**Environment, Development and Sustainability**
2023, Volume 25, Pages 9227-9250
https://doi.org/10.1007/s10668-022-02432-1
https://archimer.ifremer.fr/doc/00774/88624/



# Unintended effects of single-species fisheries management

Tolotti Mariana [1,*], Guillotreau Patrice [1], Forget Fabien [1], Capello Manuela [1], Dagorn Laurent [1]

[1] MARBEC, University of Montpellier, CNRS, Ifremer, IRD, Sète, France

* Corresponding author : Mariana Tolotti, email address : mariana.travassos@ird.fr

**Abstract :**

Ecosystem-based management is widely recognized as the path to achieve sustainability of ecosystem services. Tuna Fisheries Management Organizations have incorporated an ecosystem approach into their mandate, but their decision-making process essentially relies on individual stock assessments. This study investigates possible unintended consequences of management measures that primarily focus on single target species. In 2016, the Indian Ocean Tuna Commission (IOTC) adopted a plan for rebuilding yellowfin tuna stock. We examined the impacts that this measure might have had on the fishing strategy of purse seine fleets and on silky shark mortality, their main elasmobranch bycatch. The economic dimension of this possible ecological impact was also explored. Logbook and observer data from the French fleet, coupled with IOTC data from Spain, Seychelles and Mauritius, were used. After the implementation of the measure, an increase on the number of fish aggregating device (FAD) sets and an expansion of the fishing effort were observed. These resulted in a 35% increase on silky shark bycatch for the French fleet and a 18% increase for all fleets combined. Based on the estimated catches, the mean forgone consumptive value of silky shark bycatch was evaluated at US$ 1.6 million. Taking the conservation value into account, the social cost of this forgone ecosystem service could increase up to USD 14 million. This work is a first exploration into to the socioeconomic dimension of trade-offs between the use of FADs in tuna purse seine fisheries and shark bycatch and can be applied to other FAD-associated species.

**Keywords** : Tropical tuna fisheries, Fish aggregating devices (FADs), Bycatch, Silky shark, Ecosystem approach to fisheries (EAF), Indian Ocean

## 1. Introduction

Ecosystem services illustrate how nature processes and outcomes can directly or indirectly benefit humans and human societies (Costanza et al. 1997; MA 2005). As a framework, the concept of ecosystem services describes the interconnections between nature and society, rendering value to the awarded benefits (cultural and provisional) in both monetary and non-monetary ways (Cavanagh et al. 2016; Pascual et al. 2017). For the past two decades, the concept of ecosystem services is increasingly becoming the focal point in policy management, development and environmental research (Chaudhary et al. 2015; Costanza et al. 2017), with trade-off assessments being at the center of the debate (Naidoo et al. 2008; Börger et al. 2014; Ferreira et al. 2017; Martino et al. 2019). The fundamental challenge of valuing ecosystem services is providing an accurate description of the multitude of connections that outline the network of social-ecological systems.

The challenges encompassing marine ecosystem services are among the most complex, given the practical difficulties in studying the ocean and the low visibility of some of the resources and services provided (Cavanagh et al. 2016; Villasante et al. 2016), which can often exceed local boundaries and reach global scales (Drakou et al. 2017). Tuna fisheries generate ecosystem services to a great number of beneficiaries that transcend countries and ocean borders, contributing to socio-economic well-being and food security worldwide (Hamilton et al. 2011; Drakou et al. 2018). Accordingly, the social-ecological systems originating from the tuna-supply chain are numerous and their intricate relationships compose a delicate balance between humans and nature, as well as within humans. Sustaining the balance of these systems is extremely challenging, as stressors like market fluctuations, flawed legislation, overfishing and climate change can trigger disturbances at any level (Mullon et al. 2017; Drakou et al. 2018). These disturbances have the potential to generate a cascade effect that could jeopardize the well-being of the different beneficiaries involved in tuna fisheries systems across the globe.

Ecosystem-based management is the path to actively monitor ecosystem services and prevent their collapse. This approach recognizes the complex interactions governing socio-ecological systems and ultimately seeks to deliver sustainable ecosystem services through integrative and transdisciplinary management (CBD 2004; Granek et al. 2010). The notion of ecosystem-based fisheries management is not novel (Pitcher 2001; Pikitch et al. 2004) and scientists, as well as policy makers, have been advocating its implementation for a long time (Andrew A. Rosenberg and Karen L. McLeod 2005; Garcia and Cochrane 2005; Berkes 2012; Möllmann et al. 2014; Crespo et al. 2019). However, despite being conceptually well-established, ecosystem-based fisheries management still remains a practical challenge and its implementation has been limited. One of the issues lies in the fact that the valuation of ecosystem services still gravitates towards the more obvious services, like fishery targets, neglecting biodiversity and ignoring the wider ecosystem context and impact (Cavanagh et al.

2016), including socio-economic aspects. Accurately evaluating the trade-offs between services, as well as the impacts their use generate, is an essential step for a successful ecosystem-based management. Nonetheless, this step will unlikely be achieved if the value of less visible ecosystem services are systematically overlooked (Cavanagh et al. 2016; Villasante et al. 2016).

Tuna fisheries fit well in the scenario described above. Tuna Regional Fisheries Management Organizations (RFMOs) have all incorporated an ecosystem-based approach into their mandate, typically by monitoring and adopting conservation measures for target and bycatch species alike. Still, the decision-making process of tuna RFMOs essentially relies on individual stock assessments, which focus on maximizing the catch of target species without jeopardizing their reproductivity capacity, and few conservation measures consider the multifactorial aspects of an ecosystem-based fisheries management (Gilman et al. 2014; Karim et al. 2020). Single-species management is certainly not adapted to the complex network of social-ecological systems originating from tuna fisheries and can lead to substantial socio-economic and ecological costs (Hamilton et al. 2011; Drakou et al. 2018). An example of such costs is given by Pikitch et al. (2004), who highlighted how the mortality of white marlin (an ecologically threatened species) caused by tuna and swordfish longliners could threaten a $2 billion dollar recreational fishing industry. Moreover, when shifts in market, governance or the environment take place, fleets tend to adapt their fishing strategy in order to maximize their well-being (Salas and Gaertner 2004; Branch et al. 2006) and these adaptations could equally generate unintended ecological and socio-economic effects (O’Keefe et al. 2014; Sardà et al. 2015; Escalle et al. 2016).

The aim of this study is to investigate possible unintended consequences of implementing management measures that primarily focus on single target species. We wish to encourage fisheries scientists and management bodies to use a more holistic approach, founded on transdisciplinarity, to achieve sustainability. With that aim, we selected the example of the Indian Ocean Tuna Commission (IOTC) and its interim plan, first adopted in 2016, for rebuilding the stock of yellowfin tuna (*Thunnus albacares*) (CMM 16-01), one of the main target species of tropical tuna fisheries. The primary measure mandates that, as of January 2017, contracting parties whose purse seine catches of yellowfin tuna reported for 2014 were above 5000 metric tons shall reduce their catches by 15 % from the 2014 levels. This particular measure targets purse seine fleets, which account for 44% of Indian Ocean tuna catches (IOTC Secretariat 2020), with the objective of reducing the fishing pressure on the yellowfin tuna stock. In response, the purse seine fleets have likely adapted their fishing strategy to maximize catches of skipjack (*Katsuwonus pelamis*), also one of the main target species, while reducing their yellowfin catches due to the total allowable catch (TAC).

In the Indian ocean, the tropical tuna purse seine fleets have two main fishing strategies: they either set on free-swimming schools or they set on schools that are associated with Fish Aggregating Devices (FADs). Free-swimming schools sets mostly yield large yellowfin tuna, while FAD sets mostly yield skipjack as well as small bigeye and yellowfin tuna (Dagorn et al. 2013; Fonteneau et al. 2013). We hypothesize that, as a result of the yellowfin TAC, the purse-seine fleets would favor to fish on FADs. This would have consequences on the catch of other species, as the composition of FAD sets is much more diverse and includes sharks, turtles, billfishes and other teleost fish (Amandè et al. 2012; Bourjea et al. 2014; Torres-Irineo et al. 2014; Lezama-Ochoa et al. 2018). We here focus on silky sharks (*Carcharhinus falciformis*), a species of global concern due to the vulnerable state of its population (Rigby et al. 2017), which accounts for up to 90% of purse seine elasmobranch bycatch (Gilman 2011). Besides quantifying the impacts of the yellowfin tuna TAC on silky shark catches, we also explore the economic dimension of this possible ecological impact, as a practical illustration of the strong links between ecological and economic effects.

## 2. Material and methods

### *2.1. Fisheries data – French purse seine fleet*

Logbook and observer data from the French tropical tuna purse seine fleet were used in the analyses. The data were provided by the Observatory of Exploited Tropical Pelagic Ecosystems (Ob7). Logbook data spanned from 1981 to 2019, while observer data were limited to 2014 to 2019. During this period the observer coverage ranged from 37% to 51%. Both datasets contain information on set type, date, and geographic position for each purse seine set. Logbook data also includes a unique vessel code, making it possible to quantify the number of operating purse seine vessels and to calculate their average number of sets. Silky shark bycatch data, reporting the number of caught individuals per set, is only available from the observer dataset. This dataset also includes size information from a sample of the captured sharks.

To evaluate the possible effects of the yellowfin tuna TAC implemented in 2017, the datasets were divided into two periods of equal duration, consisting of three years before the TAC (2014-2016) and three years after (2017-2019). The datasets were further divided into three distinct areas based on the spatial pattern of fishing sets, as shown on Figure 1: (1) Northern, comprising sets above 05°N; (2) Central, representing the core of the fishery and ranging from 10°S to 05°N; and (3) Southern, below 10°S. Table 1 shows the numbers of FAD sets for each period and areas in both datasets.

Table 1. Number of FAD sets conducted by the French tuna purse seine fleet by area and period.

| | **Logbook data** | | **Observer data** | |
|---|---|---|---|---|
| | 2014-2016 | 2017-2019 | 2014-2016 | 2017-2019 |
| Northern | 81 | 388 | 31 | 271 |
| Central | 4297 | 5425 | 1857 | 2621 |
| Southern | 408 | 304 | 189 | 166 |

*2.1.1. Raising observed silky catch to total catches*

To estimate the total number of silky sharks caught by the French purse seine fleet, the proportion of observed FAD sets ($P_n^{A,T}$) with the presence of $n$ silky sharks was calculated for each area $A$ and period $T$ (Figure 2). Based on these proportions, total silky shark catches were estimated considering the total number of FAD sets declared in the logbook data for each period and area as described in Equation 1:

$$TCatch^{A,T} = S^{A,T} \sum_{n=1}^{N^{A,T}} n\, P_n^{A,T}$$

(Equation 1)

where, $TCatch^{A,T}$ is the estimated total number of silky sharks caught by the French purse-seine fleet within a given area $A$ and period $T$, while $S^{A,T}$ is the total number of FAD sets declared in the logbook dataset within the same strata. The value $N^{A,T}$ represents the observed maximum number of silky sharks caught within a purse seine set in each spatial stratum.

#### *2.1.2. GLM modeling of observer's data*

To better understand the factors affecting silky shark catches, a Poisson GLM with a log link function was performed using observers' data. Silky shark catch was the response variable, while catch rate (average number of sharks per fishing set), number of sets, proportion of FAD sets relative to the total number of purse-seine sets, area (classified as Northern, Central and Southern) and period (classified into before and after the implementation of the TAC) were the independent variables. Due to the non-uniformity of the fishing sets across areas and periods, an interaction term between sets and areas was also included. The data was grouped into squares of 1°x1° degrees and squares with only one FAD set were excluded from the analysis.

The numeric predictors included in the GLM (number of sets, proportion of FAD sets and catch rates) have different units. Therefore, in order to compare the magnitude of their effects, their corresponding coefficients were standardized according with the Agresti method. This standardization method is the most recommended and consists of multiplying the coefficients of each numeric variable by the standard deviation of their estimate, so that each regression coefficient represents the effect of a standard deviation change in a predictor, controlling for the other variables (Agresti 2007). All analysis were performed in the statistical computing software R using *stats* and *dplyr* packages (R Core Team 2019).

Table 2. Summary statistics of the French observer data grouped into squares of 1°x1° for the GLM model fitting (N = 701). Catch = number of silky sharks; Catch rate = average number of sharks per fishing set; Sets = Number of observed purse seine sets; FAD prop = proportion of observed FAD sets.

| | Mean | Median | Minimum | Maximum | 1st quartile | 3rd quartile |
|---|---|---|---|---|---|---|
| **Catch** | 47.1 | 32.0 | 0 | 413 | 14.0 | 65.0 |
| **Catch rate** | 5.5 | 4.5 | 0 | 31 | 2.5 | 6.8 |
| **Sets** | 9.6 | 7.0 | 2* | 69 | 4.0 | 12.0 |
| **FAD prop** | 0.8 | 1.0 | 0 | 1 | 0.7 | 1.0 |

*Squares with less than 2 sets were excluded from the analysis.

Sample selection bias is inherent to fisheries-dependent data because samples are not random. However, silky sharks are not the target of purse seine fisheries and their presence at FAD sets are indeed subject to some degree of randomness. Sample selection bias is, therefore, a negligible issue in this case.

Nevertheless, the GLM model contains other intrinsic biases pertaining to endogeneity, correlation, and heteroscedasticity. To make sure those biases did not lead to incorrect parameter estimations, additional models were tested. Two main approaches were used: spatial regressions based on the Manski (1993) generic model, and a panel data framework, comparing Pooling, Random Effect, Fixed-Effect (Within) and Between methods. The heteroscedasticity issue was considered by testing the standard errors with a Pooling regression. All results confirmed the robustness of the original GLM model. The additional models are fully detailed and discussed in the Supplementary Materials section.

### *2.2. Fisheries data – Main IOTC purse seine fleets*

To evaluate how the implementation of the yellowfin tuna TAC affected other CPCs operating in the western Indian Ocean, additional FAD fishing information was obtained from the IOTC Secretariat. Specifically, information on the number of FAD sets per area and period was collated through IOTC 3FA forms which are used to report to the IOTC Secretariat mandatory information on FAD activities (deployment, retrieval, encounter, loss at sea, etc.) as well as catch and effort on FADs for all purse seine fishing fleets in activity in the IOTC area of competence, according to IOTC Resolution 19/02 "*On a Fishing Aggregating Devices (FADs) management plan*". The IOTC 3FA forms included data from 2014 to 2018, however inconsistencies were noted in some of the forms that prevented their inclusion in the analysis, as alternative sources for verification were lacking. This as was the case with the Korean and Japanese fleets.

Nonetheless, data from Spain, Seychelles and Mauritius could be verified through CPCs reports (Assan et al. 2019; Báez and Ramos 2019; Kawol et al. 2019) and were exploitable for the purpose of this study. Together with the French fleet, Spain and Seychelles are the main industrial purse seine fleets operating in the western Indian Ocean, accounting for 34% of total tuna catches (IOTC Secretariat 2020). The IOTC dataset was divided into the same areas as the French datasets. Available data within each time interval (before and after the yellowfin TAC) had to be limited to a single year (2016 and 2018, respectively) because Spanish data for 2017 has not been submitted to IOTC (Table 3).

Table 3. Number of FAD sets conducted by the Spanish, Seychellois and Mauritian tuna purse seine fleets by area and period.

| | 2016 | 2018 |
|---|---|---|
| Northern | 524 | 1432 |
| Central | 6278 | 5937 |
| Southern | 664 | 318 |

By combining the French and IOTC datasets, total silky shark catches for the western Indian Ocean were estimated for each area and period as described in Equation 1, considering $S^{A,T}$ as the total number of FAD sets declared in both French and IOTC datasets. For this estimation, the proportion of FAD sets with $n$ sharks ( $P_n^{A,T}$) obtained from the French observer's data (Figure 2) was used.

### *2.3. Economic assessment*

In terms of welfare economics, the bycatch issue can be seen as an external cost (or social cost) issue (Pascoe 1997), i.e. not embodied in the private (market) value of fish. Because society values canned skipjack, the whole social costs and benefits of FAD fishing have to be considered before deciding how to internalize these external costs (Ovando et al. 2021). As a result, the amount of acceptable bycatch is the tradeoff between the social costs and the benefits of FAD fishing.

With such an approach, bycatch represents a marginal abatement cost or, symmetrically, a decreasing marginal benefit for the fishing fleet[1]. However, increasing the level of bycatch may also represent a social damage that is not taken into consideration by the market. At a wide extent, such damage depends on the forgone value of ecosystem services attached to silky shark bycatch. As a first and approximate valuation, we developed a meta-analysis of the potential ecosystem services associated with sharks in general to propose a range of potential values for the external cost of bycatch. The various ways of internalizing this cost are examined in the results section as well.

[1] For instance, increasing the fishing effort with additional FAD sets in the northern part of the Indian Ocean would provide a declining profit per set because the yield per unit effort would be decreasing and the trip cost might be increasing simultaneously.

Considering the most suitable ways of internalizing the cost of shark bycatch, an approximated value for the forgone social cost of silky shark bycatch was also proposed. The proposed value consists of the product between the estimated number of shark bycatch (section 3.2.), the average weight (kg) and the unit price in USD per kg as defined by the literature (meta-analysis). To account for the variability of these 3 factors, their range were incorporated into a Monte Carlo analysis across 1500 iterations. A normal law with a 32% standard deviation (SD) was chosen for the unit weight of silky sharks. This distribution corresponds to the weights of silky shark bycatch reported by French observers. A random uniform law distribution of integer numbers between the minimum and maximum values was preferred for the estimated silky shark bycatch to account for the uncertainty surrounding the implementation of the yellowfin TAC (before/after). For the unit price of sharks, a normal law centered on the recreational value with a 20% SD was selected to reflect the random distribution of consumptive values reported by the literature.

## 3. Results

### *3.1. Fishing strategy adaptations*

The number of FAD sets conducted by the French purse seine fleet has consistently fluctuated over the years. However, it has never been as high as in the past four years and after the implementation of the yellowfin tuna stock rebuilding plan (Figure 3 – panel A). A maximum of 2315 FAD sets was reached in 2018, one year after the implementation of the TAC. It is important to mention, however, that the number of FAD sets started to increase in 2016 – the year of the TAC adoption and one year before its implementation. In 2019, the number of FAD sets has decreased to the levels of 2016 and 2017. Following the same trend as the number of FAD sets, the average number of FAD sets per vessel as well as the FAD to FSC sets ratio have considerably increased since 2016, reaching their peaks in 2018 (Figure 3 – panels B and C). In contrast, the number of operating vessels decreased over the years, but has remained relatively stable since 2014 (Figure 3 – panel C).

It appears that there was also a spatial component to the fishing adaptive strategy. In the three years that followed the yellowfin TAC implementation (2017-2019), the distribution of the fishing effort expanded to the north and to the east of its core (Figure 1). The most marked change was the increase of FAD sets in the Northern area, towards the Arabian Sea, form 81 in the years preceding the TAC (2014-2016) to 388 in the years following the TAC (2017-2019) (Table 1).

When combining the data from the French fleet with the main industrial purse-seine fleets operating in the same area, which include Spain, Seychelles and Mauritius, only a slight overall increase in the number of FAD sets is observed (Figure 4). However, in the Northern area, the number of FAD sets tripled, going from 538 in 2016 to 1604 in 2018 (Figure 4). On the other hand, FAD effort remained relatively stable in the Central, while in the Southern area a decrease was observed

### *3.2. Increase in silky shark catches*

In the years preceding the TAC implementation (2014-2016), the estimated number of silky sharks caught by the French fleet corresponded to 30,707 individuals, while after the TAC, the estimated silky shark catches increased to 41,325 (Figure 5) corresponding to a 35% increase. The most significant increase in silky shark catch occurred in the Northern area, where catches were estimated to be 379% higher than the pre-TAC years.

The estimated silky shark catches for the main industrial purse seine fleets operating in the western Indian ocean (including France, Spain, Seychelles and Mauritius) reached 73,987 individuals in 2018, against 62,442 in 2016 - an increase of 18% (Figure 6). This trend was entirely led by the increase in the number of FAD sets in the Northern area, where catch estimates were 198% higher in 2018.

The GLM model fitted on French observer's data provided a good fit and all factors where significant ($p<0.05$) (Table 4). The number of FAD sets was the most important variable, followed closely by silky shark catch rates. The period before the implementation of the yellowfin TAC had a negative impact on silky shark catches when compared to the period after. The interaction term between sets and areas showed a higher importance of the Northern area. Model predictions and residuals are shown in Supplementary Figures 2 to 4.

**Table 4.** Model summary (Catch ~ Catch rate + Sets + FAD prop + Period + Sets:Area, family = Poisson). Std.error = standard error, Conf.low and Con.high = lower and upper bound of the 95% confidence interval for each estimate.

| Term | Estimate | Std.error | Statistic | p.value | Conf.low | Conf.high |
|---|---|---|---|---|---|---|
| (Intercept) | 3.7079 | 0.0085 | 438.3404 | 0.00E+00 | 3.6913 | 3.7245 |
| Catch rate | 0.4418 | 0.0051 | 87.3393 | 0.00E+00 | 0.4319 | 0.4517 |
| Sets | 1.0623 | 0.0298 | 35.6356 | 3.93E-250 | 1.0035 | 1.1204 |
| FAD prop | 0.2374 | 0.0087 | 27.3178 | 2.61E-150 | 0.2204 | 0.2544 |
| Period (before) | -0.2368 | 0.0124 | -19.0950 | 2.78E-67 | -0.2611 | -0.2125 |
| Sets:Area (Northern) | 0.4301 | 0.0430 | 10.0096 | 1.38E-09 | 0.3461 | 0.5146 |
| Sets:Area (Central) | -0.5379 | 0.0301 | -17.8479 | 3.00E-43 | -0.5966 | -0.4785 |

### *3.3. Economic loss associated with silky shark bycatch*

On the basis of a meta-analysis of shark ecosystem values found in the literature, we attempted to estimate the external cost of bycatch through some potential forgone uses ranging from consumptive values to eco-tourism and recreational services. The ecological (existence, option, and bequest) values of silky sharks were left out of the analysis because of incomplete knowledge regarding the abundance of stocks and the ecological importance of this species for the whole oceanic ecosystem.

#### *3.3.1. Consumptive value of provisioning ecosystem services*

Silky sharks are caught as bycatch and discarded by purse seine fleets operating in the western Indian Ocean. Consequently, the economic damage begins with the forgone commercial value of sharks. The consumptive value of sharks was valuated to US$630m per year (Cisneros-Montemayor et al. 2013). According to Dent and Clarke (2015), the value of shark products would even approach US$1 billion per year in the early 2010s. Most official data presumably under-estimate the total tonnage and value of marketed sharks because of an opaque and sometimes illegal business for this very high-valued product (particularly shark fins sold in Asia). The mere trade of shark fins (including skates and rays) would be worth valuing half of this amount for 15,000 t traded of net products in the mid-2010s and 10,500 t in 2018, and a unit value reaching around US$25 per kilo (FAO). It is important to highlight that the practice of finning (cutting off the fins of the shark and discarding its carcass at sea) is banned from many fisheries worldwide, including those under IOTC mandate (CMM 17-05). However, if finning ban requirements are met, the trade of shark fins and meat remains legal. Shark fishing is a sensitive subject, but to fully grasp the economic loss associated with shark bycatch their consumptive value needs to be quantified.

Conversion factors are required to retrieve the live weight equivalent of prices. A common fin ratio (fin weight as a percentage of whole weight) for sharks was estimated at 3.33%, upgrading the conversion factor to 30, although factors could be different between shark species (Francis 2014). For dried fins, the conversion factor could rise up to 150 because of the water loss weight (Caillart et al. 1996). The LWE price observed in the official trade statistics of FAO varied between US$0.20/kg for dried fins to US$3.58/kg for fresh and chilled shark meat in 2018. What matters for the lost value of discards is actually the price paid to fishers. In Palau, the catch value of one single shark was estimated at US$108 (Vianna et al., 2012), i.e., a price between 5 and 6 USD per kg if we convert it by the average weight of the two most frequent species, the whitetip (*Triaenodon obesus*) and the grey reef shark *(Carcharhinus amblyrhynchos*). The two most important countries harvesting and trading silky sharks reported by FAO are Costa Rica (2279 t in 2018) and Sri Lanka (709 t), with the noticeable exception of Tanzania for year 2018 (2,155 t). Their LWE price would be around $0.16 per kg for Sri Lanka and $0.60 per kg for Costa Rica, much more in connection with the price of $0.75 per kg reported by Sumaila et al. (2007). Taking a conservative value from the trade statistics of FAO converted in LWE, we suggest retaining a minimum price of $0.40 per kg (average trade price 2015-2016 in LWE) as a possible minimal reference for the forgone consumptive value of silky sharks.

#### *3.3.2. Conservation value and cultural ecosystem services*

The ecological role of sharks in pelagic ecosystems has been evidenced in several studies but is rarely described at an ocean-wide scale (Kinney and Simpfendorfer 2009; Lew 2015; Murphy et al. 2018). The economic value of alive sharks goes nonetheless far beyond the extractive value of fishing reported above: one may add the non-consumptive use value of ecotourism associated to shark diving, which is present in many studies (Davis et al. 1998; Davis and Tisdell 1999; Clua et al. 2011; Vianna et al. 2011; Cagua et al. 2014; Pires et al. 2016; Zimmerhackel et al. 2019), other use values such as the film industry or research (Haas et al. 2017), but also indirect use value through the regulation of the whole ecosystem (Kinney and Simpfendorfer 2009), and non-use values such as the existence, option (possible uses in the future such as genetic inputs) and bequest values for future generations (Grafeld et al. 2016; Skubel et al. 2019). If the marginal damage of accidentally fishing a silky shark cannot be the sum of all these values, because some uses represent alternative choices (e.g., shark diving vs fishing), others could be very well aggregated (tourism, ecosystem regulation, existence value...). Most of the literature attempting to demonstrate the value of shark conservation focuses on the economic value of shark diving ecotourism (Table 5).

Table 5. The revealed value of alive sharks borne with the diving and ecotourism industries.

| STUDY | AREA | ACTIVITY | REVENUE (MILLION USD) |
|---|---|---|---|
| Cisneros-Montemayor et al., 2013 | World | Watching + diving | 314 |
| Haas et al., 2017 | Bahamas | Shark diving | 109 |
| Vianna et al., 2011 | Fiji | Shark diving | 42.2 |
| Huveneers et al., 2017 | Australia | Shark diving | 25.5 |
| Vianna et al., 2012 | Palau | Shark diving | 18 |
| Grafeld et al. 2016 | Guam | Shark scuba diving | 15-20 |
| Vianna et al. 2018 | Borneo | MPA + shark diving | 10 |
| Cagua et al., 2014 | Maldives | Whaleshark diving | 9.4 |
| Clua et al., 2011 | French Polynesia | Shark watching + feeding | 5.4 |
| Indab 2016 | Philippines | Whale shark conservation | 0.7 |

Globally, the value of recreational ecosystem services would amount to US$314m in 2013 (Cisneros-Montemayor et al. 2013). Based on Travel Cost Methods (TCM) to evaluate indirectly the non-market value of sharks through the expenditures of divers or simple watchers and the business of tourist operators, various regional studies have been published for the last decade (Table 5). The shark diving or watching (tourism) industry represents several millions USD of earnings, hence a substantial contribution to GDP for some small island developing states, like in Palau where shark-related tourism amounted to 8% of GDP (Vianna et al. 2012).

Besides this direct valuation through revealed preference methods, other authors combined travel-cost approaches with stated preference models (contingent valuation method or CVM, conjoint analysis, choice experiment) to test for the willingness-to-pay of divers and tourists for various conservation policies (Mieras et al. 2017; Murphy et al. 2018; Vianna et al. 2018;

Zimmerhackel et al. 2019). For instance, in addition to the current US$32.5 ticket to watch Manta rays in the Fiji Islands, 82% of tourists were willing to pay an extra amount greater than US$2.5 (54% of divers would even pay US$10 or more) to dive with Mantas and support educational and environmental policies protecting sharks (Murphy et al. 2018). Another study showed that the consumer surplus of divers along with the diving industry revenue would be halved in the Maldives if sharks could not be observed during dive trips or if illegal fishing was exercised (Zimmerhackel et al. 2019). Vianna et al. (2018) developed a survey mixing a TCM approach with a scenario of Marine Protected Area (MPA) creation in Semporna (Borneo, Malaysia). In particular, the authors compared the high value generated by the diving industry revenue, the tax income collected by the Malaysian government and the salaries paid to households working in the diving sector (>$10m overall) to the much lower value created by the local fishing industry with the annual 462 tons of harvested sharks (<$0.5m). However, in some developing countries, the willingness-to-pay for a whale shark conservation program is close to zero because the local citizens just cannot afford it, although they are perfectly aware of the environmental stakes of such programs (Indab 2016).

### *3.3.3. The recreational value of shark angling*

All these studies demonstrate the high non-consumptive value of sharks. The problem with CVM studies is that they can hardly be used to estimate an individual value of fish so as to apply benefit transfer (or value transfer function) methods (Plummer 2009). They are more designed to valuate conservation programs as a whole, and do not respond *per se* to the economic theory of utility when it comes to associate a value to a variable quantity of individuals to be preserved. Some authors go then further by valuating an individual price of an alive shark over its life span, amounting to $180,000 per year in Palau, and therefore nearly $2m over 16 years with a discount rate of 5% (Vianna et al. 2012). Another study reported an individual value by shark of $316,699 annually (Clua et al. 2011). When comparing these huge amounts to the market price of shark consumed as food stated in previous section (e.g., approximately US$70 for a 20-kg shark marketed as fresh or chilled meat in 2018), conservation looks like a much better option for society.

Nonetheless, these comparisons are not straightforward as some of the aforementioned species are highly recognizable and charismatic (e.g., whale shark, manta ray), unlike grey reef or silky sharks. Additionally, it is often unknown what proportion of a shark's population visits diving sites and therefore attract tourists. Silky sharks, for example, are a popular attraction for SCUBA divers coming to the central Red Sea but, at present, we are not able to quantify how much of the Indian Ocean population actually visits the area and supports this touristic activity (Clarke et al. 2011, 2013a). One could also argue that the presence of other shark species would be enough to meet the tourism demand if silky sharks no longer visited the site. Therefore, it is possible that only a small fraction of the population would be enough to maintain the economic activity, which would interfere with the utility theory assumption on which the revealed methods of valuation are based. This means that we cannot simply multiply the number of bycaught individuals by the unit value of sharks estimated in shark diving valuations.

Stated preference methods like CVM are more likely to approach the value of an environmental asset when scenarios are closer to market-type conditions. In this regard, recreational fisheries can represent a good proxy of the opportunity cost of discarding silky sharks. Johnston et al. (2006) developed a meta-analysis of WTP values per recreational fish, including what they called big game fish (dogfish, ray, sharks, billfish, swordfish...). For this research, they collected 48 studies including 391 observations of individual WTPs between 1977 and 2001 (all values were converted in constant US$ of 2003). They could estimate several econometric models to explain the values of recreational fish, while controlling for the method (discrete choice models, TCM, CVM, Choice experiment, etc.), the targeted species, the water body type, the catch rate, the angler demographics, and the fishing method. The estimated value for big game fish issued by the WTP econometric model would give a value of US$25 per individual fish, i.e. US$1.26 per kg for a 20-kg specimen. Converting the constant price of 2003 into a constant price of 2018, it would give a US$40 per shark (or a US$2 per kg if discards of silky sharks are estimated in weight). This latter price would represent another reference for the opportunity cost of silky shark bycatch.

### *3.3.4. The forgone social cost of silky shark bycatch*

Summarizing the previous sections dedicated to the monetary cost of the ecosystem services forgone with shark bycatch, we can report the following values (Table 6):

**Table 6.** Alternative use values of silky sharks.

| ECOSYSTEM SERVICES | VALUE (US$ PER KG) |
|---|---|
| Consumptive value (shark fins LWE) | 0.40 |
| Recreational value (angling) | 2.00 |
| Consumptive value (shark fresh meat) | 3.58 |
| Conservation value (ecotourism)* | 15,000.00 |

*Annual discounted revenue per kg of an alive shark exploited by diving tourism in Palau over 16 years with a discount rate of 5% for a 22-kg shark (calculated from Vianna et al., 2012)

The prices reported in Table 6 represent alternative values of the marginal damage (i.e. external cost) of bycatch. Given that silky sharks caught accidentally are not marketed by purse-seine fishers, the opportunity cost of discarding lies in the alternative uses which are lost for other end-users (other fishers, recreational anglers, divers, eco-tourists…). To compute an approximated social cost of silky shark bycatch we considered the recreational value of $2.00 per kg with a 20% SD (2.00$\pm$0.40), since it reflects the random distribution of consumptive values between $0.40 and $3.58 (Table 6). However, we did not consider the discounted conservation value, as it would result in an extremely high figure, by far exceeding the global value of recreational ecosystem services estimated by Cisneros-Montemayor et al. (2013). The other two terms used to estimate the social cost of silky shark bycatch were the average weight of 12.10 $\pm$ 3.85 kg (32% SD) and a range of 62,442 to 73,987 sharks caught (estimated in section 3.2.).

The combination of random input values gave a 90% probability of forgone value estimated between US$ 709,992 and US$ 2,806,602 for the sole consumptive value (Figures 7A and 7B), with a mean at US$ 1,640,928. The average weight, whose distribution is skewed on both sides, has a prevailing impact on the output value, with a swing between US$ 0.1 and 3.2 million, exceeding by far the effect of the unit value or the number of harvested individuals (Figure 7C). However, we used a very conservative range of consumptive values representing the mere loss of provisioning ecosystem services caused by the bycatch of sharks, and not any conservation value as showing the support or cultural ecosystem services.

Looking at the forgone value through the eyes of a conservationist may increase substantially the social cost of shark bycatch, as seen with the net present value of ecological diving. Other studies discounting the value of an alive shark attracting tourists throughout its lifespan have considered values as high as $180,000 per year (Palau) or even $316,699*yr$^{-1}$ (French Polynesia). To grant a similar value for every single silky shark killed as purse seine bycatch would be inadvisable, given that not all of these sharks would visit diving sites. However, assuming that a small proportion (say 1‰ only) of this forgone biomass visits open ocean areas where tourists come to dive, such as the Red Sea or the Maldives, and taking the conservation value of Table 6 ($15,000 per kg) and the average weight of silky sharks from the observers' sample (12 kg), the social cost of the forgone ecosystem service would increase between USD 11 and 14 million. This amount corresponds to 3 or 4% of the value of landings for the European purse seine fleet harvesting in the Indian Ocean[2]. Given the non-certain probability of use in other alternatives, the forgone consumptive or non-consumptive values should be considered alternatively and not simultaneously.

## 4. Discussion

This study indicates that the industrial purse seine fleets operating in the western Indian ocean have adapted their fishing strategy in response to the yellowfin tuna TAC first implemented by the IOTC in 2017 (CMM 16-01) and these adaptations have indirectly resulted in an increase of silky shark bycatch. For the French purse seine fleet, total silky shark catches increased by 35% (Figure 5). For the main purse seine fleets combined (including France, Spain, Seychelles and Mauritius), the increase reached 18% (Figure 6). Two major strategy adaptations, consisting of fishing mode shift and effort expansion, were identified. Most large yellowfin tuna are caught on free-swimming schools sets (Dagorn et al. 2013; Fonteneau et al. 2013). Hence, the first obvious adaptation of the French fleet was to stop searching for yellowfin tuna free-swimming schools and direct most of its effort to tuna schools associated with floating objects. This fishing mode shift had a direct impact on the increased shark bycatch, as the overwhelming majority of silky sharks are caught on FAD sets (Amandè et al. 2012; Torres-Irineo et al. 2014; Lezama-Ochoa et al. 2018). The French fleet particularly targeted free-swimming yellowfin tuna schools before the TAC, therefore an increase in the number of FAD sets was not as pronounced for the other fleets. The second major strategy adaptation was the effort expansion to the North, towards the Arabian Sea.

---

[2] STECF 19-06 - AER - Economic and Transversal data tables; https://stecf.jrc.ec.europa.eu/reports/economic. The total revenue of 11 French PS and 13 Spanish PS was US$ 322 million in 2018.

This area was historically known for its high catch rates of the skipjack tuna (IOTC Secretariat 2020), but its exploitation was minimal during the years preceding the implementation of the yellowfin TAC (Figures 1 and 4). After the TAC, silky shark catches were 379% higher in the Northern area for the French fleet and 198% for the main fleets combined. This large increase reflects the higher silky shark catch rates in the area, which is a known hotspot for the species (Mannocci et al. 2020). It should be noted that the analyses cannot predict how the fishing strategy of purse seine fleets would have evolved if the TAC measure had not been implemented. The FAD-fishing effort could have increased and further expanded in the northern area regardless. However, the results of the modeling approach report a significant dummy period effect (see Supplementary Materials), which can be at least partly explained by the implementation of this management measure. Furthermore, no other major event (i.e., climate oscillation, piracy) was reported throughout the sample period, strengthening the hypothesis that silky catches have collaterally increased due to the yellowfin tuna TAC.

There are obvious ecological impacts caused by an increase in silky shark bycatch. Elasmobranch species exhibit low population growth rates (Cortés 2000), which makes them much more vulnerable to overfishing when compared to teleost fish (Musick et al. 2000; Frisk et al. 2005). Many studies have laid out the fragile state of pelagic shark populations worldwide due to the increasing fishing induced mortality across their range (Dulvy et al. 2008; Camhi 2009; Worm et al. 2013). The silky shark is classified as vulnerable to near threatened by the IUCN red list and (Rigby et al. 2017), whereas uncertainties still remain due to lack of data, there is a general consensus that its populations have declined (Baum and Blanchard 2010; Clarke et al. 2013b). In the Indian Ocean, silky sharks are highly susceptible to longline and gillnet fisheries with the aggravating factor of poor data collection (IOTC Secretariat 2021). Even if the tropical purse seine fishery is not the main source of silky shark bycatch, any augmentation in fishing pressure on threatened species poses an important ecological risk. Additionally, the at-vessel mortality rate of silky sharks caught by purse vessels is extremely high as most individuals are already dead by the time they reach the deck. Their total mortality (at vessel plus post-release) has been estimated at 80% across several studies conducted in the Pacific, Atlantic and Indian oceans (Poisson et al. 2014; Hutchinson et al. 2015; Eddy et al. 2016).

Like in many high sea fisheries, there is no specific regulation for bycatch such as a tax penalty or limited quotas of FAD sets in the Indian Ocean Tuna fisheries (Dagorn et al. 2013). We saw that the implementation of a TAC for yellowfin tuna in 2017 has shifted the fishing strategy of the purse seine fleet towards an increasing use of FADs over a wider and northward expanding fishing area, resulting in a significant increase of silky shark bycatches. The latter represent external costs for alternative ecosystem services (Pascoe 1997). Among other users might be considered other fleets targeting sharks for their consumptive value, but also the ecotourism industry making a living out of shark diving or watching (Cisneros-Montemayor et al. 2013; Haas et al. 2017; Huveneers et al. 2017; Vianna et al. 2018; Zimmerhackel et al. 2019). We can also mention the a range of other non-use values resulting from conservation: regulation of ecosystems, genetic wealth, cultural value… (Kinney and Simpfendorfer 2009; Indab 2016; Skubel et al. 2019).

The lack of regulation means that the purse-seine fleet will catch as much as possible until the marginal benefit is exhausted at point *H* in Figure 8, for a bycatch quantity $D_n$. This quantity was estimated at 73,987 individuals for the whole Indian Ocean in 2018. The external cost is illustrated by the marginal damage curves, with different slopes according to the marginal opportunity cost of discarding (e.g. the minimum consumptive value of fins could be represented by $MD_1$, the recreational value of angling by $MD_2$, fresh meat by $MD_3$, etc. in Figure 8). The social optimum would therefore be achieved at the intersection of the marginal abatement cost (or marginal benefit) curve and the marginal damage curve, respectively in points I, J, or K according to the shape of the damage curve, therefore reducing the level of bycatch (from $D_0$ to $D_1$, $D_2$, or $D_3$).

With a more conservationist opportunity cost, such as the eco-touristic or ecological value of sharks fixed at a much higher level (Vianna et al. 2012; Haas et al. 2017; Zimmerhackel et al. 2019), or the net loss of the tuna value chain induced by e-NGO campaigns against bycatch or FAD fishing (Teisl et al. 2002; Gomez et al. 2020), the optimal level of bycatch could even tend to zero (point L in Figure 8). However, such a limitation of FAD fishing would not be very realistic nor socially desirable because economic trade-offs should compare the discounted value of non-harvested tuna due to FAD prohibition on the one hand, and the conservation value of sharks on the other hand (Hoagland and Jin 1997; Ovando et al. 2021). A rough estimate of the forgone consumptive value of silky shark bycatch without discounting would result in an annual value between US$ 1.5 and 1.8 million for the sole consumptive value, i.e. representing 0.5% to 0.6% of annual revenue for the EU fleet harvesting in the Indian Ocean.

Consequently, the tuna fishing industry could easily afford to compensate for the lost ecosystem services associated with sharks, but the question lies in the incentives to internalize this social cost. Ovando et al. (2021) suggest a Coasean solution through right-based markets rather than a Pigouvian tax or regulation which is costly and difficult to implement in the case of international high seas fisheries, hence poorly enforceable. The authors estimated the revenue loss of longliners because of bigeye bycatches caused by FAD fishing from purse-seiners in the west and central Pacific Ocean. They concluded that the economic costs of large-scale reductions in FAD use far outweigh the benefits and proposed a Coasean-bargaining solution where conservationist interests, fishing fleets and any other stakeholder group (states, IOTC, e-NGOs…) could sell or purchase FAD-use rights according to the value placed on silky shark conservation. This could be done through a tax levied on shark-diving tourism, or a price premium on FAD-free canned skipjack paid by consumers. In the Pacific case study, a 4% price premium on free-school skipjack would cover the complete removal of FAD fishing from the Vessel Day Scheme (Ovando et al. 2021).

The problem with Coasean solutions stems from uncertainty and transaction costs to organize and monitor such right-based incentives. In the present case, their implementation would assume that the stocks of yellowfin, skipjack and silky sharks would be better known, as well as their interactions within the ecosystem, that the end users (either consumers of FAD-free tuna or shark divers) would be willing to pay a premium for the sake of conservation interests, that the use of FADs can be monitored and enforced, etc. This is not out of reach but would require a more thorough and comprehensive study about the ecological value of sharks and the awareness about the consequences of FAD fishing by end users. In particular, the valuation of the social cost would be different for non-consumptive ecosystem services, such as cultural or recreational services related to shark-diving and tourism in the Indian Ocean (Seychelles, Maldives, Red Sea, Mauritius, etc.). Assuming only a small proportion (1‰) of the forgone biomass visits the diving sites where the tourists like to observe silky sharks, the external cost would be valued between USD 11 and 14 million, i.e. representing 3 to 4% of the annual earnings of the EU fleet. This would make a huge difference and would significantly increase the stakes of the trade-off between the conflicting ecosystem services (provisioning, or recreational and cultural) derived from the presence of sharks, and not even discussing the unknown role of sharks in the regulation of marine ecosystems.

**5. Conclusions**

Our work narrates a practical example of how managing bycatch and target species that share similar habitats is a challenging task. Tuna RFMOs have been trying to incorporate the principles of an ecosystem-based fisheries management for many years, but, ultimately, the decision-making process remains purely based on single-species management (Gilman et al. 2014; Karim et al. 2020). To assure sustainability in the economic, social and ecological spheres we need to let go of the single-species approach as the foundation of our fisheries management and adopt a more holistic approach.

Efforts to move towards an ecosystem approach have been made by tuna RFMOs in the past few years. These included the creation of bycatch and ecosystem working groups inside the tuna commissions and the development of ecosystem report cards, which consist of a set of indicators to monitor several ecosystem components as a whole (Juan-Jordá et al. 2018). Additional efforts could be directed to the creation of working groups dedicated to the socio-economic aspects of fisheries at the same level as the other groups that comprise the scientific committees. Discussion groups focused on possible unintended effects of a particular management measure should be conducted on a regular basis. These discussion groups should be composed by scientists from the main tuna RFMOs working groups (e.g., tropical tunas, billfishes, neritic tunas, ecosystem, and bycatch and the *still-to-be-created* socio-economic group), as well as fishery stakeholders. The possible unintended effects should then be closely monitored, so that mitigating actions can quickly be taken. For the specific case of bycatch mitigation, the implementation of credit systems, such as cap-and-trade, are certainly worth investigating (Ovando et al. 2021; Squires et al. 2021).

This is a first exploration into to the socio-economic dimension of trade-offs between the use of FADs in tuna purse seine fisheries and shark bycatch. Our work can equally be used as a basis to discuss the trade-offs of other FAD-associated species. It is important to highlight that fundamental knowledge regarding stock status and population dynamics are essential to support accurate ecosystem services valuations. Undoubtedly, there are many other caveats that need to be considered when shifting tuna fisheries management from single-species to ecosystem-based, but the work described here certainly outlines changes need to happen more rapidly. Maybe, the effort should be put into an Ecosystem Service-Based Fisheries Management rather than just Ecosystem-Based Fisheries Management.

## 6. Acknowledgements

The authors are grateful to all people and national institutes of the Indian Ocean Tuna Commission (IOTC) involved in the collection, management, and curation of the data made available by the IOTC Secretariat for the present study. MT and FF were funded by the Research Project INNOV-FAD (European Maritime and Fisheries Fund, measure n°39, OSIRIS #PFEA390017FA1000004, and France Filière Pêche).

## 7. References

Agresti A (2007) Logistic Regression. In: An Introduction to Categorical Data Analysis. pp 99–136

Amandè MJ, Chassot E, Chavance P, et al (2012) Precision in bycatch estimates: The case of tuna purse-seine fisheries in the Indian Ocean. ICES J Mar Sci 69:1501–1510. https://doi.org/10.1093/icesjms/fss106

Andrew A. Rosenberg and Karen L. McLeod (2005) Implementing ecosystem-based approaches to management for the conservation of ecosystem services Author ( s ): Andrew A . Rosenberg and Karen L . McLeod Published by : Inter-Research Science Center Stable URL : http://www.jstor.org/stable/24869751 REFEREN. Mar Ecol Prog Ser 300:270–274

Assan C, Lucas J, Chassot E (2019) Statistics of The Seychelles Purse Seine Fleet Targeting Tropical Tunas In The Indian Ocean (2000-2018). IOTC Work Party Trop Tuna IOTC-2019-WPTT21–14

Báez JC, Ramos ML (2019) Free school fishery trends for Spanish tropical purse seiners in the Indian Ocean. IOTC Work Party Trop Tuna IOTC-2019-WPTT21–12

Baum JK, Blanchard W (2010) Inferring shark population trends from generalized linear mixed models of pelagic longline catch and effort data. Fish Res 102:229–239. https://doi.org/10.1016/j.fishres.2009.11.006

Berkes F (2012) Implementing ecosystem-based management: Evolution or revolution? Fish Fish 13:465–476. https://doi.org/10.1111/j.1467-2979.2011.00452.x

Börger T, Beaumont NJ, Pendleton L, et al (2014) Incorporating ecosystem services in marine planning: The role of valuation. Mar Policy 46:161–170. https://doi.org/https://doi.org/10.1016/j.marpol.2014.01.019

Bourjea J, Clermont S, Delgado A, et al (2014) Marine turtle interaction with purse-seine fishery in the Atlantic and Indian oceans: Lessons for management. Biol Conserv 178:74–87. https://doi.org/10.1016/j.biocon.2014.06.020

Branch TA, Hilborn R, Haynie AC, et al (2006) Fleet dynamics and fishermen behavior: Lessons for fisheries managers. Can J Fish Aquat Sci 63:1647–1668. https://doi.org/10.1139/F06-072

Cagua EF, Collins N, Hancock J, Rees R (2014) Whale shark economics: A valuation of wildlife tourism in South Ari Atoll, Maldives. PeerJ 2014:1–17. https://doi.org/10.7717/peerj.515

Caillart B, Borel G, Merrien C (1996) Etude comparative des coefficients de conversion utilisés pour estimer le poids vif des captures des flottilles de pêche de l'Union

Camhi M (2009) The conservation status of pelagic sharks and rays

Cavanagh RD, Broszeit S, Pilling GM, et al (2016) Valuing biodiversity and ecosystem services: A useful way to manage and conserve marine resources? Proc R Soc B Biol Sci 283:. https://doi.org/10.1098/rspb.2016.1635

CBD (2004) The ecosystem approach. Secretariat of the Convention on Biological Diversity, Montral

Chaudhary S, McGregor A, Houston D, Chettri N (2015) The evolution of ecosystem services: A time series and discourse-centered analysis. Environ Sci Policy 54:25–34. https://doi.org/https://doi.org/10.1016/j.envsci.2015.04.025

Cisneros-Montemayor AM, Barnes-Mauthe M, Al-Abdulrazzak D, et al (2013) Global economic value of shark ecotourism: Implications for conservation. Oryx 47:381–388. https://doi.org/10.1017/S0030605312001718

Clarke C, Lea JSE, Ormond RFG (2011) Reef-use and residency patterns of a baited population of silky sharks, Carcharhinus falciformis, in the Red Sea. Mar Freshw Res 62:668–675. https://doi.org/10.1071/MF10171

Clarke CR, Lea JSE, Ormond RFG (2013a) Changing relative abundance and behaviour of silky and grey reef sharks baited over 12 years on a Red Sea reef. Mar Freshw Res 64:909–919. https://doi.org/10.1071/MF12144

Clarke SC, Harley SJ, Hoyle SD, Rice JS (2013b) Population Trends in Pacific Oceanic Sharks and the Utility of Regulations on Shark Finning. Conserv Biol 27:197–209. https://doi.org/10.1111/j.1523-1739.2012.01943.x

Clua E, Buray N, Legendre P, et al (2011) Business partner or simple catch? The economic value of the sicklefin lemon shark in French Polynesia. Mar Freshw Res 62:764–770. https://doi.org/10.1071/MF10163

Cortés E (2000) *Life History Patterns and Correlations in Sharks*. Rev Fish Sci 8:299–344. https://doi.org/10.1080/10408340308951115

Costanza R, D'Arge R, de Groot R, et al (1997) The value of the world's ecosystem services and natural capital. Nature 387:253–260

Costanza R, de Groot R, Braat L, et al (2017) Twenty years of ecosystem services: How far have we come and how far do we still need to go? Ecosyst Serv 28:1–16. https://doi.org/https://doi.org/10.1016/j.ecoser.2017.09.008

Crespo GO, Dunn DC, Gianni M, et al (2019) High-seas fish biodiversity is slipping through the governance net. Nat Ecol Evol 3:1273–1276. https://doi.org/10.1038/s41559-019-0981-4

Dagorn L, Holland KN, Restrepo V, Moreno G (2013) Is it good or bad to fish with FADs? What are the real impacts of the use of drifting FADs on pelagic marine ecosystems? Fish Fish 14:391–415. https://doi.org/10.1111/j.1467-2979.2012.00478.x

Davis D, Banks S, Birtles A, et al (1998) Whale Sharks in Ningaloo Marine Park: Managing Tourism in an Australian Marine Protected Area. Derrin Davis, Simon Banks, Alastair Birtles, Peter Valentine, and Michael Cuthill. Tourism Management, vol. 18, no. 5, 1997, pp. 259-72. Elsevier

Science, P.O. . J Travel Res 36:90–91. https://doi.org/10.1177/004728759803600499

Davis D, Tisdell CA (1999) Tourist levies and willingness to pay for a whale shark experience. Tour Econ 5:161–174

Dent F, Clarke S (2015) State of the global market for shark products. FAO Fish Aquac Tech Pap I

Drakou EG, Pendleton L, Effron M, et al (2017) When ecosystems and their services are not co-located: Oceans and coasts. ICES J Mar Sci 74:1531–1539. https://doi.org/10.1093/icesjms/fsx026

Drakou EG, Virdin J, Pendleton L (2018) Mapping the global distribution of locally-generated marine ecosystem services: The case of the West and Central Pacific Ocean tuna fisheries. Ecosyst Serv 31:278–288. https://doi.org/10.1016/j.ecoser.2018.05.008

Dulvy NK, Baum JK, Clarke S, et al (2008) You can swim but you can't hide: the global status and conservation of oceanic pelagic sharks and rays. Aquat Conserv Mar Freshw Ecosyst 18:459–482. https://doi.org/10.1002/aqc.975

Eddy C, Brill R, Bernal D (2016) Rates of at-vessel mortality and post-release survival of pelagic sharks captured with tuna purse seines around drifting fish aggregating devices (FADs) in the equatorial eastern Pacific Ocean. Fish Res 174:109–117. https://doi.org/10.1016/j.fishres.2015.09.008

Escalle L, Gaertner D, Chavance P, et al (2016) Consequences of fishing moratoria on catch and bycatch: the case of tropical tuna purse-seiners and whale and whale shark associated sets. Biodivers Conserv. https://doi.org/10.1007/s10531-016-1146-2

Ferreira AM, Marques JC, Seixas S (2017) Integrating marine ecosystem conservation and ecosystems services economic valuation: Implications for coastal zones governance. Ecol Indic 77:114–122. https://doi.org/10.1016/j.ecolind.2017.01.036

Fonteneau A, Chassot E, Bodin N (2013) Global spatio-temporal patterns in tropical tuna purse seine fisheries on drifting fish aggregating devices ( DFADs ): Taking a historical perspective to inform current challenges. Aquat Living Resour 26:37–48. https://doi.org/10.1051/alr/2013046

Francis MP (2014) Estimation of fin ratios and dressed weight conversion factors for selected shark species. New Zeal Fish Assess Rep 68:31

Frisk MG, Miller TJ, Dulvy NK (2005) Life histories and vulnerability to exploitation of elasmobranchs: Inferences from elasticity, perturbation and phylogenetic analyses. J Northwest Atl Fish Sci 35:27–45. https://doi.org/10.2960/J.v35.m514

Garcia SM, Cochrane K (2005) Ecosystem approach to fisheries: a review of implementation guidelines. ICES J Mar Sci 62:311–318. https://doi.org/10.1016/j.icesjms.2004.12.003

Gilman E, Passfield K, Nakamura K (2014) Performance of regional fisheries management organizations: Ecosystem-based governance of bycatch and discards. Fish Fish 15:327–351. https://doi.org/10.1111/faf.12021

Gilman EL (2011) Bycatch governance and best practice mitigation technology in global tuna fisheries. Mar Policy 35:590–609. https://doi.org/10.1016/j.marpol.2011.01.021

Gomez G, Farquhar S, Bell H, et al (2020) The IUU Nature of FADs: Implications for Tuna Management and Markets. Coast Manag 48:534–558. https://doi.org/10.1080/08920753.2020.1845585

Grafeld S, Oleson K, Barnes M, et al (2016) Divers' willingness to pay for improved coral reef conditions in Guam: An untapped source of funding for management and conservation? Ecol Econ 128:202–213. https://doi.org/10.1016/j.ecolecon.2016.05.005

Granek EF, Polasky S, Kappel C V., et al (2010) Ecosystem services as a common language for coastal ecosystem-based management. Conserv Biol 24:207–216. https://doi.org/10.1111/j.1523-1739.2009.01355.x

Haas AR, Fedler T, Brooks EJ (2017) The contemporary economic value of elasmobranchs in The Bahamas: Reaping the rewards of 25 years of stewardship and conservation. Biol Conserv 207:55–63. https://doi.org/10.1016/j.biocon.2017.01.007

Hamilton A, Lewis A, McCoy MAM, et al (2011) Market and industry dynamics in the global tuna supply chain. Forum Fish Agency, … 394

Hoagland P, Jin D (1997) A model of bycatch involving a passive use stock. Mar Resour Econ 12:11–28. https://doi.org/10.1086/mre.12.1.42629179

Hutchinson MR, Itano DG, Muir JA, Holland KN (2015) Post-release survival of juvenile silky sharks captured in a tropical tuna purse seine fishery. Mar Ecol Prog Ser 521:143–154. https://doi.org/10.3354/meps11073

Huveneers C, Meekan MG, Apps K, et al (2017) The economic value of shark-diving tourism in Australia. Rev Fish Biol Fish 27:665–680. https://doi.org/10.1007/s11160-017-9486-x

Indab AL (2016) Willingness to Pay for Whale Shark Conservation in Sorsogon, Philippines. Mar Coast Ecosyst Valuation, Institutions, Policy Southeast Asia 93–128. https://doi.org/10.1007/978-981-10-0141-3_6

IOTC Secretariat (2020) Review of the statistical data and fishery trends for tropical tunas

IOTC Secretariat (2021) Review of the Statistical Data Available for Neritic Tuna Species. IOTC Work Party Ecosyst Bycatch IOTC-2021-:33

Johnston RJ, Ranson MH, Besedin EY, Helm EC (2006) What determines willingness to pay per fish? a meta-analysis of recreational fishing values. Mar Resour Econ 21:1–32

Juan-Jordá MJ, Murua H, Arrizabalaga H, et al (2018) Report card on ecosystem-based fisheries management in tuna regional fisheries management organizations. Fish Fish 19:321–339. https://doi.org/10.1111/faf.12256

Karim MS, Techera E, Arif A Al (2020) Ecosystem-based fisheries management and the precautionary approach in the Indian Ocean regional fisheries management organisations. Mar Pollut Bull 159:111438. https://doi.org/10.1016/j.marpolbul.2020.111438

Kawol D, Sooklall T, Shung CL (2019) Analysis of catch and effort data of tropical tuna from purse seine and longline fishery in Mauritius ( 2014-2018 ). IOTC Work Party Trop Tuna IOTC-2019-WPTT21–19

Kinney MJ, Simpfendorfer CA (2009) Reassessing the value of nursery areas to shark conservation and management. Conserv Lett 2:53–60. https://doi.org/10.1111/j.1755-263x.2008.00046.x

Lew DK (2015) Willingness to pay for threatened and endangered marine species: A review of the literature and prospects for policy use. Front Mar Sci 2:1–17. https://doi.org/10.3389/fmars.2015.00096

Lezama-Ochoa N, Murua H, Ruiz J, et al (2018) Biodiversity and environmental characteristics of the bycatch assemblages from the tropical tuna purse seine fisheries in the eastern Atlantic Ocean. Mar Ecol e12504. https://doi.org/10.1111/maec.12504

MA (2005) Millennium Ecosystem Assessment: Ecosystems and Human Well-being. Island Press, Washington DC.

Mannocci L, Forget F, Tolotti MT, et al (2020) Predicting bycatch hotspots in tropical tuna purse seine fisheries at the basin scale. Glob Ecol Conserv 24:.

https://doi.org/10.1016/j.gecco.2020.e01393

Manski CF (1993) Identification of endogenous social effects: The reflection problem. Rev Econ Stud 60:531–542

Martino S, Tett P, Kenter J (2019) The interplay between economics, legislative power and social influence examined through a social-ecological framework for marine ecosystems services. Sci Total Environ 651:1388–1404. https://doi.org/10.1016/j.scitotenv.2018.09.181

Mieras PA, Harvey-Clark C, Bear M, et al (2017) The Economy of Shark Conservation in the Northeast Pacific: The Role of Ecotourism and Citizen Science, 1st edn. Elsevier Ltd.

Möllmann C, Lindegren M, Blenckner T, et al (2014) Implementing ecosystem-based fisheries management: from single-species to integrated ecosystem assessment and advice for Baltic Sea fish stocks. ICES J Mar Sci 71:1187–1197. https://doi.org/10.1093/icesjms/fst123

Mullon C, Guillotreau P, Galbraith ED, et al (2017) Exploring future scenarios for the global supply chain of tuna. Deep Sea Res Part II Top Stud Oceanogr 140:251–267. https://doi.org/https://doi.org/10.1016/j.dsr2.2016.08.004

Murphy SE, Campbell I, Drew JA (2018) Examination of tourists' willingness to pay under different conservation scenarios; Evidence from reef manta ray snorkeling in Fiji. PLoS One 13:1–15. https://doi.org/10.1371/journal.pone.0198279

Musick JA, Burgess G, Cailliet G, et al (2000) Management of Sharks and Their Relatives (Elasmobranchii). Fisheries 25:9–13. https://doi.org/10.1577/1548-8446(2000)025<0009:MOSATR>2.0.CO;2

Naidoo R, Balmford A, Costanza R, et al (2008) Global mapping of ecosystem services and conservation priorities. Proc Natl Acad Sci U S A 105:9495–9500. https://doi.org/10.1073/pnas.0707823105

O'Keefe CE, Cadrin SX, Stokesbury KDE (2014) Evaluating effectiveness of time/area closures, quotas/caps, and fleet communications to reduce fisheries bycatch. ICES J Mar Sci 71:1286–1297. https://doi.org/10.1093/icesjms/fst063

Ovando D, Libecap GD, Millage KD, Thomas L (2021) Coasean approaches to address overfishing: Bigeye tuna conservation in the western and central pacific ocean. Mar Resour Econ 36:91–109. https://doi.org/10.1086/711853

Pascoe S (1997) Bycatch management and the conomics of discards. FAO Fish Tech Pap 370:137p.

Pascual U, Balvanera P, Díaz S, et al (2017) Valuing nature's contributions to people: the IPBES approach. Curr Opin Environ Sustain 26–27:7–16. https://doi.org/10.1016/j.cosust.2016.12.006

Pikitch EK, Santora C, Babcock EA, et al (2004) Ecosystem-based fishery management. Science (80-. ). 305:346–347

Pires NM, Garla RC, Carvalho AR (2016) The economic role of sharks in a major ecotourism archipelago in the western South Atlantic. Mar Policy 72:31–39. https://doi.org/10.1016/j.marpol.2016.06.016

Pitcher TJ (2001) Fisheries managed to rebuild ecosystems? Reconstructing the past to salvage the future. Ecol Appl 11:601–617. https://doi.org/10.1890/1051-0761(2001)011[0601:FMTRER]2.0.CO;2

Plummer ML (2009) Assessing benefit transfer for the valuation of ecosystem services. Front Ecol Environ 7:38–45. https://doi.org/10.1890/080091

Poisson F, Filmalter JD, Vernet A, Dagorn L (2014) Mortality rate of silky sharks (Carcharhinus falciformis) caught in the tropical tuna purse seine fishery in the Indian Ocean. Can J Fish Aquat

Sci 71:795–798. https://doi.org/http://dx.doi.org/10.1139/cjfas-2013-0561

R Core Team (2019) R: A language and environment for statistical computing

Rigby CL, Sherman CS, Chin A, Simpfendorfer C (2017) Carcharhinus falciformis. In: IUCN Red List Threat. Species

Salas S, Gaertner D (2004) The behavioural dynamics of fishers: Management implications. Fish Fish 5:153–167. https://doi.org/10.1111/j.1467-2979.2004.00146.x

Sardà F, Coll M, Heymans JJ, Stergiou KI (2015) Overlooked impacts and challenges of the new European discard ban. Fish Fish 16:175–180. https://doi.org/https://doi.org/10.1111/faf.12060

Skubel RA, Shriver-Rice M, Maranto GM (2019) Introducing relational values as a tool for shark conservation, science, and management. Front Mar Sci 6:1–21. https://doi.org/10.3389/fmars.2019.00053

Squires D, Lent R, Dutton PH, et al (2021) Credit Systems for Bycatch and Biodiversity Conservation. Front Mar Sci 8:1–14. https://doi.org/10.3389/fmars.2021.613279

Sumaila UR, Marsden AD, Watson R, Pauly D (2007) A global ex-vessel fish price database: Construction and applications. J Bioeconomics 9:39–51. https://doi.org/10.1007/s10818-007-9015-4

Teisl MF, Roe B, Hicks RL (2002) Can eco-labels tune a market? Evidence from dolphin-safe labeling. J Environ Econ Manage 43:339–359

Torres-Irineo E, Amandè MJ, Gaertner D, et al (2014) Bycatch species composition over time by tuna purse-seine fishery in the eastern tropical Atlantic Ocean. Biodivers Conserv 23:1157–1173. https://doi.org/10.1007/s10531-014-0655-0

Vianna G, Meeuwig JJ, Pannell DJ (2011) The socio-economic value of the shark-diving industry in Fiji. Perth Univ West … 26

Vianna GMS, Meekan MG, Pannell DJ, et al (2012) Socio-economic value and community benefits from shark-diving tourism in Palau: A sustainable use of reef shark populations. Biol Conserv 145:267–277. https://doi.org/10.1016/j.biocon.2011.11.022

Vianna GMS, Meekan MG, Rogers AA, et al (2018) Shark-diving tourism as a financing mechanism for shark conservation strategies in Malaysia. Mar Policy 94:220–226. https://doi.org/10.1016/j.marpol.2018.05.008

Villasante S, Lopes PFM, Coll M (2016) The role of marine ecosystem services for human well-being: Disentangling synergies and trade-offs at multiple scales. Ecosyst Serv 17:1–4. https://doi.org/10.1016/j.ecoser.2015.10.022

Worm B, Davis B, Kettemer L, et al (2013) Global catches, exploitation rates, and rebuilding options for sharks. Mar Policy 40:194–204

Zimmerhackel JS, Kragt ME, Rogers AA, et al (2019) Evidence of increased economic benefits from shark-diving tourism in the Maldives. Mar Policy 100:21–26. https://doi.org/10.1016/j.marpol.2018.11.004

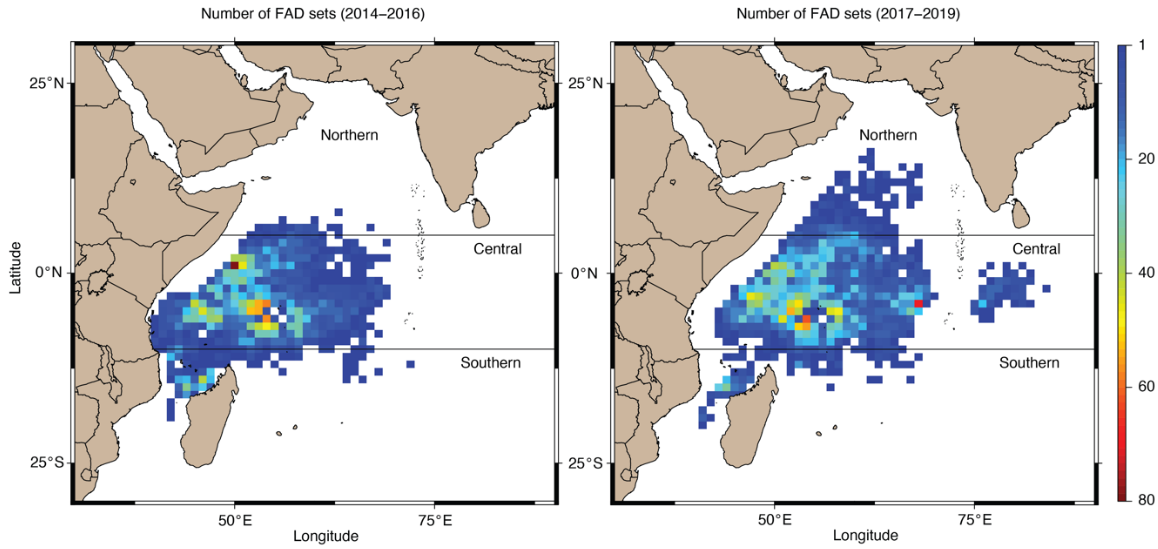



Figure 1. Number of FAD sets per 1°x 1° squares, conducted by the French purse seine fleet in the Indian Ocean before (left) and after (right) the introduction of the yellowfin tuna TAC.

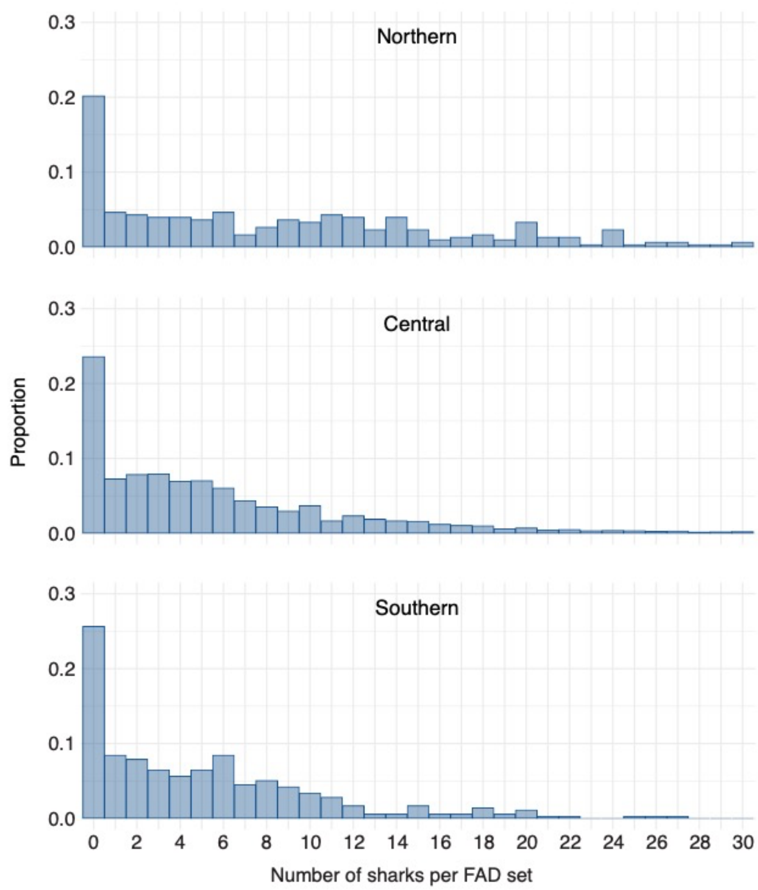



Figure 2. Proportion of silky shark catches (number of individuals) per FAD set in the Indian Ocean, including sets with 0 sharks. For visualisation purposes, the histograms are truncated at sets with 30 sharks. For each area, the observed maximum number of sharks per set is: Northern = 116, Central= 200 and Southern = 90.

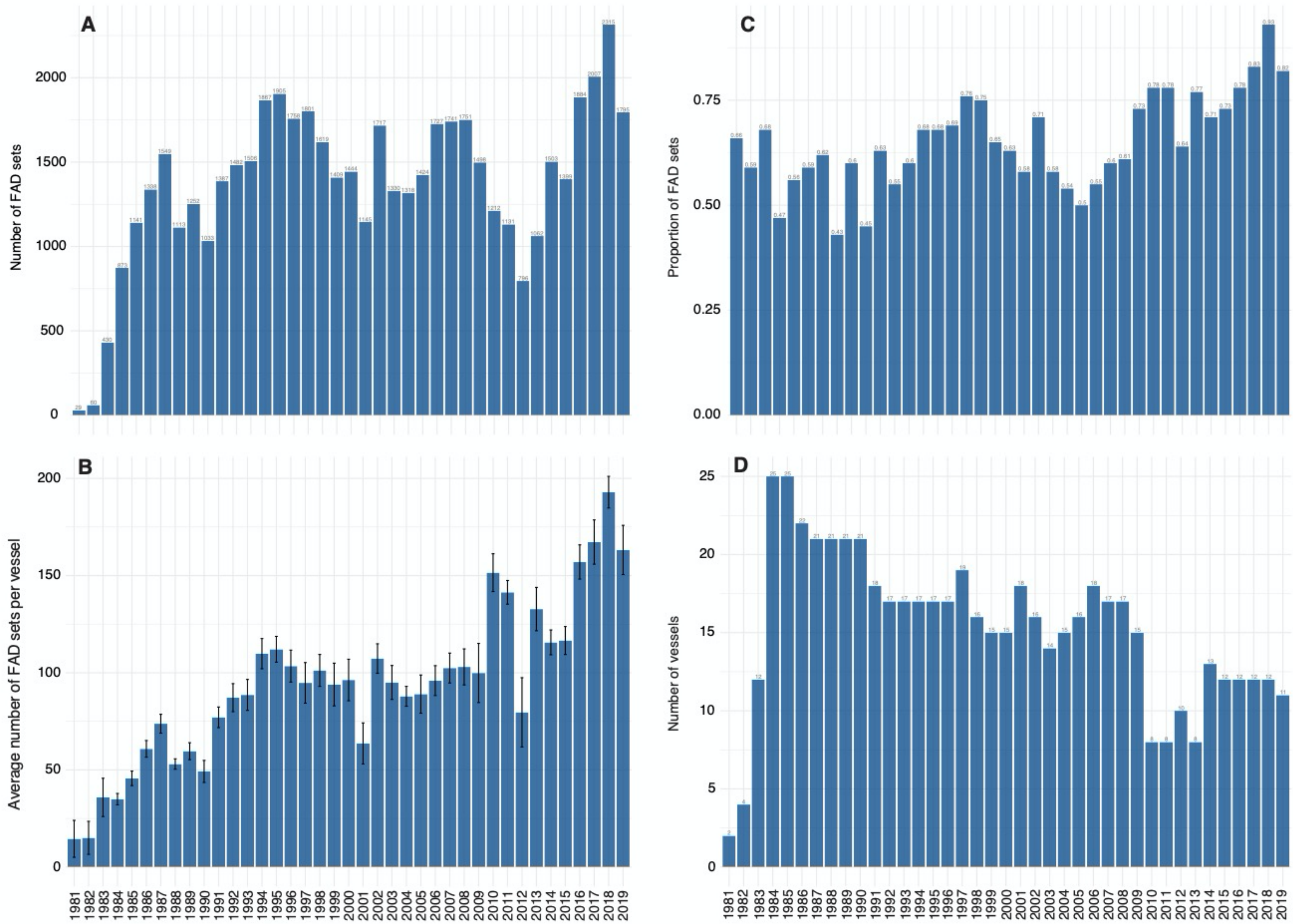



Figure 3. Yearly evolution of the fishing strategy of the French tropical tuna purse seine fleet in the Indian ocean. A) Number of FAD sets; B) Average number of FAD sets per vessel (vertical bars represent the standard error); C) Overall proportion of FAD sets and D) Number of operating vessels.

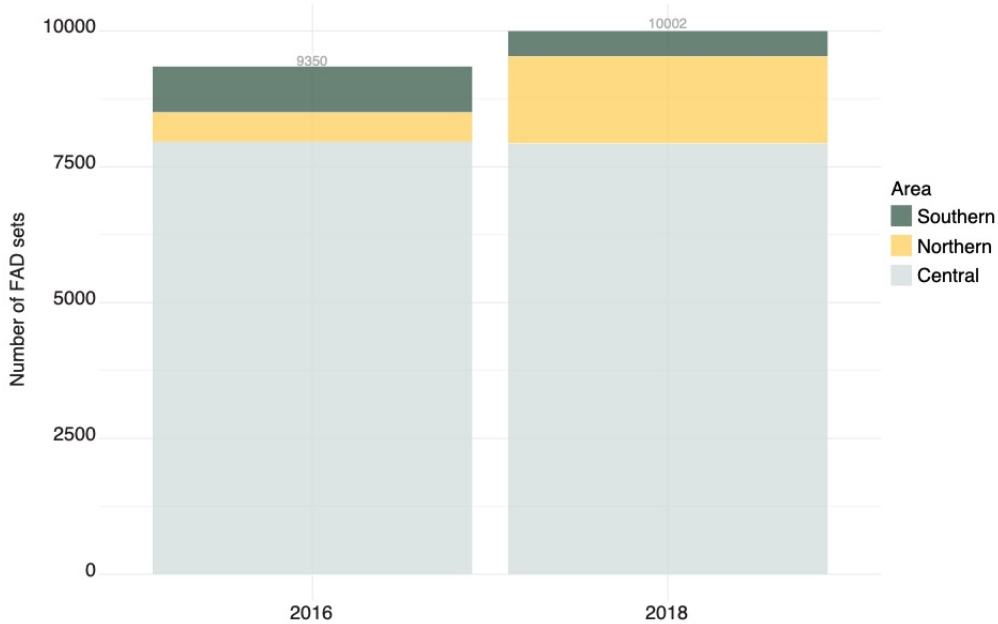



Figure 4. Yearly number of FAD sets by area conducted by the industrial tuna purse seine fleets operating in the western Indian Ocean (Spain, France, Seychelles and Mauritius) before (2016) and after (2018) the introduction of the yellowfin tuna TAC.

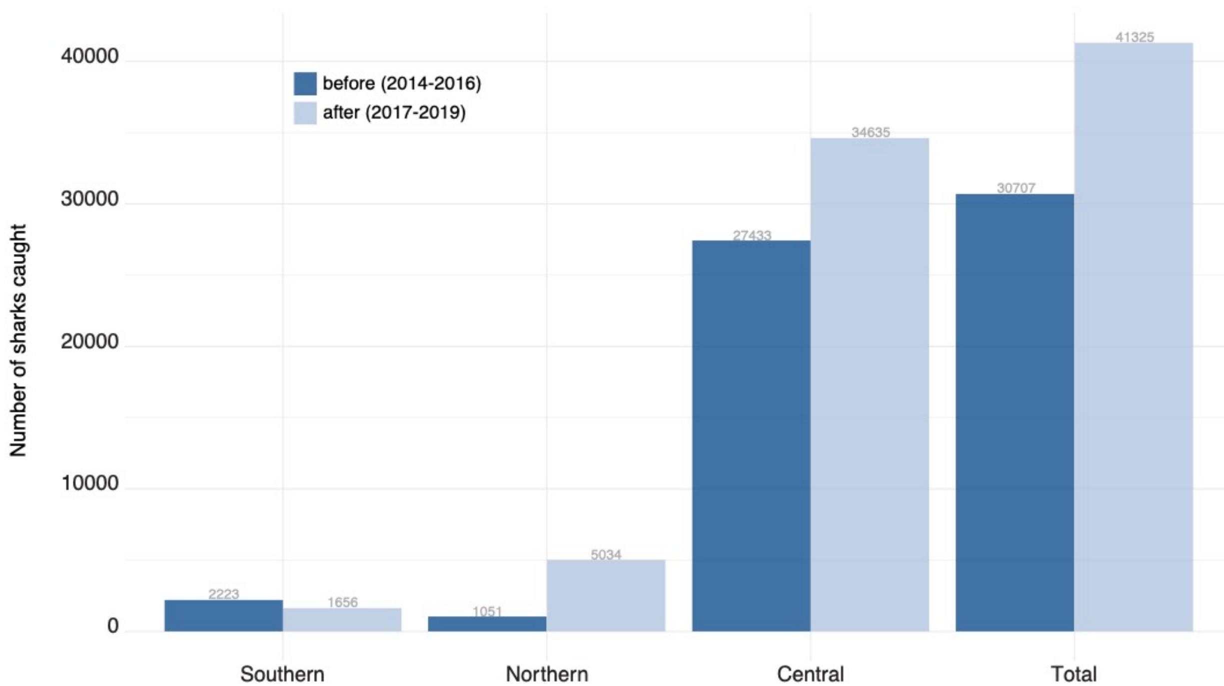



Figure 5. Estimated total catches of silky shark by the French purse seine fleet in the Indian Ocean, before and after the implantation of the yellowfin tuna TAC.

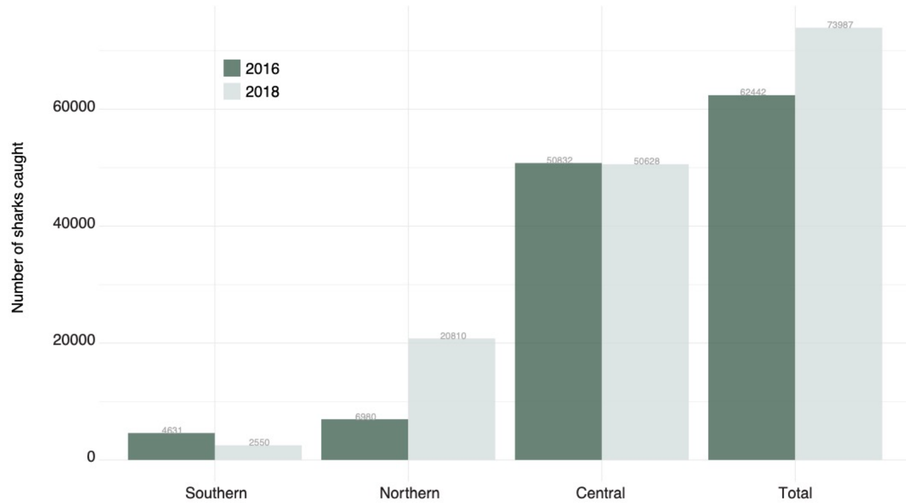



Figure 6. Estimated catches of silky shark for the main tuna purse seine fleets operating in the western Indian Ocean (Spain, France, Seychelles and Mauritius) before (2016) and after (2018) the introduction of the yellowfin tuna TAC.

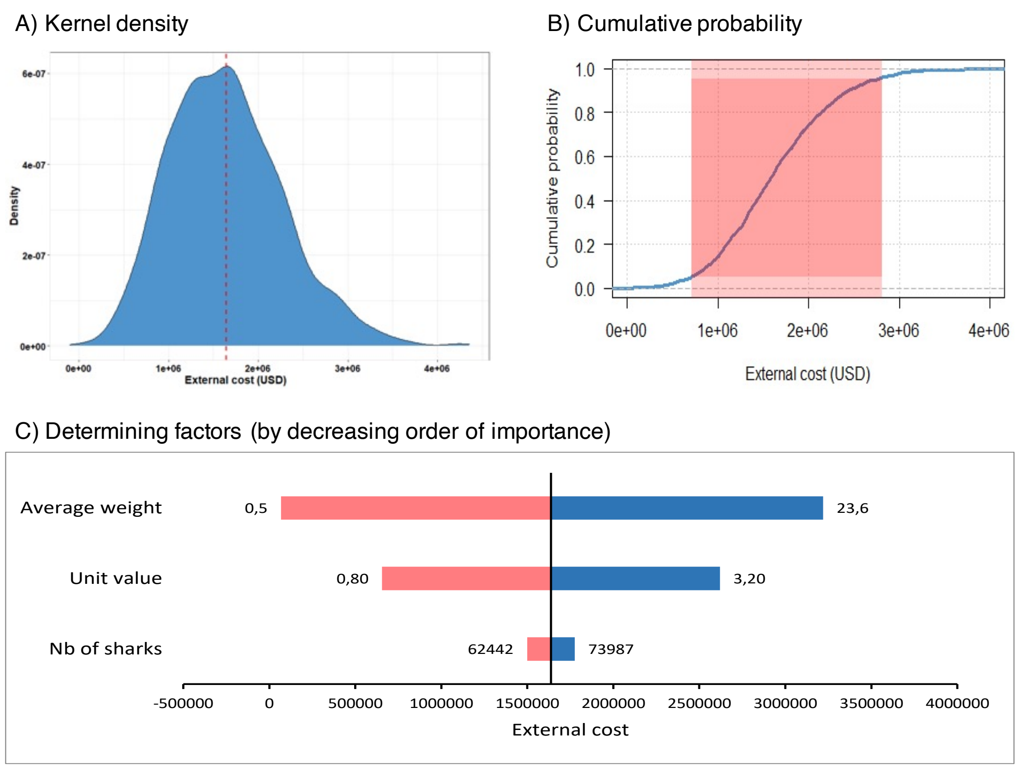



Figure 7. Estimated value of external costs (USD) for silky shark bycatches. A) Kernel density of the Monte Carlo (MC) distribution of external costs (US$). The statistics of output values from the MC analysis were the following ones after 1,500 iterations: Mean=1,640,928 (vertical dashed red line); Median = 1,600,362; St.-Dev. = 636,234; Skewness = 0.51; Kurtosis = 0.37.; B) Cumulative probability of the MC distribution. The red polygon represents the 90% confidence interval, between 709,992 (5%) and 2,806,602 (95%) USD. C) Sensitivity analysis by input (upper and lower values for each input, in kg, USD and number, respectively, and US$ for the external cost on the horizontal axis).

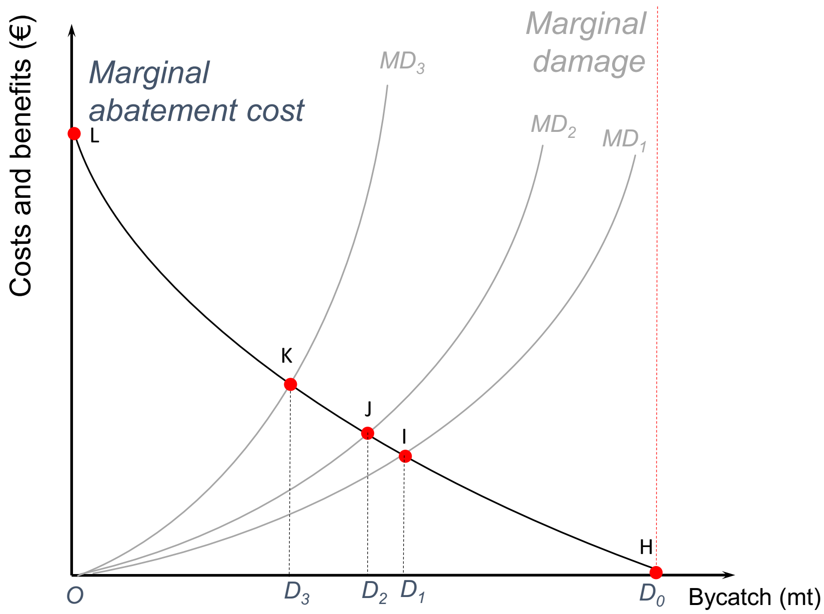
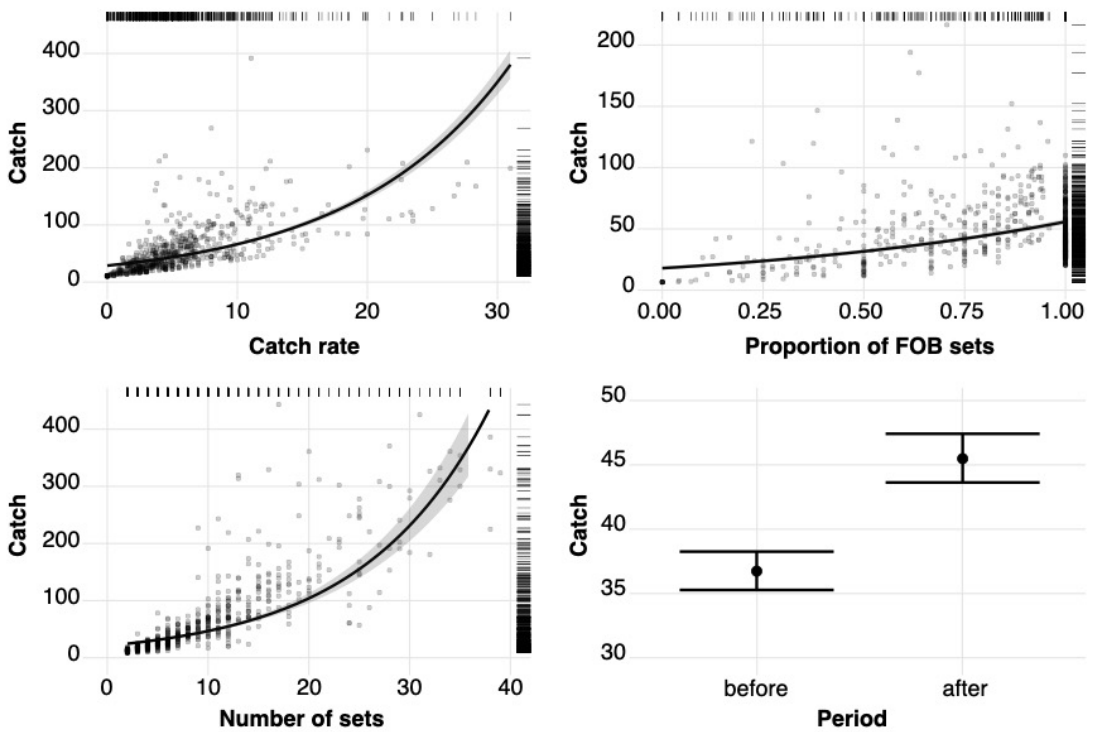
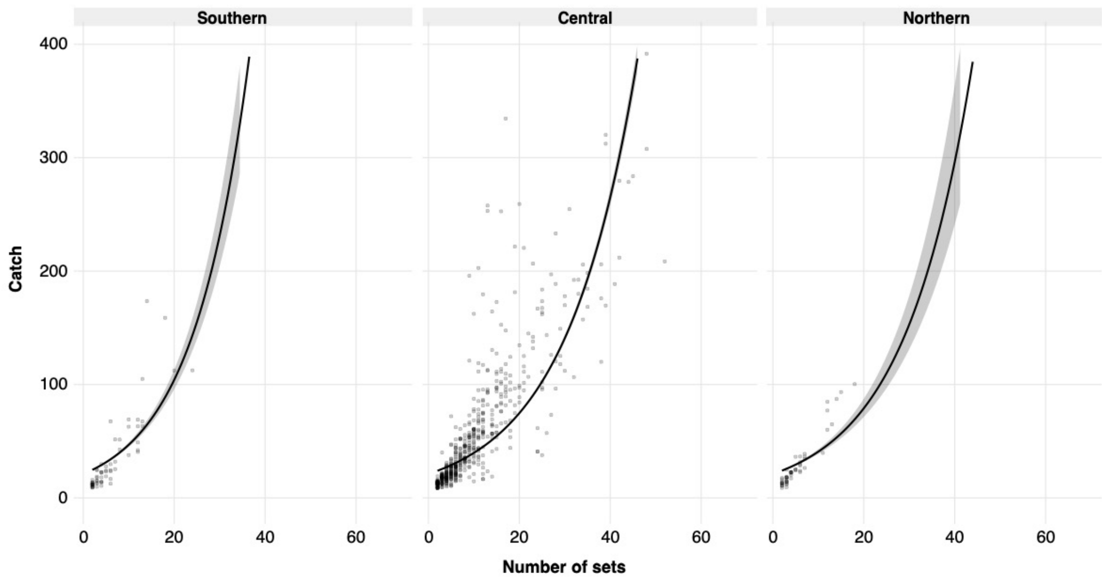



Figure 8. External costs and potential "optimal" levels of silky shark bycatch in the northern area of the Indian Ocean.

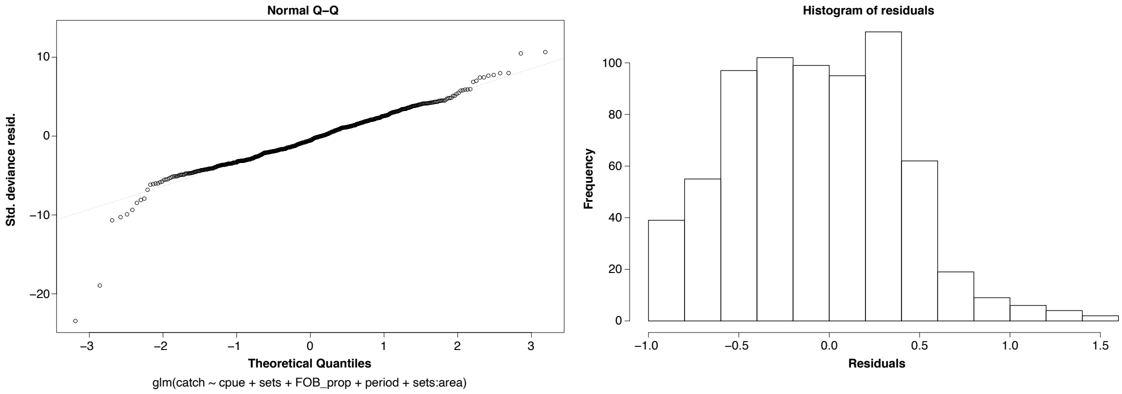
*Supplementary Figures*




**Suppl. Fig. 2.** Predictions and 95% confidence intervals of model terms. The black points represent the partial residuals. (FOB= floating object)




**Suppl. Fig. 3.** Predictions and 95% confidence intervals of interaction term. The black points represent the partial residuals.




**Suppl. Fig. 4.** Model residuals and QQ-plot.

## *Supplementary Analyses*

The Poisson GLM model has silky shark catch as the response variable. The independent variables are catch rate (average number of sharks per fishing set), number of sets, proportion of FAD sets relative to the total number of purse-seine sets, area (classified as Northern, Central and Southern) and period (classified into before and after the implementation of the TAC). This model contains some intrinsic biases pertaining to endogeneity, variable correlation, and heteroscedasticity. To make sure those biases did not lead to incorrect parameter estimations, additional models were tested.

Through a spatial regression approach, the original model was re-estimated to look for spatial autocorrelation. Using the Manski (1993) generic model, various specifications to deal with the endogeneity problem were tested (Suppl. Table 1). The original model has also been re-estimated in a Panel data framework, comparing the Pooling, Random Effect, Fixed-Effect (Within) and Between methods (Suppl. Table 5). The new models are fully detailed and discussed below.

The Manski (1993) model allows to determine the type of interactions between the variables in the grid squares (endogenous interaction, exogenous interaction, or spatial correlation of effects). It can be written as follows:

$$Y = \rho WY + X\beta + WX\theta + u \qquad \text{(Suppl. 1)}$$

where $u = \lambda Wu + \varepsilon$

$Y$ represents the silky catch, $X$ the vector of independent variables (sets, catch rate, FAD prop and period), $W$ is the neighbourhood matrix, $\rho, \beta, \theta, \lambda$ are parameters, $u$ and $\varepsilon$ error terms. We then study the outcomes of various models derived from the Manski model:

**SDEM** (*Spatial Durbin Error Model*) if we assume no endogenous interaction ($\rho = 0$)

$$Y = X\beta + WX\theta + u \qquad \text{(Suppl. 2)}$$

**SAC** (*Spatial Autoregressive Model*) if we assume no exogenous interaction ($\theta = 0$)

$$Y = \rho WY + X\beta + u \qquad \text{(Suppl. 3)}$$

**SDM** (*Spatial Durbin Model*) if there is no residual spatial autocorrelation ($\lambda = 0$):

$$Y = \rho WY + X\beta + WX\theta + \varepsilon \quad \text{(Suppl. 4)}$$

The last two models include specific cases of SAR, SEM and SLX models:

**SAR** (*Spatial Auto Regression*) or **LAG**: $Y = \rho WY + X\beta + \varepsilon$ (Suppl. 5)

**SEM** (*Spatial Error Model*): $Y = X\beta + u$ (Suppl. 6)

To test for SEM, the following constraint $\theta = -\rho\beta$ is introduced in the SDM model (Suppl. 4), namely the «Common Factor» hypothesis.

**SLX** (*Spatial Lag X*) corresponds to the case where $\rho = \lambda = 0\ and\ \theta \neq 0$:

$$Y = X\beta + WX\theta + \varepsilon \quad \text{(Suppl. 7)}$$

The Moran test confirms spatial autocorrelation (relation between the variable and its spatially lagged values in its vicinity) with a statistics of 12.373 and a quasi-null p-value 0.000). The results of the various models are displayed in Suppl. Table 1. R packages spdep (v1.2-3), spgwr (v0.6-35) and spatialreg (v1.2-1) were used in the analysis (R Core Team, 2022).

**Suppl. Table 1.** Results of spatial regression models.

| | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* |
|---|---|---|---|---|---|---|---|---|
| | **OLS** | **SEM** | **SAR** | **SDM** | **SAC** | **SLX** | **SDEM** | **Manski** |
| ***INTERCEPT*** | -43.570*** | -35.779*** | -47.897*** | -56.847*** | -42.992*** | -71.247*** | -68.563*** | -58.856*** |
| | (4.456) | (4.656) | (4.475) | (8.007) | (5.004) | ('7.602) | (8.845) | (11.849) |
| ***SETS*** | 4.184*** | 3.984*** | 3.910*** | 3.848*** | 3.919*** | 3.899*** | 3.873*** | 3.851*** |
| | (0.12) | (0.128) | (0.127) | (0.136) | (0.130) | (0.139) | (0.133) | (0.137) |
| ***CATCH RATE*** | 5.262*** | 5.317*** | 5.136*** | 5.361*** | 5.315*** | 5.383*** | 5.372*** | 5.355*** |
| | (0.243) | (0.241) | (0.240) | (0.239) | (0.240) | (0.245) | (0.240) | (0.238) |
| ***FAD PROP*** | 30.532*** | 24.296*** | 28.403*** | 24.007*** | 24.888*** | 26.809*** | 24.970*** | 24.208*** |
| | (4.56) | (4.532) | (4.456) | (4.450) | (4.500) | (4.538) | (4.492) | (4.631) |
| ***PERIOD (BEFORE)*** | -7.653*** | -10.537*** | -8.456*** | -11.322*** | -10.197*** | -10.396*** | -10.614*** | -11.216*** |
| | (2.075) | (2.074) | (2.027) | (2.054) | (2.055) | (2.098) | (2.043) | (2.121) |
| | | | | | | | | |
| $\hat{\rho}$ | | | 0.205*** | 0.308*** | 0.155*** | | | 0.266 |
| | | | (0.038) | (0.065) | (0.052) | | | (0.205) |
| $\hat{\lambda}$ | | 0.395*** | | | 0.291*** | | 0.313*** | 0.062 |
| | | (0.063) | | | (0.084) | | (0.068) | (0.245) |
| $\hat{\theta}$, ***SETS*** | | | | -0.409 | | 0.870*** | 0.883*** | -0.222 |
| | | | | (0.363) | | (0.241) | (0.277) | (0.896) |
| $\hat{\theta}$, ***CATCH RATE*** | | | | -1.715*** | | -0.280 | 0.226 | -1.425 |
| | | | | (0.605) | | (0.506) | (0.555) | (1.219) |
| $\hat{\theta}$, ***FAD PROP*** | | | | 16.369* | | 22.994** | 18.736** | 16.847* |
| | | | | (8.542) | | (8.686) | (9.526) | (9.203) |
| $\hat{\theta}$, ***PERIOD:BEFORE*** | | | | 18.336*** | | 18.610*** | 18.459*** | 18.476*** |
| | | | | (5.132) | | (5.261) | (6.516) | (5.361) |
| | | | | | | | | |
| ***NUMBER OF OBS.*** | 701 | 701 | 701 | 701 | 701 | 701 | 701 | 701 |
| ***AIC*** | 6567.3 | 6541.3 | 6544.8 | **6521.5** | 6534.7 | 6538.3 | 6524.0 | 6523.4 |
| ***ADJUSTED R2*** | 0.720 | | | | | 0.733 | | |
| ***MORAN TEST*** | 0.000 | | | | | 0.000 | | |
| ***LM-ERROR TEST*** | 0.000 | | | | | 0.000 | | |
| ***LM-LAG TEST*** | 0.000 | | | | | 0.000 | | |
| ***ROB. LM-ERROR TEST*** | 0.001 | | | | | 0.634 | | |
| ***ROB. LM-LAG TEST*** | 0.011 | | | | | 0.049 | | |
| ***COMMON FACTOR TEST*** | | | | 0.000 | | | | |
| ***LM RES. AUTO. TEST*** | | | 0.000 | 0.659 | | | | |

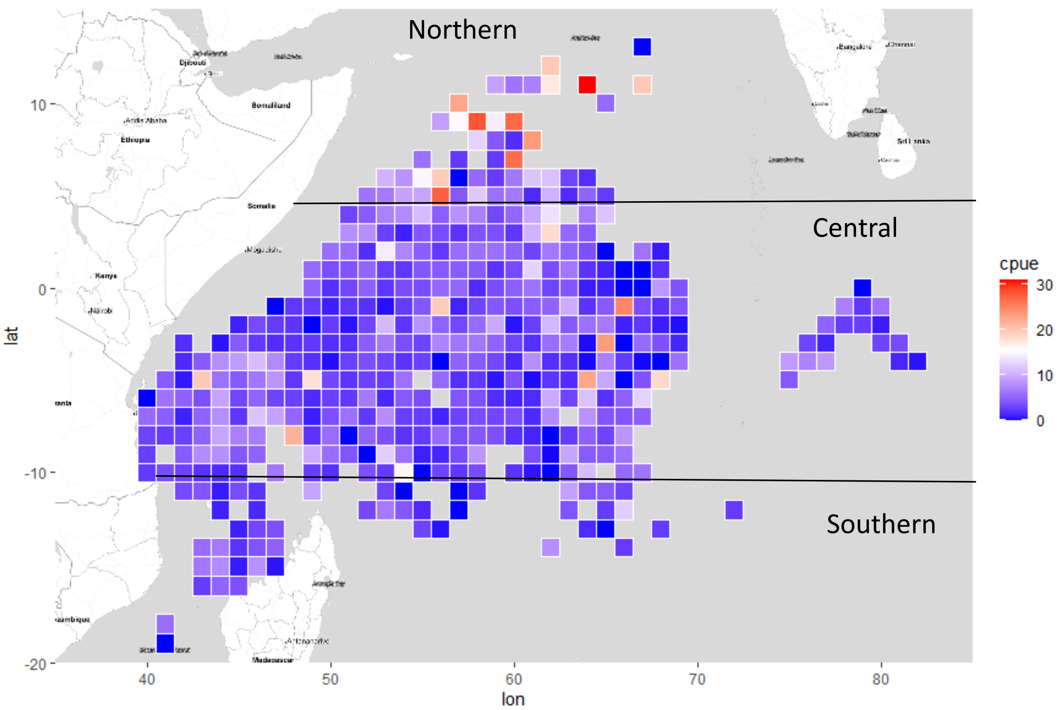
Note: Standard deviations are in brackets. p-values: (***), (**) and (*) denote the significance levels at 1%, 5%, 10%, respectively.

Suppl. Table 1 shows that results are reasonably stable regardless the model, even when comparing the spatial econometric models with the OLS reference. This is a good indication that, despite possible spatial endogeneity, the results of the original GLM are accurate. In the estimated spatial regression models included in Suppl. Table 1, the W-matrix is of QUEEN type (contiguity of each 1° x 1° square). The best model (SDM) according to AIC criterion and spatial Hausman test[1] was also tested with other types of matrices (with 2, 3, 5 and 10 closest

[1] Spatial Hausman test (asymptotic) applied to the SEM vs OLS = 23.449, df = 5, p-value = 0.000277, hence the SEM is rejected.

neighbours, and inverse distance). Results were again very similar, further indicating robustness. The Moran test and the $\hat{\rho}$ statistic are significant in several of the models, showing the strong spatial interactions between observations. The SDM model indicates the presence of endogenous interaction but does not report any residual autocorrelation. However, other models would be acceptable, like the SDEM with a significant residual interaction term $\hat{\lambda}$. The Common Factor test is not rejected in the SDM model too, proving that the SEM model with residual autocorrelation is not appropriate when compared to the SDM and its spatially lagged dependent and independent variables.

In model SDM (Suppl. 4), we can see that the level of catch in the neighbouring squares have an influence on the catch in the observed square (endogenous interaction). The observable variables have also a negative feedback effect on the local catch of silky sharks. Abundance of sharks in the closest squares will somehow mitigate the catch of sharks in the square itself. However, the catches of silky shark tend to be higher if local abundance in the square is also important. More interesting is the significant and negative relationship between the period (before/after) variable and the catch: catches are substantially higher after the break, confirming the results of the original GLM. However, the feedback effect from the vicinity plays in an opposite way: if the catch in the closest cells was high during the first period, this will affect positively the catch of sharks in the cell for the second period. This second effect outperforms the direct effect, showing the high level of spatial autocorrelation: there are clearly zones where silky sharks are more abundant and catchable than others, as clearly evidenced by the hotspots of silky shark catch per set in Suppl. Figure 1. However, another influence is also clear: a higher proportion of FAD sets increases the level of catch, and this time the feedback effect from the closest cells adds to the positive effect. The zones where FAD fishing is more intensive will increase the catch with a cluster effect. Concerning the effort (number of sets), only the direct effect is significant, with no influence of effort in the neighbouring squares.




**Suppl. Figure 1.** Catch per set of silky sharks by the French Purse Saine fleet from 2014 to 2019.

The marginal effects need to be re-computed to account for the direct and indirect spatial effects:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon \qquad \text{(Suppl. 8)}$$

The feedback effects can therefore be re-written as follows:

$$Y = (1-\rho W)^{-1}X\beta + (1-\rho W)^{-1}WX\theta + (1-\rho W)^{-1}\varepsilon \qquad \text{(Suppl. 9)}$$

$$Y = \sum_{r=1}^{k} S_r(W)^{-1}X_r + (1-\rho W)^{-1}\varepsilon \qquad \text{(Suppl. 10)}$$

Where $S_r$ represents the direct and indirect marginal effects from each square on others, from which average effects can be obtained (i.e., through the mean of diagonal terms for the direct effects). The results are displayed in Suppl. Table 2.

**Suppl. Table 2.** Average effects from the SDM model (Suppl. 4).

| | ***1*** | ***2*** | ***3*** |
|---|---|---|---|
| | **Direct effects** | **Indirect effects** | **Overall effects** |
| ***SETS*** | 3.874 | 1.108 | 4.982 |
| | [3.621 , 4.122] | [0.506 , 1.737] | [4.420 , 5.539] |
| **CATCH RATE** | 5.362 | -0.062 | 5.299 |
| | [4.927 , 5.829] | [-1.503 , 1.263] | [3.748 , 6.743] |
| **FAD *PROP*** | 24.803 | 33.137 | 57.940 |
| | [16.045 , 33.467] | [8.397 , 60.836] | [31.288 , 87.507] |
| ***PERIOD*** | -10.830 | 21.206 | 10.376 |
| | [-14.989 , -6.954] | [8.137 , 35.101] | [-4.446 , 24.638] |

The magnitude of coefficients is different from the original GLM model because the variables are not standardized in these ones, but all results remain consistent. The only exception is the positive overall effect of the "before" period, as though the catch was more prominent before the YFT quota implementation and the increase of FAD sets, especially in the northern area. This is a problem with the interpretation of endogenous autocorrelation which can be spurious in the SDM model (Floch & Le Saout, 2018).

### Robustness test

To clarify this point and increase the robustness of results, the data was divided into two periods and two separate models were tested. The various LM tests suggest using a SAR model in the first period and a SDM in the second (Suppl. Table 3).

**Suppl. Table 3.** Spatial models by sub-periods.

| | **2014 – 2016** | **2017 – 2019** |
|---|---|---|
| | **SAR** | **SDM** |
| ***INTERCEPT*** | -31.812*** | -82.686*** |
| | (3.968) | (10.713) |
| ***SETS*** | 2.717*** | 4.997*** |
| | (0.134) | (0.212) |
| ***CATCH RATE*** | 5.319*** | 5.337*** |
| | (0.327) | (0.302) |
| ***FAD PROP*** | 13.268*** | 35.192*** |
| | (4.422) | (7.510) |

| | | |
|---|---|---|
| $\hat{\rho}$ | 0.222*** | 0.172** |
| | (0.052) | (0.073) |
| ***$\hat{\theta}$, SETS*** | | 0.429 |
| | | (0.523) |
| ***$\hat{\theta}$, CATCH RATE*** | | -0.947 |
| | | (0.625) |
| ***$\hat{\theta}$, FAD PROP*** | | 22.073** |
| | | (10.635) |
| | | |
| ***OBSERVATIONS*** | 317 | 384 |
| ***AIC*** | 2790.7 | 3591.8 |
| ***TEST FACT. COMMUN*** | | 0.000 |
| ***TEST LM RES. AUTO.*** | 0.096 | 0.873 |

The common factor cannot be rejected at 5% in the first period, hence the choice of a SAR model as a null value of $\theta$ is not rejected either. On the other hand, the LM test on $\lambda = 0$ is rejected, as well as the residual autocorrelation test (p=0.096). In the second period, the Moran test confirms the presence of spatial autocorrelation, but the common factor null is rejected and the Hausman test rejects the SEM alternative to OLS. In Suppl. Table 3, we can see that the effect of effort (number of sets) on silky shark catches is two times bigger, and the effect of the proportion of FAD sets is three times more important in the second period relatively to the pre YFT quota period. The endogenous interaction measured by $\hat{\rho}$ , though significant, is slightly lower than in the model with the complete dataset (Suppl. Table 1), possibly because the fishing zones covered in the second period are extended, diluting the influence of neighbouring square observations. The average (direct, indirect, and overall) effects can be computed by using the same method as before (Suppl. Table 4).

**Suppl. Table 4.** a) Average effects of the SAR model in the 1$^{st}$ period.

| | ***1*** | ***2*** | ***3*** |
|---|---|---|---|
| ***SAR*** | **Direct effects** | **Indirect effects** | **Overall effects** |
| ***SETS*** | 2.750 | 0.746 | 3.496 |
| | [2.492 , 2.992] | [0.367 , 1.179] | [3.094 , 3.981] |
| ***CATCH RATE*** | 5.385 | 1.469 | 6.855 |
| | [4.736 , 6.016] | [0.678, 2.390] | [5.707 , 8.035] |
| ***FAD PROP*** | 13.411 | 3.630 | 17.041 |
| | [4.829 , 22.218] | [1.073 , 7.135] | [5.771 , 28.161] |

b) Average effects of the SDM model in the 2$^{nd}$ period.

| | ***1*** | ***2*** | ***3*** |
|---|---|---|---|
| ***SDM*** | **Direct effects** | **Indirect effects** | **Overall effects** |
| ***SETS*** | 5.019 | 1.521 | 6.540 |
| | [4.584 , 5.438] | [0.846 , 2.256] | [5.975 , 7.156] |
| ***CATCH RATE*** | 5.334 | -0.013 | 5.321 |
| | [4.758 , 5.908] | [-1.047 , 1.086] | [4.233 , 6.473] |
| ***FAD PROP*** | 35.951 | 32.845 | 68.796 |
| | [21.130 , 50.965] | [6.696 , 58.854] | [41.091 , 97.689] |

Confidence interval (quantiles 2.5 % and 97.5 % of 1000 MCMC Bayesian simulations) in brackets.

The coefficient estimates are more accurate for the number of sets and catch per set (catch rate) for the direct effects when comparing with the indirect ones. The second period overall effect is significantly stronger for the fishing effort and the proportion of FAD sets, but not so much for catch rate where the direct effect is slightly reduced by the indirect effect. The same is observed in Suppl. Table 2 with the full dataset model. The results of the two models (full dataset and by period) fully confirm the increasing effect that fishing effort has on silky shark catches.

**Panel data models and their estimated results**

Panel data econometrics can be used when several observations for the same individuals are available at various dates. It looks at unobserved heterogeneity between individuals or time periods, with its own testing procedures to choose the suitable specification. In this approach, the coefficients are estimated not only through their inter-individual differences, but also to their intra-individual differences. An OLS model can be written as follows:

$$Y_{i,t} = \beta_0 + \sum_{k=1}^{K} \beta_k X_{i,t}^k + \epsilon_{i,t} \qquad \text{(Suppl. 11)}$$

Where $Y_{i,t}$ is the dependent variable for individuals *i* at time *t*, $X_{i,t}^k$ the set of *K* independent variables, $\beta$ are parameters with $\beta_0$ a unique intercept for all individuals, and $\epsilon_{i,t}$ is the error term. It may happen that missing (or unobservable) variables included in the error term are correlated with the explanatory (observable) variables, hence resulting in residual autocorrelation and biased estimators. We can introduce dummy variables (either for individuals, time or both) to extend the OLS model into a fixed effect model:

$$Y_{i,t} = a_i + \sum_{k=1}^{K} \beta_k X_{i,t}^k + \epsilon_{i,t} \qquad \text{(Suppl. 12)}$$

The first problem is residual autocorrelation if Cov$(\epsilon_{i,t}, \epsilon_{i,t+1}) \neq 0$. In our case, such a problem is expected because an under-value of silky shark catches in square *i* before the YFT quota is likely to be under-valued too in the after period. The second problem is heteroscedasticity if $\epsilon_{i,t} = c.inobs + \varepsilon$ and Cov$(X_i^k, inobs) \neq 0$. The residual term $\epsilon_{i,t}$ can be re-written $\epsilon_{i,t} = a_i + e_{it}$, as the sum of a constant individual error ($a_i$) and a temporary error ($e_{it}$,). Then, we can test if the constant error term $a_i$ is independent or not from observables: Cov$(a_i, X_i^k) = 0$? If the answer is yes, the pooling model (homogenous, close to OLS) or the random effect model are suitable. If not, the OLS model is not appropriate and the model must be estimated with fixed effects (FE) or with first differences (FD). In our case, because there are only two periods, there is no useful distinction between FE and FD models.

Therefore, the homogenous model was tested first (Suppl. 11, or Pooling regression model) to solve the autocorrelation problem, either by using a Huber-White approach (robust standard errors) or robust clustered standard errors (RCSE), or by modelling the error term with two terms ( $a_i$ and $e_{it}$ ) through a random effect model (Suppl. 12). For the heteroscedasticity problem, the null hypothesis of the Hausman test is that the unique errors ($a_i$) are not correlated with the regressors of $X_i^k$. If the p-value is close to zero, we can reject the null and the fixed effect (or *Within*) model must be preferred to the random one. With small samples (<1000 obs.), we can introduce both the constant intercept and a dummy variable for individuals in a *Least Square Dummy Variable* (*LSDV*) model. The Within model consists of removing the constant term and demeaning the dependent and independent variables:

$$(Y_{i,t} - \overline{Y_i}) = \sum_{k=1}^{K} \beta_k (X_{i,t}^k - \overline{X_i^k}) + (\epsilon_{i,t} - \overline{\epsilon_i}) \qquad \text{(Suppl. 13)}$$

This can be done also with two fixed effects (i.e., *two ways*) by demeaning both on individuals and on time:

$$(Y_{i,t} - \overline{Y_\iota} - \overline{Y_t} + \overline{Y}) = \sum_{k=1}^{K} \beta_k (X_{i,t}^k - \overline{X_t^k} - \overline{X_\iota^k} + \overline{X_k}) + (\epsilon_{i,t} - \overline{\epsilon_\iota} - \overline{\epsilon_t} + \overline{\epsilon}) \quad \text{(Suppl. 14)}$$

We can finally re-focus the specification on the inter-individual variance, dropping the time dimension for the mere cross-sectional one, through the '*Between'* model where each individual (i.e., each square) has only one average observation combining the "*before"* and "*after"* periods:

$$\overline{Y_\iota} = \sum_{k=1}^{K} \beta_k \overline{X_\iota^k} + \overline{\epsilon_\iota} \quad \text{(Suppl. 15)}$$

Because we assumed that the two periods matter to show an increasing level of silky shark catches due to the increase of FADs sets, this "*Between*" specification is perhaps not the most suitable specification for our study.

In our present case, the dataset is unbalanced (i.e., some squares have either a "before" or "after" observation, and not both), therefore the data frame needs to first be re-balance by replicating the missing rows of geo-referenced data and adding null values to the variables (no sets and no catch). Moreover, the estimated GLM is a count (Poisson) model, therefore the Hausman test is not available for this type of estimation, although such test exists for more standard panel models. Alternatively, the R package *pglm* (v0.2-3), which allows for such Poisson procedures, was used (Suppl. Table 5).

**Suppl. Table 5.** Estimations on balanced panel data with a Poisson GLM model (R package *pglm*).

| | ***POOLED OLS*** | ***RE*** | ***FE (DUMMIES)*** | ***FE WITHIN (2 WAYS)*** | ***BETWEEN*** |
|---|---|---|---|---|---|
| ***INTERCEPT*** | 1.018*** | 0.682*** | 0.597*** | - | 0.477*** |
| | (0.029) | (0.049) | (0.175) | - | (0.115) |
| ***SETS*** | 0.069*** | 0.079*** | 0.075*** | 0.075*** | 0.100*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.003) |
| ***CATCH RATE*** | 0.083*** | 0.129*** | 0.132*** | 0.132*** | 0.122*** |
| | (0.001) | (0.003) | (0.003) | (0.003) | (0.007) |
| ***FAD PROP*** | 1.756*** | 1.582*** | 1.558*** | 1.558*** | 1.571*** |
| | (0.029) | (0.044) | (0.047) | (0.047) | (0.134) |
| ***PERIOD (BEFORE)*** | -0.172*** | -0.117*** | -0.113*** | -0.113*** | - |
| | (0.012) | (0.015) | (0.015) | (0.015) | - |
| ***$\sigma^2$*** | | 4.218*** | | | 4.673*** |
| | | (0.334) | | | (0.369) |
| ***LOG LIKELIHOOD*** | -6423 | -4027 | -3191 | -1935 | -2067 |
| ***RESIDUAL DEVIANCE*** | | | 2828.2 | | |
| ***AIC*** | | | 7310.9 | | |

Interestingly, the pooled and random effect models tend to overestimate the effect of most variables and underestimate the size of the standard errors. This could be a sign of spurious regression. However, the signs of estimators never change from a model to another, which is a good indicator of robustness and confidence in the previous models. The $\sigma^2$ value (variance in the individual effects) is also significant for both random and between effects. This means that these two models should be preferred to the pooled model because of the significant unobserved heterogeneity of individuals. Comparing RE and FE is not straightforward as the coefficients and the standard errors show the same magnitude for all dependent variables, which is again a good sign of stable and robust results. However, the log-likelihood is clearly larger for the two Fixed Effect models (particularly the "*Within"* model), indicating their superiority of FE over the RE model, FE then being the best choice in this case. The Between model confirms the results of the spatial regression models: beyond the period effect, the spatial variance between the grid squares dominates the analysis. However, the "before" period is significant in all models and shows the expected negative sign: once all other effects are controlled, the catch level of silky sharks has substantially increased between the two periods ("before" values are smaller than "after" values).

### Heteroscedasticity

The heteroscedasticity issue was considered by testing the standard errors with a Pooling regression (i.e., OLS). The heteroscedasticity was then corrected with a Huber-White approach, and for both heteroscedasticity and autocorrelation with a *Robust Clustered Standard Error* (*RCSE*) method (Suppl. Table 6).

**Suppl. Table 6.** Comparison of standard errors.

| | ***POOLED OLS*** | ***HUBER-WHITE*** | ***RCSE*** |
|---|---|---|---|
| ***INTERCEPT*** | -2.740 | -2.740* | -2.740* |
| | (1.937) | (1.200) | (1.177) |
| ***SETS*** | 3.497*** | 3.497*** | 3.497*** |
| | (0.097) | (0.271) | (0.277) |
| ***CATCH RATE*** | 5.348*** | 5.348*** | 5.348*** |
| | (0.229) | (0.426) | (0.428) |
| ***FAD PROP*** | -8.923*** | -8.923** | -8.923** |
| | (2.578) | (3.046) | (3.001) |
| ***PERIOD (BEFORE)*** | -7.597*** | -7.597*** | -7.597*** |
| | (1.711) | (1.604) | (1.630) |
| | | | |
| ***RSE*** | 24.69 | | |
| ***$R^2$*** | 0.73 | | |
| ***ADJ. $R^2$*** | 0.73 | | |
| ***F-STAT*** | 617.4*** | | |

Note: standard errors between brackets. Signif. codes 0'***', 0.001'**', 0.01'*', 0.1' '

Jointly correcting for the heteroscedasticity and autocorrelation increases estimators' accuracy for both the Intercept and the Period effect, but not for the other variables. This probably means that some fixed effects should be considered in the analysis (see the Panel data econometric approach in Suppl. Table 5).

### References

Floch, J.M. & Le Saout, R. 2018. Spatial econometrics - Common models. Handbook of spatial analysis: Theory and practical application with R: 149-177.

Manski, C. F. 1993. Identification of endogenous social effects: the reflection problem. Review of Economic Studies, 60: 531–542

R Core Team. 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.