have also used species with vulnerability scores < 1.5 or < 1.8 as classification criterion for low vulnerable species (Faruque and Matsuda, 2021; Lin et al., 2020; Fatema et al., 2022). Of course, different studies may use different classification standards depending on the study region, the species, the attributes used in the assessment and their scoring thresholds. Nonetheless, it has been confirmed that PSA, as a precautionary approach, has the potential to falsely assess low-risk species in reality into a higher vulnerability category (Patrick et al., 2010; Hobday et al., 2011). Hence, while it is reasonable to adopt this approach until we have more reliable data, there is still a need for clearer and uniform criteria to define species vulnerability, which could facilitate the application of PSA.

Our results indicated good concurrence with the PSA results applied to all longline fisheries in the EPO (Table 3). In particular, for moderately vulnerable species, the vulnerability categories were consistent across the 13 species, but their vulnerability scores still differed significantly, such as SSP, WAH and DOL. However, the largest difference between the two studies lies in the number of highly vulnerable species. For instance, Striped marlin (*Kajikia audax*) was considered having high vulnerability in the IATTC study, but the vulnerability score of MLS in the present study was only 1.23. The above difference can be primarily attributed to the estimation of susceptibility scores. Study of Faruque and Matsuda (2021) revealed that fishing mortality corresponds to vulnerability scores. Since we didn't consider other longline fisheries in the EPO, which may be the main source of fishing mortality for some species (Duffy et al., 2019). Obviously, species in the IATTC study have more geographic overlap with fishing effort, higher encounterability with fishing gears and lower post-capture survival rates.

Another issue of concern is the apparent discrepancies in species vulnerability between EASI and our outcomes. With the exception of BET, the eight low vulnerable species in the EASI study were associated with medium vulnerability in our assessment. This phenomenon can be explained by the propensity of precautionary attribute scoring methods used in PSA to overestimate the vulnerability of species (Hobday et al., 2011; Osio et al., 2015). Unlike EASI, when the values of areal overlap and encounterability are 0, PSA still assumes a minimum score of 1 for the two attributes. On the other hand, species with relatively high productivity are less sensitive in PSA, i.e., changes in attribute value have a slight effect on the vulnerability categories after a threshold is reached (Hobday et al., 2011; Zhou et al., 2016). The vulnerability scores for SSP and WAH were 1.02, pretty close to low-risk species (Fig. 2). Several

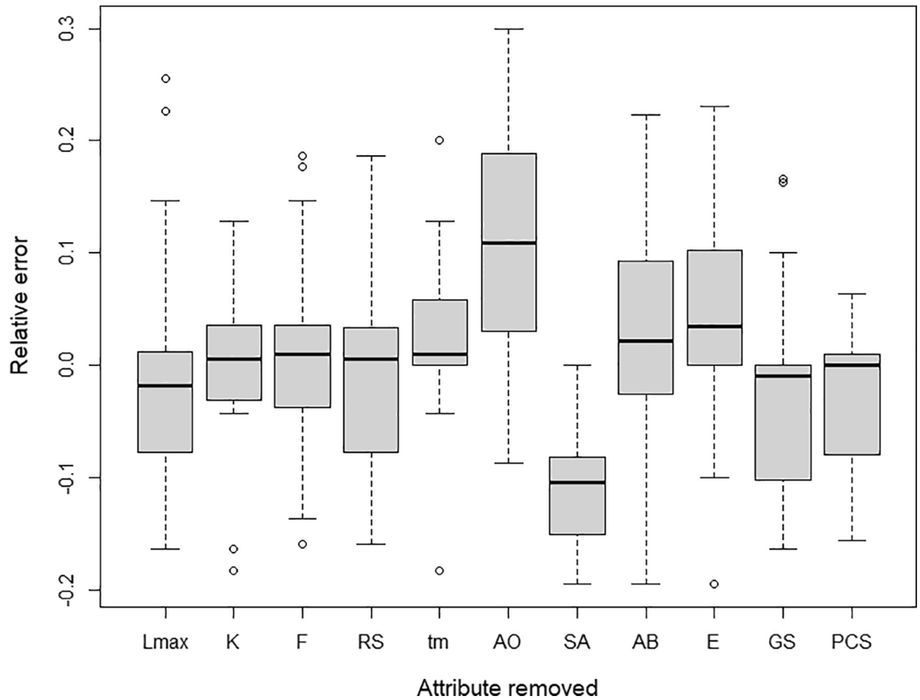

Fig. 3. Relative error of vulnerability when removing 11 attributes sequentially from PSA of Chinese tuna longline fishery in the eastern Pacific Ocean.

other species also have low susceptibility and high productivity, including Skipjack (*Katsuwonus pelamis*), Escolar (*Lepidocybium flavobrunneum*), Dorado (*Coryphaena hippurus*) and WAH. It means that these species have the ability to recover rapidly even when subjected to higher fishing pressure. For example, WAH is frequently found in surface waters from 0 to 30 m (Sepulveda et al., 2011), which makes them rarely interact with Chinese longline gear. Also, WAH is highly productive compared to sharks because it is short-lived and produces millions of eggs every year (Zischke et al., 2013). In consideration of this, these medium-sized moderately vulnerable species in our study may actually be at low risk in reality. Interestingly, three species, BUM, MLS and PLS, were found to be in the high-risk category by EASI, despite being classified as moderately vulnerable in our PSA assessment. The possible misclassifications may be due to the inability of PSA to accurately characterize the ecological risk of species with intermediate vulnerability scores (Hordyk and Carruthers, 2018). Zhou et al. (2016) compared the vulnerability classifications of PSA with stock assessments, and it was shown that the overall misclassification rate of PSA was 50 %. The failure of PSA to identify some potentially high vulnerability species indicated the limitation of its application (Hobday et al. 2011), as species categorized as moderately vulnerable were not typically prioritized for further management (Georgeson et al., 2020).

4.2. Sensitivity analysis

In fact, not all productivity and susceptibility attributes are equally valuable in terms of their impact on species vulnerability (Hordyk and Carruthers, 2018). The results of the sensitivity analysis suggested that species vulnerability was driven more by susceptibility than by productivity attributes. Although the attributes used were not identical, several PSA studies had also observed a greater contribution of susceptibility attributes to species vulnerability scores (Hordyk and Carruthers, 2018; Lin et al., 2020; Georgeson et al., 2020). Among the susceptibility attributes, the three attributes, AO, SA, and AB, greatly influenced the overall vulnerability score of each species, especially areal overlap (Table 4). A low score of spatial overlap between species distribution and fishing effort can effectively make a species less vulnerable to fishing (Georgeson et al., 2020). This phenomenon was also correlated with our assumption about the spatial extent of the longline fishery (Zhou et al., 2016). That is, all species in our assessment had interactions with the longline fishery, even if they were not distributed within this range. Conversely, the removal of the productivity attributes had only a slight effect on the vulnerability scores.

The outcomes of the sensitivity analysis of the susceptibility scores demonstrated that the vulnerability categories of most species varied greatly with susceptibility scores (Table 5). A particular concern was that under positive scenarios, more species changed their vulnerability category. In other words, vulnerability scores were more sensitive to the decreases than increases in susceptibility scores, a finding that is consistent with the view of Georgeson et al. (2020). More importantly, this finding can guide us to adopt appropriate management measures to mitigate the impacts of multiple fisheries on vulnerable species in the EPO. There are various possible ways to reduce the species' susceptibility that we can explore. In particular, research on fishery parameters would be useful to identify management measures that can effectively minimize species susceptibility (Georgeson et al., 2020). For instance, species availability and gear selectivity would certainly decline by increasing the existing closure days of purse-seine fishery and increasing the size at first capture. Recognizing the high vulnerability of shark species, China and other IATTC members should attach great importance on the conservation and management of sharks, with specific priority given to improving the post-capture survival rates.

4.3. Limitations

Despite PSA has been applied to >1000 target and by-catch species in different waters (Hordyk and Carruthers, 2018), the underlying assumptions of the approach and the reliability of the results still need further evaluation and validation. Firstly, PSA results are precautionary in contrast to quantitative assessment methods, which are associated mainly with the attribute scoring and vulnerability classification criteria used in PSA. Multiple species in the assessment may have different applicable criteria as they differ markedly in life history characteristics, such as teleost and elasmobranch species. As proposed in Zhou et al. (2016), even if tunas and sea turtles have the same vulnerability scores, this does not imply that this score stands for the same biological

Table 5
Changes in vulnerability scores of 24 species caught by Chinese tuna longline fishery in the eastern Pacific Ocean when susceptibility scores varied by ± 10 %, ±20 % and ± 30 %. The red, yellow and green shadings correspond to high vulnerability, medium vulnerability and low vulnerability, respectively.

Code	-30%	-20%	-10%	Vulnerability	10%	20%	30%
BET	1.12	1.41	1.71	2.01	2.31	2.61	2.91
YFT	1.00	1.28	1.56	1.84	2.13	2.41	2.69
ALB	1.06	1.33	1.60	1.88	2.15	2.43	2.71
SWO	1.10	1.28	1.48	1.70	1.92	2.15	2.39
BUM	0.79	0.95	1.12	1.31	1.51	1.71	1.91
MLS	0.65	0.84	1.03	1.23	1.44	1.65	1.86
BLM	1.08	1.17	1.28	1.41	1.56	1.72	1.89
BSH	1.42	1.56	1.73	1.92	2.12	2.33	2.55
SMA	1.72	1.82	1.94	2.08	2.24	2.41	2.59
OCS	1.68	1.76	1.86	1.98	2.12	2.26	2.42
BTH	2.10	2.18	2.28	2.40	2.54	2.69	2.85
FAL	1.46	1.52	1.61	1.72	1.84	1.98	2.13
LMA	2.04	2.09	2.15	2.24	2.33	2.44	2.56
SPL	1.84	1.90	1.97	2.06	2.16	2.28	2.41
SKJ	0.75	1.00	1.25	1.50	1.75	2.00	2.25
SSP	0.45	0.63	0.82	1.02	1.22	1.41	1.61
WAH	0.45	0.63	0.82	1.02	1.22	1.41	1.61
LEC	0.85	0.93	1.03	1.16	1.29	1.44	1.60
ALX	0.65	0.84	1.03	1.23	1.44	1.65	1.86
DOL	0.55	0.76	0.97	1.18	1.40	1.61	1.83
GES	0.75	0.95	1.17	1.39	1.62	1.84	2.07
PLS	1.23	1.29	1.36	1.46	1.57	1.70	1.83
PSK	1.31	1.41	1.53	1.67	1.83	2.00	2.18
PTH	1.65	1.71	1.79	1.89	2.00	2.13	2.26

significance for them. More importantly, the precautionary principle can lead to an overestimation of the vulnerability of data-poor species, thus undermining the efficiency of PSA as a screening tool. In addition, PSA assumes that all attributes are weighted in equal measure when assessing species vulnerability (Hobday et al., 2011), which would possibly bias the results. For instance, the areal overlap was found to be the most influential susceptibility attribute in our study, and the study by Hordyk and Carruthers (2018) study revealed that gear selectivity had the largest effect on species vulnerability scores. Several studies have attempted to use weighting systems to scale the contribution of different attributes to the overall vulnerability of species (Patrick et al., 2010; Cope et al., 2011), but this remains an issue that should be considered in PSA implementation.

Another shortcoming of the PSA approach is its incapability to address the cumulative impacts of multiple fisheries on potentially affected species (Hobday et al., 2011; Griffiths et al., 2019). This is primarily due to the PSA assumption that only simply linear and additive relationships exist between each productivity and susceptibility attribute (Patrick et al., 2010; Williams et al., 2018). Different fishing gears lead to differing levels of encounterbility and selectivity. Accordingly, this makes it problematic to assess the combined impacts of several fisheries operating in the same region. Some researchers have attempted to resolve these problems in PSA by adopting new methods. For example, Duffy et al. (2019) weighted susceptibility scores for three purse-seine fisheries based on the proportion of each fishery, and a study by Micheli et al. (2014) developed an aggregated susceptibility (AS) index associated with the fishery. But still, it is uncertain whether these PSA results are actually reflective of multiple fisheries. Considering the continued expansion of purse-seine fisheries in the EPO since 1990, their catches have far exceeded those of longline fisheries (Griffiths et al., 2021). As a result, the implications of other fisheries also should not be ignored when evaluating the viability of populations in the EPO (Griffiths et al., 2017). Additionally, interactions between Chinese fleets and other fishing fleets in the EPO are also an important consideration to better evaluate species vulnerability, and collaborative research is required to quantitatively assess all EPO fishing fleets.

Undoubtedly, data quality and availability present a key challenge to our assessment, especially for data used to score the susceptibility attributes. Given our limited knowledge of the interactions of many bycatch species with longline fisheries, only simple assumptions were made based on available data for two attributes (Supplementary material Table S1), namely gear selectivity and post-capture survival. Also, there is still a great deal of uncertainty about the current encounterability data of EPO longline gear (Griffiths et al., 2017), which calls for improved species distribution and biological information, notably for bycatch species. Last but not least, species attributes are clearly affected by climate change (Watters et al., 2003; Pecl et al., 2014; Ramos et al., 2022), which was not considered in the present study. Improved data collection can provide more reliable PSA outcomes and allow us to move further toward quantitative assessments.

5. Conclusions

Despite the limitations in the implementation of PSA, it still provides valuable insights into the relative vulnerability of species caught in the Chinese tuna longline fishery. This study confirms that shark species require further data collection and management due to their low productivity, especially the Bigeye thresher. In addition, the misclassifications in PSA compared to the EASI study highlights the need for improved data collection and further assessment with a quantitative approach.

CRediT authorship contribution statement

Qinqin Lin: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Yong Chen:** Conceptualization, Writing – review & editing. **Jiangfeng Zhu:** Resources, Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The fishing effort and catch data of Chinese tuna longline fishery used in the paper can be found in the public database of Inter-American Tropical Tuna Commission (https://www.iattc.org/en-US/Data/Public-domain).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2022.109284.

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