Indonesia Marine Fellows Program - MFP

INVESTING IN FISHERIES MANAGEMENT: ASSESSMENT OF FADs AND UNREPORTED CATCH

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Applied Economic Research on Fisheries Management and Marine Conservation

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1. Introduction

Indonesian fishermen have been using anchored Fish Aggregation Devices (FADs) since the 1980s, and as such, the use of FADs has a pivotal role in supporting fishing activities, especially for tuna and other pelagic species. FADs increase the efficiency of fishing activities, but can also potentially increase fishing pressure on oceanic tuna stocks and the pelagic ecosystem. High demand for tuna on the international market plays a strong role in increasing fishing pressure and may lead to an excessive use of FADs. Therefore, a management of FADs-based fisheries is necessary to protect fish stock from overexploitation. Managing FADs-based fisheries poses a big question, namely, what are the utilization dynamics of FADs in tuna fisheries? This question requires a clear understanding of the current state of this fishery, and of fishers as the main actor.

Stakeholders in Indonesia have a strong desire for effective management strategies or harvest control rules in the tuna fishery. In this study, we will conduct a management strategy evaluation by simulating several harvest control rules. We will also consider multiple scales, multiple species, and account for data-poor areas of the fishery. Our evaluation will show conflicts that should be taken into account by a fisheries manager, and we will discuss the impact of the control rules in terms of aggregate profit and distribution of profit.

Additionally, underestimation of catch is a problem in Indonesian tuna fisheries is that has been acknowledged in several studies (Dudley and Harris, 1987; Proctor et al., 2003; Pauly and Budimartono, 2015; Yuniarta et al., 2017). The causes are illegal and unreported catch, problems in data collection, and remote fishing grounds. Underestimation of catch can lead to failure in the management plan (Kurota et al., 2010), and should be considered in the process of decision making for any fisheries management strategy.

We will look at both FAD dynamics and underestimated catch in this report by first reviewing the characteristics of FADs-based tuna fisheries, and then conducting a FAD assessment. We will incorporate the value of additional information of unreported catch, and conduct a simulation of the impact of Indonesian tuna fisheries policies. Finally, we will generate a production function analysis of FADs-based tuna fisheries based on fishing logbook data.

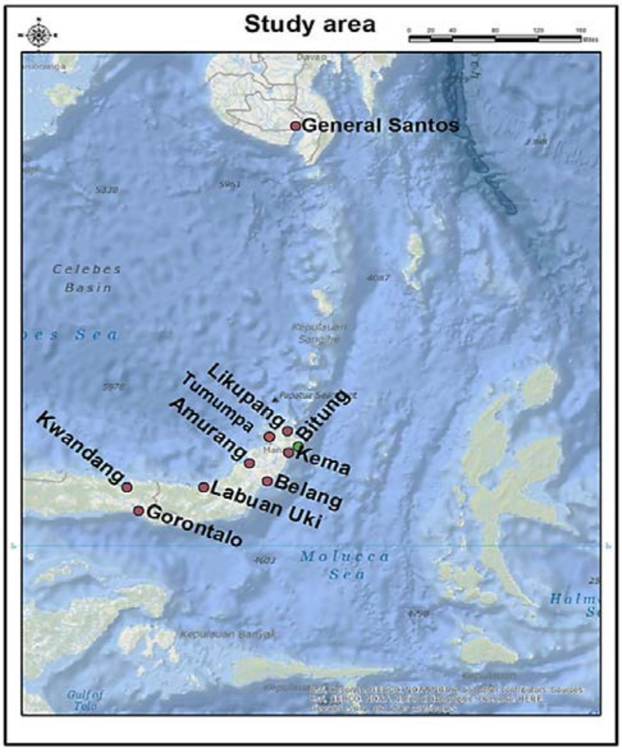


Figure 1. The study area of North Sulawesi Province surrounded by two main tuna fishing grounds, the Molucca Sea and The Celebes Sea

2. Characteristic of FADs-based tuna fisheries

This section will focus on the characteristics of FADs-based tuna fisheries in North Sulawesi as an early stage in understanding the behavior of fishers. Interviews were carried out from September 2013 - February 2014 in three main fishing harbours: Bitung and Kema, both adjacent to the Molucca Sea, and Labuan Uki where most fishers operate in the Celebes Sea (Figure 1). In total 89 in-depth interviews were conducted with tuna fishers who use FADs, and included questions about fishing experience, type of boat, and fishing operations. We differentiated fishers based on gear type, port of landing, and point of origin. All interviewees used purse seine, hand line, or pole and line gear. Summary results of the survey can be seen in Table 1 below.

Table 1. Overview of data used to characterize the fisheries & estimate number of FADs

Fishing port	Fishing gear	Size (GT)	Interview (N)	Fishers logbook (N)	Transect survey (N)	Operation Area
	PS	19-34	25	10	14	Molucca
Bitung	Indonesian HL	6-29	25	25	-	Celebes
	Filipino HL	2-3	10	10	-	
	PL	53-91	10	10	-	
Kema	PS	24-32	67	7	7	Molucca
Labuhan Uki	PS	18-48	13	14	-	Celebes
Tumumpa	PS	25-49	-	3	23	Celebes**
		Total	89	79	44	

Note: Characterization of the scale of operation given by the gross tonnage (GT) of the vessels owned by these fishers. GT=Gross tonnage, HL=Hand line, PS = Purse seine, PL=pole and line, N=number.
**There was no interview survey in the Tumumpa fishing harbour. The harbour is adjacent to the Celebes Sea.

2.1 Experience of the fishers

From the interview results of hand line fishers, those originating from the Philippines have, on average, more experience than Indonesian fishers (Table 2). Hand line fishers from Indonesia indicated that they all function only as captain of the vessel, in contrast to hand line fishers from the Philippines who function both as captain and as fishing master. Pole and line fishers are the most experienced compared to the other interviewed tuna fishers; they have on average of 29 years of experience. All pole and line fishers indicated that they function as captain and fishing master of the boat. Purse seiners landing in Labuan Uki have, on average, the least experience of all interviewed fishers. Only one purse seine fisher from Bitung indicated functioning only as a fishing master on the boat, the other purse seiners operated as captain, or both as captain and fishing master.

Table 2. Summary statistics of fishers' total years of experience

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	20.4	8.0	41.0	8.3	41
Bitung Hand line Filipino	23.3	10.0	40.0	10.8	46
Bitung Pole and line	29.0	20.0	41.0	7.5	26
Bitung Purse seine	22.3	10.0	38.0	7.3	33
Kema Purse seine	24.5	15.0	31.0	7.6	31
Labuan Uki Purse seine	19.7	5.0	33.0	7.9	40

2.2 Boat characteristics

Boats can be considered a long-term investment for fishers. Variables characterizing boats include capacity, length, weight, engine size, building material, boat type, and type of technology used during fishing operations.

Data on the fleet capacity of the respondents show that pole and line fishers use the largest capacity boats, in gross tonnage (GT) and engine size, compared to other vessels (Table 3 and 4).

Table 3. Summary statistics of boat weight per fishery, in GT

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	11.6	6.0	29.0	8.3	71
Bitung Hand line Filipino	2.5	2.0	3.0	0.5	21
Bitung Pole and line	77.5	53.0	91.0	13.0	17
Bitung Purse seine	27.5	19.0	34.0	3.4	12
Kema Purse seine	27.8	24.0	32.0	2.7	10
Labuan Uki Purse seine	27.8	18.0	48.0	8.0	29

Table 4. Summary statistics of engine per fishery, in horsepower

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	120.2	60.0	250.0	51.0	42
Bitung Hand line Filipino	57.1	30.0	80.0	14.2	25
Bitung Pole and line	566.1	350.0	630.0	91.2	16
Bitung Purse seine	246.0	100.0	380.0	74.6	30
Kema Purse seine	228.3	90.0	350.0	103.6	45
Labuan Uki Purse seine	318.1	220.0	440.0	86.8	27

Table 5. Summary statistics of boat length per fishery, in meters

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	15.6	11.0	27.0	3.6	23
Bitung Hand line Filipino	10.3	8.0	12.0	1.4	14
Bitung Pole and line	30.6	28.0	36.0	2.5	8
Bitung Purse seine	21.3	17.0	25.0	2.5	12
Kema Purse seine	20.2	17.0	22.5	2.2	11
Labuan Uki Purse seine	22.7	18.0	29.0	3.3	14

We found that the minimum boat length among pole and line fishers was greater than the maximum boat length of hand line fishers (28.0 versus 17.0 meters respectively) (Table 5). Summary statistics in Tables 3 and 4 for both weight and engine size correspond with these findings. Hand line fishers operate the lightest boats with the least powerful engines. Purse seiners operate the heaviest boats with higher engine capacities. None of the interviewed fishers owns the vessel on which they operate; all of them are employed by a fishing company that owns multiple vessels. This may indicate that the captain of the boat cannot make all decisions independently; the boat owner may affect decision-making. All the vessels were relatively young in age, only seven of the 88 vessels were older than 15 years, and all of those were registered in Bitung. According to anecdotal evidence, fishers stated that there was an increase in boat investments and, correspondingly, an increase in the total number of boats around 10-15 years ago.

With regard to the difference between Indonesian and Filipino hand line fishers, vessels operated by Filipinos are smaller in length, and lower in both weight and engine size. Data on purse seine vessels operating from different harbours presented no remarkable differences in length, weight or engine size. Hand line fishers operate with more than one boat. Next to their motorized 'mother' boat, described in Tables 2 – 4, more small boats without any special features for gear handling are used during fishing. These small boats, named *pakuras,* are used in catching tuna, after which the catch is moved to the 'mother' boat. The number of pakuras depends on the capacity of the mother vessel. On average, hand line vessels from the Philippines operate with 3 pakuras and vessels from Indonesia operate with 4 pakuras.

2.3 Supply and Crew

Tables 6 – 8 present descriptive statistics on the number of crew, the normal amount of fuel used, the number of ice blocks, and the tons of water taken on an average trip. Similar to the boat characteristics data (Table 3), pole and line boats operate with the highest number of crew and quantity of supplies, including on average 181 buckets of live bait per trip. In contrast, hand line vessels operate with the lowest number of crew and quantity of supplies. Filipino hand line fishers recorded lower numbers of crew and supplies, including fuel for the *pakuras* (166.0 liters), on their trips compared to Indonesian hand liners (435.1 liters). For the purse seiners, fishers landing in Kema recorded the lowest numbers of crew and supplies on their trips. None of the interviewed fishers has ever run out of fuel.

Table 6. Summary statistics of the number of crew per fishery

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	8.7	4.0	23.0	5.0	57
Bitung Hand line Filipino	6.4	4.0	8.0	1.7	26
Bitung Pole and line	49.2	27.0	69.0	14.5	30
Bitung Purse seine	26.4	18.0	38.0	4.6	17
Kema Purse seine	20.8	15.0	27.0	4.6	22
Labuan Uki Purse seine	28.5	20.0	44.0	6.2	22

Table 7. Summary statistics of normal amount fuel spent on a trip, in liters

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	926.0	100.0	6000.0	1260.2	136
Bitung Hand line Filipino	291.0	110.0	500.0	133.5	46
Bitung Pole and line	6800.0	4500.0	10000.0	1670.0	25
Bitung Purse seine	1226.2	2.0	3000.0	843.1	69
Kema Purse seine	950.0	400.0	1500.0	455.0	48
Labuan Uki Purse seine	1215.4	500.0	2000.0	445.1	37

Table 8. Summary statistics of number of ice blocks taken on a trip

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	143.8	50.0	400.0	89.7	62
Bitung Hand line Filipino	60.9	24.0	120.0	28.3	47
Bitung Pole and line	310.0	200.0	500.0	73.8	24
Bitung Purse seine	203.9	100.0	400.0	90.5	44
Kema Purse seine	133.3	100.0	200.0	40.8	31
Labuan Uki Purse seine	233.1	100.0	500.0	105.1	45

Table 9. Summary statistics of water taken on a trip, in tons

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	2.0	0.5	10.0	1.9	95
Bitung Hand line Filipino	0.9	0.2	1.0	0.3	29
Bitung Pole and line	9.9	5.0	16.0	3.6	37
Bitung Purse seine	3.4	1.0	7.0	1.6	48
Kema Purse seine	2.2	1.0	4.0	1.0	45
Labuan Uki Purse seine	4.2	1.0	10.0	2.9	69

2.4 FAD Utilization

Summary statistics show that pole and line fishers use the largest number of FADs during a trip compared to other gear types (Table 10). Purse seiners, and in particular those from Kema, exploit the lowest number of FADs. Data on the number of fished FADs per fishing day confirm these findings. Summary statistics on the normal fishing operating time on FADs (Table 11) show a negative relation between the number of fished FADs and the time spent fishing on a FAD i.e., fishers who fish on more FADs during a trip will spend less time fishing on each FADs. Although Indonesian and Filipino hand line fishers exploit the same number of FADs during a trip, hand liners from the Philippines fish for a shorter duration on a FAD compared to Indonesians (2.2 versus 3.3 hours). While fishing on a FAD, Indonesian and Filipino hand line fishers both usually tie their ‘mother’ vessel to the FADs for protection against strong currents and waves.

Table 10. Summary statistics on the number of fished FADs during a trip

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	3.6	1.0	15.0	3.1	85
Bitung Hand line Filipino	3.6	3.0	5.0	0.7	19
Bitung Pole and line	11.5	10.0	15.0	2.4	21
Bitung Purse seine	2.5	1.0	4.0	0.7	29
Kema Purse seine	1.8	1.0	3.0	0.8	41
Labuan Uki Purse seine	2.5	1.0	3.0	0.7	26

Table 11. Summary statistics of the normal fishing time on one FAD, in hours

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	3.3	2.0	7.0	1.4	42
Bitung Hand line Filipino	2.2	1.0	4.0	1.0	47
Bitung Pole and line	0.6	0.3	1.0	0.2	41
Bitung Purse seine	4.3	1.0	8.0	1.9	44
Kema Purse seine	5.0	4.0	7.0	1.3	25
Labuan Uki Purse seine	4.4	2.0	7.0	1.4	33

Table 12 reveals that the normal distance to the fishing grounds, in this case, the areas of FADs, does not vary much between the gear types. Differences in traveling distances do not correspond to the average capacity of the vessels. Therefore, the capacity of the vessels does not limit fishers as to where they fish. However, purse seine fishers cannot freely choose which FADs to fish on, since they can only exploit FADs owned by themselves or their company. Hand line and pole and line fishers, on the other hand, can freely choose which FADs to exploit.

Table 12. Summary statistics on the normal distance to an area of FADs, in nautical miles

Fishery	Mean	Min	Max	StDev	CV
Bitung Hand line Indonesian	89.9	40.0	320.0	52.6	59
Bitung Hand line Filipino	66.0	40.0	100.0	20.1	30
Bitung Pole and line	78.0	50.0	100.0	18.1	23
Bitung Purse seine	88.2	36.0	298.0	61.9	70
Kema Purse seine	66.2	50.0	80.0	12.5	19
Labuan Uki Purse seine	73.1	20.0	100.0	25.4	35

2.5 Analysis

Analysis was performed to address the influencing factors for fishers in investing in FADs. A simple logit model was used where the independent variables are gear type (X1), education level (X2), vessel size (GT) (X3), distance between FADs (X4), and experience of fisher both working as a fisher (X5) and working with the current operating gear (X6). The dependent variable is binary, either the value 1 or 0, as representative of the decision to invest in FADs (D_FAD). Data was extracted on the dependent variable from fishers' answers on the interview question about the number of FADs owned. A value of 1 was assigned for owning FADs, and a value of 0 for not owning FADs.

2.6 Results and Discussion

We performed several regressions using the following formulas:

$$D\_FAD_{1,0} = logit(X_1, X_2, X_3, X_{4\_min}, X_{4\_max}, X_5, X_6) \quad (1)$$
$$D\_\mathrm{F}AD_{1,0} = logit(X_1, X_2, X_3, X_{4\_min}, X_5, X_6) \quad (2)$$
$$D\_FAD_{1,0} = logit(X_1, X_2, X_3, X_{4\_max}, X_5, X_6) \quad (3)$$

The independent variables in regression (1), (2) and (3) were not significant. Therefore, we eliminated those insignificant variables and continued with variables that were significant in the equations:

$$D\_FAD_{1,0} = logit(X_1) \quad (4)$$
$$D\_FAD_{1,0} = logit(X_6) \quad (5)$$

There were 39 observations not included in regressions (1), (2) and (3) due to lack of data on independent variables, making the total observations in those regressions 50. Variable gear types and fisher's experience on operating current gear were significant in regression (4) and (5). The combination of those variables, however, yielded no significant results.

In regression (4), all observations were included in the analysis, while in regression (5) 14 observations were removed. Recall that there are three gear types in the analysis of regression (4); we went deeper to find the most significant gear type affecting the decision to invest in FADs. Our results show that hand line gear has the greatest influence on the decision to invest in FADs (P-value <0.05) (Appendix 2, part 5).

We note the following shortcomings with this analysis: 1) we were not able to differentiate investments in type of FADs owned, due to our small sample size; and 2) our analysis did not account for the scale of the fisheries.

3. FAD Assessment

In this section, we will focus on the process fishers use in utilizing FADs, particularly how fishers decide where to deploy FADs in the ocean towards the expected variation in spatial catch success (Hilborn, 1985). Our analysis encompasses the distribution of FADs, densities, and the dynamics that emerge by combining information on fishers that operate in the two main deployment areas surrounding North Sulawesi, the Molucca and Celebes Sea. The information on FADs was gathered from the fishers' logbooks over the period of September 2013 - February 2016, transect surveys, and interviews (Table 1). Data on the type of FADs deployed in the Molucca and the Celebes Seas were collected through interviews, and the following types of FADs were distinguished:

1. Bungalow FADs
2. Pontoon FADs
3. Styrofoam / Bamboo FADs

Bungalow FADs are made of bamboo, wood, and reeds and consists of an approximately 3m^2 platform with a small cabin on top; the platform is anchored to the bottom of the sea (Figure 2B). A FAD guard stays in the little cabin for roughly three or six months, after which a new FAD guard will take their place. FAD guards inspect beneath the bungalow each day to see if tuna have aggregated. When the guard determines the school is large enough to fish on, he contacts the FAD owner on the mainland via satellite radiophone, and a fishing vessel will navigate to the bungalow. Pontoon FADs are approximately 4-meter long buoys made of iron or steel, coated with a layer of paint to prevent rusting. Figure 2A presents an image of fishers performing maintenance work on a pontoon FAD. Styrofoam or Bamboo FADs (Figure 2B) are the simplest FADs, typically made of Styrofoam, wood, and bamboo.

Figure 2. Pontoon (A) and Styrofoam FAD (B)

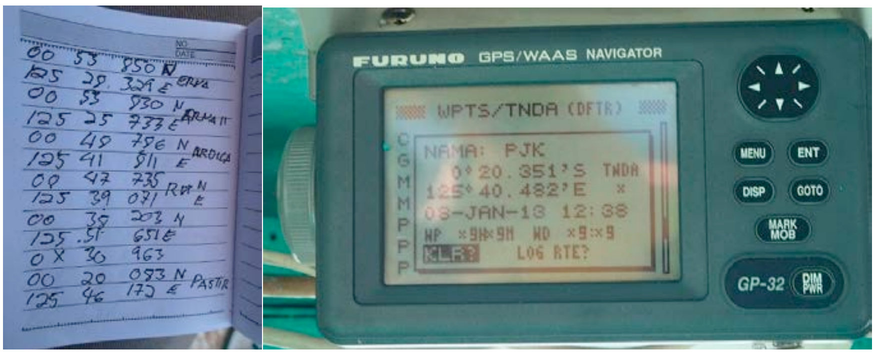


Figure 3. Examples of data on FAD locations made by fishers in a logbook and on an on-board computer (GPS)

In total, we collected 2062 FAD positions from fishers' logbooks and 8347 FAD positions from port sampling logbooks. Both datasets were screened to remove observations with following the criteria: located outside the study area, located on land, situated in shipping lanes, and FADs situated in areas less than 500 meters deep (also known as communal FADs). After cleaning the data, we obtained 1502 unique FAD positions from fishers' logbooks and 1339 FAD positions from port sampling logbooks.

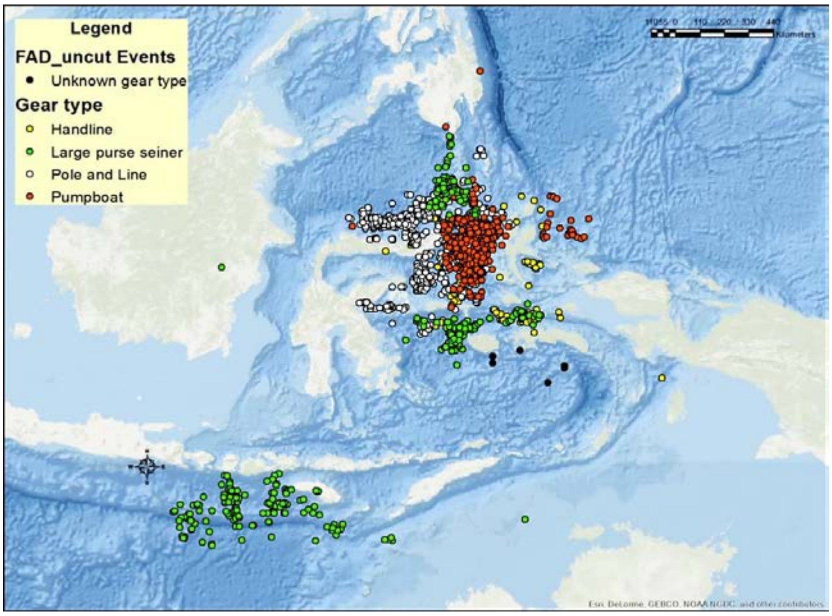


Figure 4. FAD positions gathered from fishers' logbooks

Note: This map was generated from the uncleaned data set, and each FAD can have multiple positions due to movements in the ocean and recordings of the same FAD by different fishers.

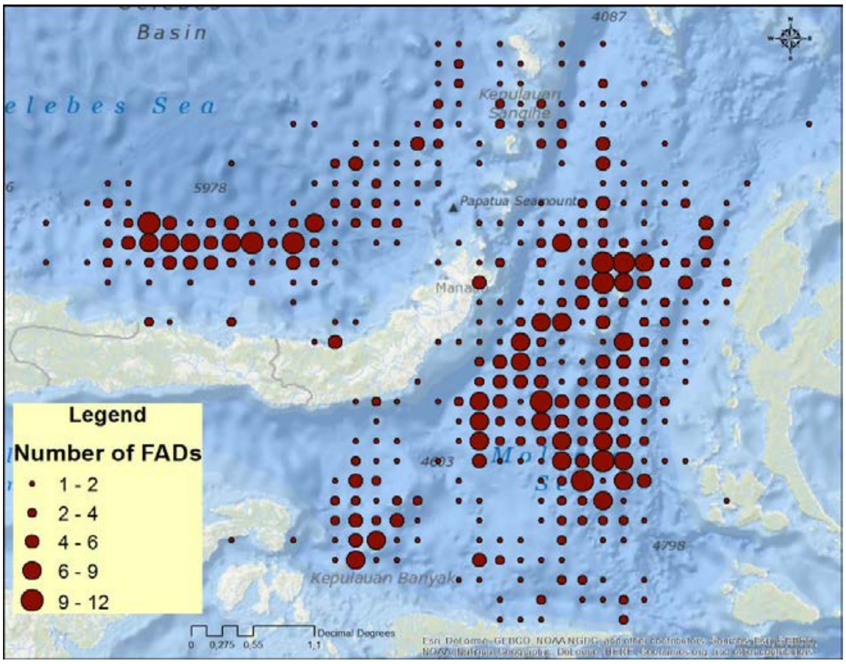


Figure 5. Density of FADs positions from fishers' logbooks

3.1 Analysis

Four iterations of minimum distance analysis on the fishers' logbook data resulted in 962 unique FAD positions that were >3.1 km apart: 673 FADs in the Molucca Sea and 289 FADs in the Celebes Sea. The geometric average of the minimum distance of FADs in this dataset was 7km. The port authority database required three iterations resulting in 906 unique FADs: 718 FADs located in the Molucca Sea and 188 in the Celebes Sea. The geometric average of the minimum distance of FADs in this dataset was 8km.

Combining both the fishers' and port logbook datasets and removing duplicate FAD positions yielded a total of 1,242 unique FAD positions: 914 in the Molucca Sea and 328 in the Celebes Sea. The combined dataset had 541 FADs originated from fishers' logbooks, 512 FADs derived from port database records, and 189 FAD positions (15%) occurring in both datasets (Figure 6). The geometric average of the minimum distance of a FAD in the combined dataset was 6.4 ± 3.5km (N=1242). The minimum distance in the Celebes Sea was higher (7.4 ± 4.78, N=328) than in the Molucca Sea (6.1 ± 2.82, N=914) (Figure 7). These results were close to the minimum distance of FADs from the line transect survey.

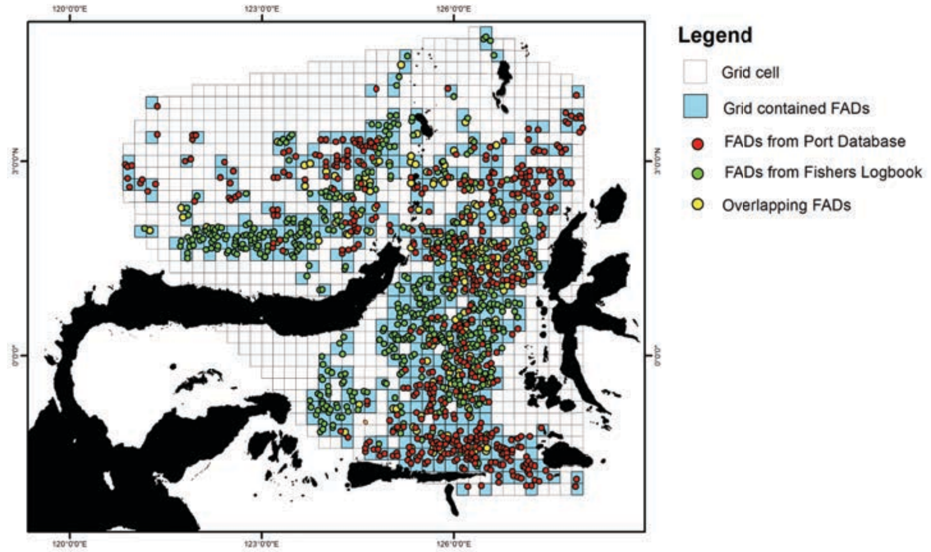


Figure 6. Unique FAD positions from the combined fishers' logbook and port authority data indicating the overlap between the two datasets

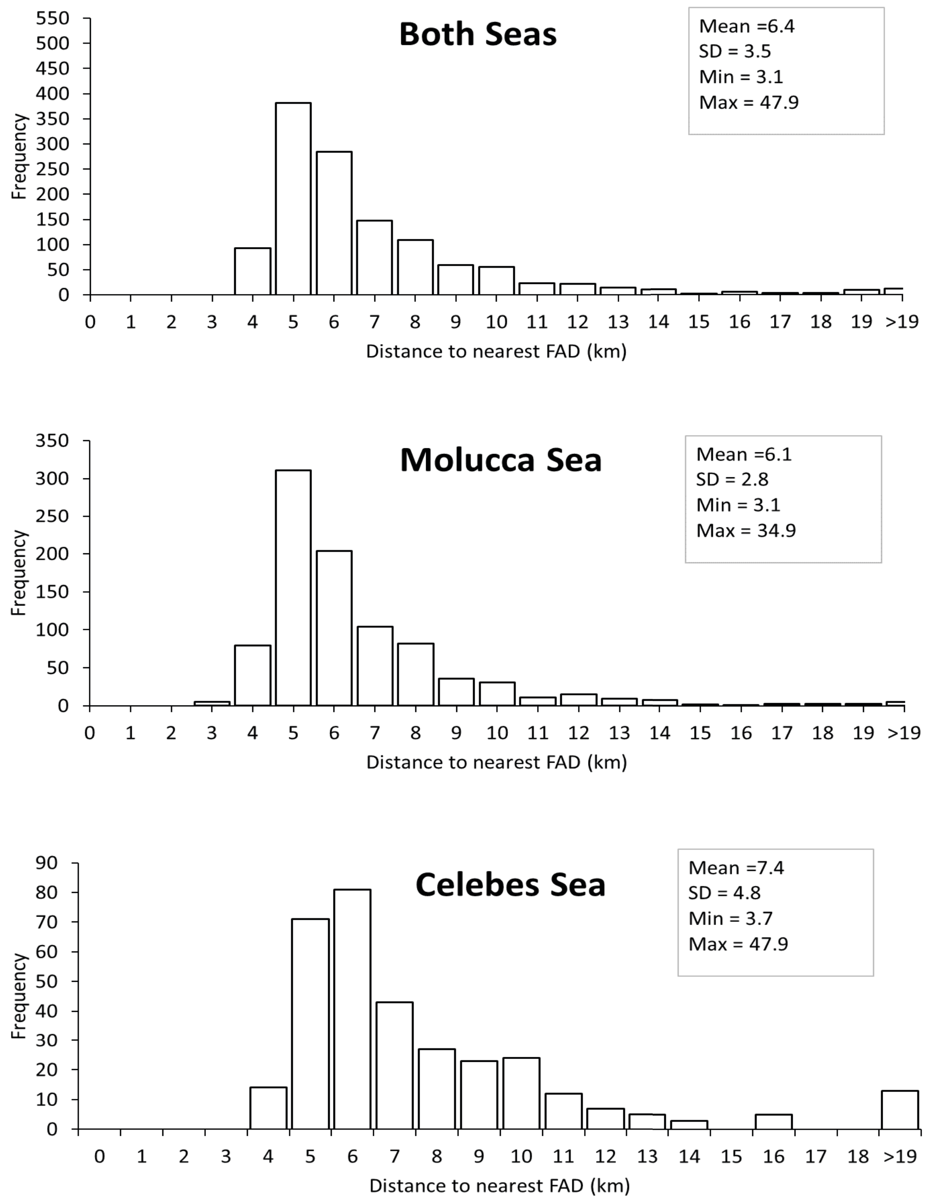


Figure 7. Frequency of distances of a FAD to a nearest neighbouring FAD in the final combined data sets

Based on the 512 FADs derived from the port authority database and the overlapping of 189 FAD positions (15%) between fishers and port authority data (Figure 6), it is interesting to analyse further the ownership of those FADs. The port authority database included information on boats such as gross tonnage (GT), fishing gear, length of the vessel, number of crew, and on fishing operation such as date of departure and return, catch position, estimation of catch amount, and catch composition by species. Further analysis related to FAD ownership and productivity will be forthcoming.

4. Alternative harvest control rules for multi-fleet and multi-species tuna fisheries under data-poor conditions in Eastern Indonesia

In this section we discuss the performance of alternative harvest control rules (HCR) for tuna fisheries in Eastern Indonesia under a framework of management strategy evaluation (MSE), which is defined as the combination of pre-specified methods of data collection and analysis, and a simulation-tested decision rule that calculates a scientific management recommendation for the fishery (Butterworth et al., 1997). This type of management procedure is useful for fisheries managers in meeting their management objectives, and particularly in data-poor conditions where standard stock assessments are not possible. Simulation testing of proposed decision rules can be conducted as an affirmation that the objective of the fishery can be achieved (Butterworth et al. 2010). By using MSE to decide the best management procedure, a fisheries manager can better predict results within a certain period.

Stakeholder demand for harvest control rules for Indonesian tuna fisheries is currently very high. As in other developing countries, harvest control rules must take fishery conditions into account, including data-poor fisheries, multi-species fisheries, and multi-scale fisheries.

Management objectives are often contradictory, and therefore, it is important for decision makers to consider trade-offs between objectives. In this study, we examine the performance of alternatives harvest control rules from ecological, economic, and social perspectives. We conducted simulations of several scenarios of harvest control rules for skipjack (*Katsuwonus pelamis*) and yellowfin tuna (*Thunnus albacares*) in Eastern Indonesia to show potential conflict between objectives.

4.1 Model

The first part of the analysis was to develop a stochastic bio-economic model for management strategies. We provide information about the operating model we used in the simulation in the Appendix of this report.

The reference points used in the HCR were catch per unit effort (CPUE), maximum effort, and minimum effort. We obtained the relationship between effort and CPUE from a simulation of the operating model over 100 years and 1000 draws. We assume that in year 100 the fishery reaches the steady state condition. First, we determined the maximum CPUE at the lowest level of effort (1 vessel). After that, we determined the limit level of CPUE to be 40% of maximum CPUE. We estimate the reference points of maximum effort in the HCR by using interpolation methods on the relationship between the CPUE limit and the associated effort. We set a minimum effort of 1000 vessels as the social policy of the fishery.

In data-poor fisheries, application of a non-model based MSE is common. We used CPUE as the representative variable for biomass in the x-axis, and effort as a control rule of the fishery in the y-axis. In the sliding HCR, we estimate the slope ($mid\ \alpha$) that connects the point of CPUE limit and minimum effort to the point of CPUE maximum and maximum effort. From that, we take fifty sequences of slope in the range:

$$\alpha = \begin{cases} mid\ \alpha \times (1 - range\ up) \\ mid\ \alpha \times (1 - range\ down) \end{cases}$$

Where range down is 0.5 and range up is 100.

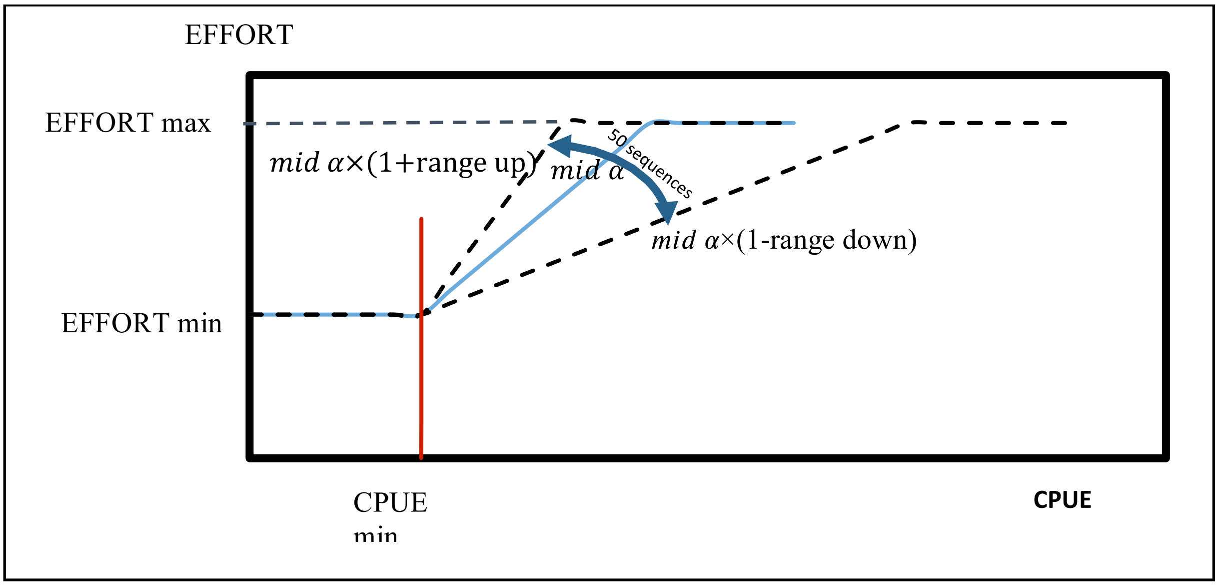


Figure 8. Sliding harvest control rule

We use three scales in the model: 1) small-scale fisheries (SSF), vessels ≤10GT, 2) medium-scale fisheries (MSF), vessels between >10GT - <100GT; and 3) large-scale fisheries (LSF), vessels >100GT. We accommodate the characteristic of multi-species in the HCR by using the lowest level of recommended effort for next year effort (Figure 9.). Therefore, we are applying a conservative approach to the rules.

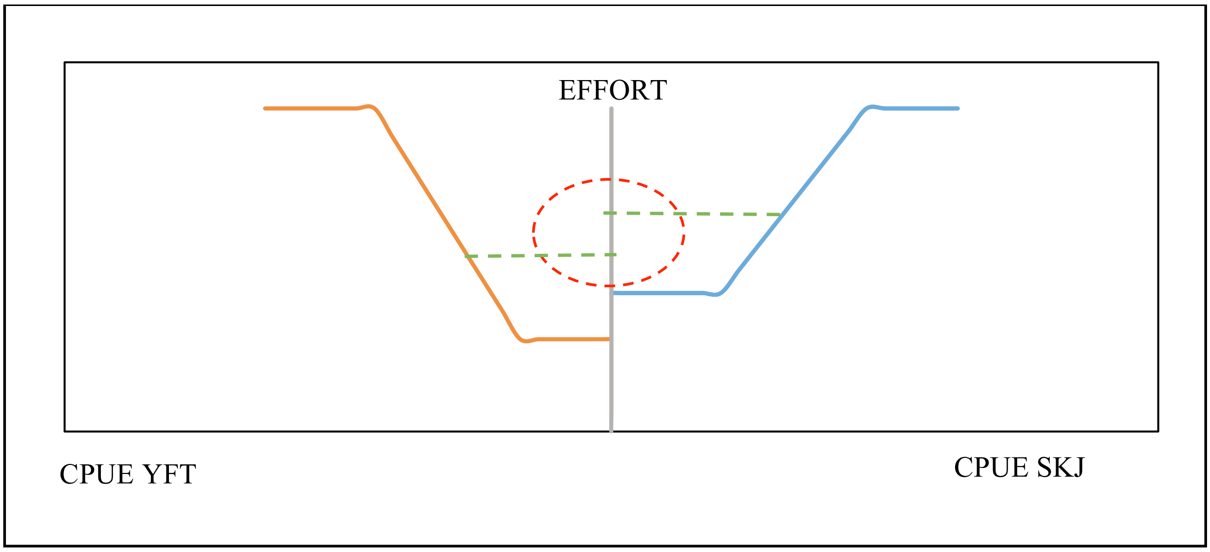


Figure 9. Decision on recommended effort for multi-species

4.2 Harvest control rules (HCRs)

We categorize three alternative HCRs in this study: 1) constant effort, 2) effort as a function of CPUE, and 3) effort as a function of CPUE with additional minimum effort equal to the number of SSF's vessels (Table 13).

Table 13. Alternative HCRs

Alternative HCRs	Name of alternative HCRs
HCR1. Constant Effort	
- Effort is constant with the same number of vessels as in the previous year	HCR1A
- Effort is increasing 50% in the first year of projection. After that the effort is constant.	HCR1B
- Effort is increasing slowly about 1% every year	HCR1C
HCR2. Effort as a function of CPUE	
- The lowest CPUE is used to update effort for the next year. Effort can decrease or increase immediately without any limitation.	HCR2A
- The lowest CPUE is used to update effort for the next year. Thresholds are applied for increasing and decreasing effort up to 20% from the previous year.	HCR2B
HCR3. HCR2 with minimum effort on SSF	
- Similar to with HCR2A with additional minimum effort equal to the total number of SSF vessels	HCR3A
- Similar with HCR2B with additional minimum effort equal to the total number of SSF vessels	HCR3B

4.3 Performances of Harvest Control Rules

Fishing Rents

Profit of the fishery is:

$$Profit_t = C_t \times p \; - \; FC_l \times f_{t,l}$$

The present value of profit is:

$$PV\ Profit = \sum_{t=1}^{\max t} \frac{Profit_t}{(1+R)^t}$$

Where

$PV\ Profit$	: Present value of profit
$Profit_t$	: Profit in year t
R	: Discount rate (0.05)
C_t	: Total catch in year t
p	: Price
FC_l	: Fishing cost for scale fisheries l
$f_{t,l}$	: Total effort of scale fisheries l in year t

Minimum effort

We set minimum effort as 1000 vessels for HCR1 and HCR2, which we assumed was the social policy of the fishery. In HCR3 we set minimum effort equal to the number of SSF vessels.

Proportion of the poorest fishers

We assumed the standard minimum wage in the study area as 30 million rupiah per year. We estimated the risk that the fishers' income would be less than the minimum wage (<Rp.30 million/year).

Status stock

We estimated the risk that total biomass in the projection years would be less than 40% of virgin biomass, or biomass without fishing, for both skipjack and yellow fin tuna.

Performances of all HCRs are evaluated for a projected 50-year timeline.

4.4 Results and Discussion

We simulated a constant effort for HCR1 and sliding HCRs for HCR2 and HCR3. In the sliding HCRs, we found a higher slope for the rules, which increases fishing profit (Figure 10). In order to evaluate the HCRs further, we used the slope of the sliding HCRs with the highest fishing profit for HCR2 and HCR3.

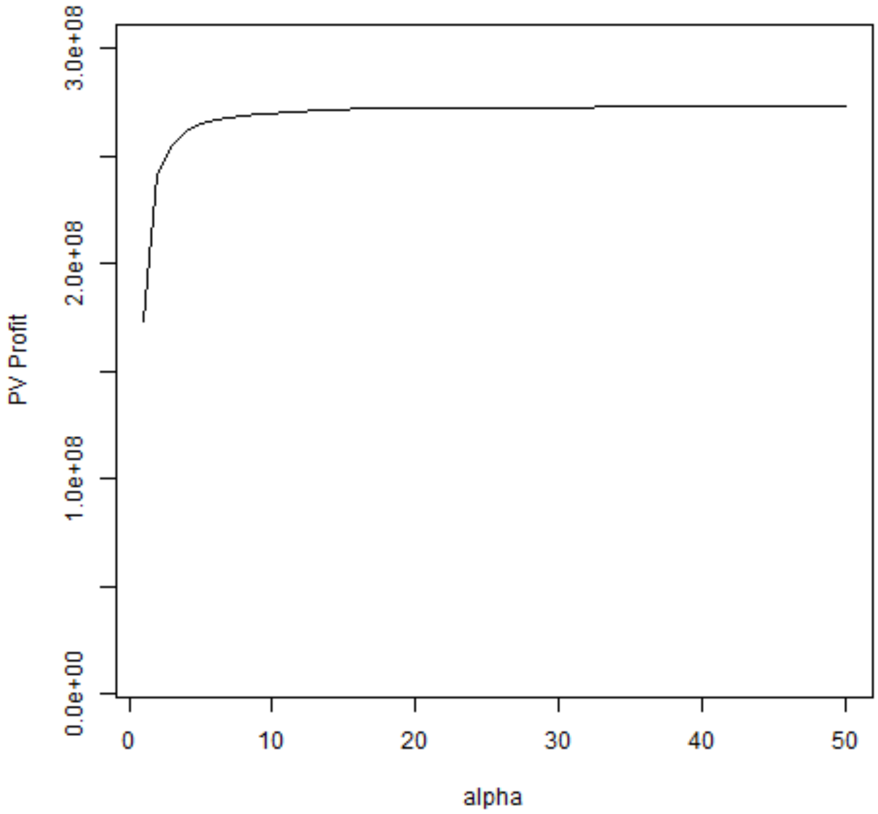


Figure 10. Relation of slope (alpha) in sliding HCRs and the mean present value of fishing profit (in millions of Rupiah)

Table 14. Performances of alternative HCRs on fishing profit

Alternative HCRs	SSF (in 10^{12} rupiah)	MSF (in 10^{12} rupiah)	LSF (in 10^{12} rupiah)
HCR1A	65	36	81
HCR1B	79	42	97
HCR1C	70	39	88
HCR2A	58-96	33-47	73-116
HCR2B	59-96	33-47	74-116
HCR3A	72-125	28-58	30-60
HCR3B	71-117	28-55	30-67

Evaluation of HCRs in relation to fishing profit (Table 14) indicated that HCR1B would be the most efficient rule for the fisheries because it has the highest total profit and the biggest proportion of LSF. A similar proportion of profit between scales is also shown in HCR1A and HCR1C. Both HCR2A and HCR2B have lower profits compared to those for HCR1. Fishing profit for MSF is stable, while fishing profit for SSF and LSF are decreasing. However, fishing profits of LSF are still the biggest proportion for those HCRs. In contrast, results for HCR3A and HCR3B show that the biggest profit is achieved by SSF, which makes sense since we set the minimum effort equal to the number of SSF vessels in this rule. We also observe the number of MSF and LSF vessels and associated profits decreasing under this rule.

Table 15. Performance of alternative HCRs on minimum effort or number of vessels

Alternative HCRs	Reaching the minimum effort (%)
HCR1A	0%
HCR1B	0%
HCR1C	0%
HCR2A	4%
HCR2B	0%
HCR3A	82%
HCR3B	90%

In HCR1A and HCR1B, the minimum effort is not achieved because we applied constant minimum effort for the fishery, while in HCR1C the effort is increasing every year. The simulation of HCR2A showed that the minimum effort is 4% during the projection years. However, when we applied a threshold of 20% in HCR2B, the simulation showed that the minimum effort was never reached. In HCR3, we protected the SSF; therefore the minimum effort for HCR3 is the same as the number of SSF vessels. The risk of having minimum effort is higher in HCR3A and HCR3B because of this, and the effort of LSF in HCR3A and HCR3B reaches zero.

Table 16. Performance of alternative HCRs on proportion of the poorest fishers

Alternative HCRs	SSF (%)	MSF (%)	LSF (%)
HCR1A	96	93	0
HCR1B	96	93	0
HCR1C	96	93	0
HCR2A	96	88	0
HCR2B	96	90	0
HCR3A	4	12	NA
HCR3B	4	13	NA

In our analysis of the performance of alternative HCRs on the proportion of the poorest fishers (Table 16.), we find that HCR3A and HCR3B have only a small proportion of the poorest fishers. Meanwhile, LSF has no income because the rules protect SSF vessels. Simulations of HCR1 (HCR1A, HCR1B, HCR1C) and HCR2 (HCR2A and HCR2B) show that the biggest impact of the HCRs is on the SSF because they have the biggest proportion of vessels in the fishery. Simulations of HCR2, however, show that the proportion of the poorest fishers in MSF is lower than those in simulations of HCR1. Simulations of those HCRs have none of the poorest fishers in LSF.

Table 17. Performance of alternative HCRs on status stock

Alternative HCRs	Skipjack (%)	Yellowfin tuna (%)
HCR1A	<2	<2
HCR1B	>90	<2
HCR1C	>40	<2
HCR2A	>80	<2
HCR2B	>90	<2
HCR3A	>90	<2
HCR3B	>90	<2

Our simulation on the performance of alternative HCRs showed that skipjack is at greater risk of biomass depletion than yellowfin tuna. These results may include some bias due to shortcomings in the estimation of the catchability parameter and lack of data fitting.

Our results show that harvest control rules on constant effort have positive outcomes on the fishing profits and the risk of reaching minimum effort. The harvest control rules, however, disproportionately affect small and medium scale fishers who are at a greater risk of making less than 30 million rupiah per year. Large-scale fishers face almost no risk of having such a low income. This finding illustrates that income is not evenly distributed among the various fishing scales.

5. Value of Information

In this section we will discuss the value of additional information on unreported catch in alternative management strategy evaluation for the tuna fishery in Eastern Indonesia. Catch underestimation generates uncertainty in the observation of fishing mortality, the impact of fishing on ecosystems, and affects to the estimation of reference points (Caddy and Mahon 1995; Patterson et al. 2001; Van Beveren et al. 2017). The problem of catch underestimation has long been acknowledged in Indonesian fisheries (Dudley and Harris 1987; Proctor et al. 2003; Pauly and Budimartono 2015; Yuniarta et al. 2017), and is caused by factors like illegal and unreported catch, and problems with data collection in remote areas. Underestimation of catch can even lead to management plan failure (Kurota et al. 2010).

The management procedure approach, also known as management strategy evaluation (MSE) or harvest control rule (HCR), acknowledges the role of uncertainty (Punt 2017), and that additional information can reduce uncertainty on the performance of rules. The outcomes of a set of alternative management strategies can be evaluated to meet the objectives of the fishery, and comparing these outcomes can lead to a structured process for choosing a fisheries management strategy. The Value of Information (VoI) approach is a method of estimating the value of a new knowledge (Mantyniemi et al. 2009), which is widely used to address the challenges of decision-making under uncertain conditions.

VoI has been implemented in several fisheries management studies, such as: (1) the value of information on price patterns with trade-off alteration in the salmon production plan (Forsberg and Guttormsen 2006), (2) evaluation of the value on the information of the stock-recruitment function of the North Sea Herring (*Clupe harengus*) (Mantyniemi et al. 2009), and (3) the value of information on invasive species control, commercial fisheries stock assessment, and marine protected area design in fisheries management (Hansen and Jones 2008). However, there is still a lack of research about the decision-making process for alternative fisheries management plans. Our study aims to complement the existing literature with a simulation of empirical MSE (for which there is poor data) by implementing the VoI approach.

We focus on small-scale (SSF), medium-scale (MSF) and large-scale (LSF) tuna fisheries in Eastern Indonesia. These are considered multi-species fisheries, and we limited our scope to by considering only two species: skipjack (*Katsuwonus pelamis*) and yellowfin tuna (*Thunnus albacares*). We will estimate the value of additional information of unreported catch for these two species on all three scales.

5.1 Analysis

We simulated the combination between two types of sliding harvest control rules (HCRs) with the possibility of the available information (imperfect and perfect information). In the first HCR, we do not set effort thresholds in the rule; therefore, effort can increase or decrease immediately depending on the CPUE in the previous year. In the second HCR, we set a limit for increasing or decreasing effort at 20% over the previous year. We combine both HCRs with perfect and imperfect information: perfect information occurs when the fisheries manager observes all catch, and imperfect information occurs when the fisheries manager observes only part of total catch. In every combination, we generated fifty iterations, yielding 200 total simulations (Table 18).

Table 18. Combination of simulations

Management Strategy 1		**Management Strategy 2**	
Imperfect information	Perfect Information	Imperfect information	Perfect Information
50 sequences	50 sequences	50 sequences	50 sequences
$1A_1$- $1A_{50}$	$1B_1$- $1B_{50}$	$2A_1$- $2A_{50}$	$2B_1$- $2B_{50}$
Combination 1A	Combination 1B	Combination 2A	Combination 2B

Decision Making
We developed a simple decision tree as a framework for choosing a management strategy when considering additional information of unreported catch in the tuna fishery in Eastern Indonesia (Figure 11). The simulation model gave feedback on the performance of alternative management strategies.

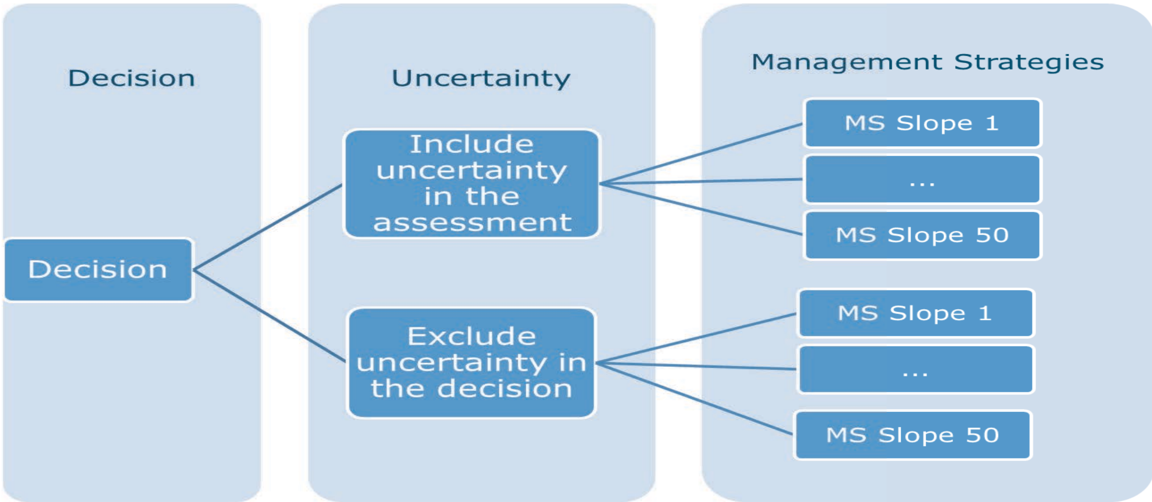


Figure 11. Decision tree analysis to consider uncertainty of unreported catch in the alternative management procedures

Performance Indicators of Management Strategies
Performance indicators of management strategies are used to estimate the advantage of using alternative management plans and additional information. We use indicators of present value of profit where the expected value (E) of an action is given by:

$$E[V(a,s)] = PV\ Profit$$

Uncertainty
In this node of the decision tree, there are two possibilities: 1) ignore uncertainty in the management procedure and 2) considering uncertainty in the management procedure. Decision 1) is called a decision with imperfect information and decision 2) is called a decision with perfect information. We took the probability of uncertainty on the unreported catch from Yuniarta et al. (2017) and used a triangle distribution of unreported catch that incorporates minimum, normal and maximum values of unreported catch. The value of decision (EV) in this node is given by:

$$EV_a = max\ E[V(a,s)]$$

Value of Information
We made a comparison between fishing rent (total present value of profit) in the HCR with perfect information and in the HCR with imperfect information. The result showed the VoI as given by:

$$VoI = EV_{observe\ unrep} - EV_{no\ observe\ unrep}$$

We continued by comparing the fishing rent between management strategies with the additional information of unreported catch and management strategies without the additional information. The result of that comparison shows the value of additional information.

5.2 Result and Discussion

We found that the expected value in the simulation of perfect information had higher results than in the simulation of imperfect information, both in HCR 1 and HCR 2. Therefore, we found additional information had a positive value. Based on our simulations, we estimated the value of additional information of unreported catch was nearly 14 billion rupiah under HCR 1 and roughly 3 billion rupiah under HCR 2.

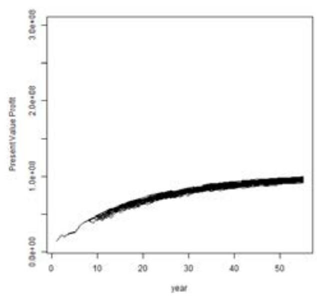
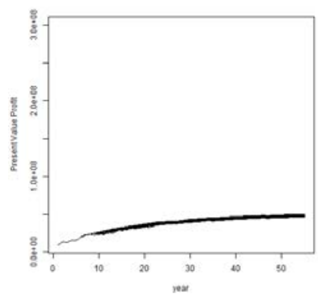
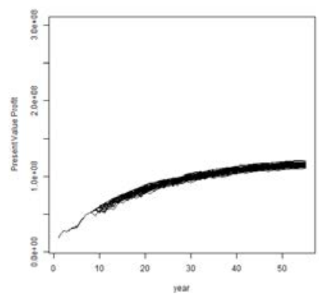
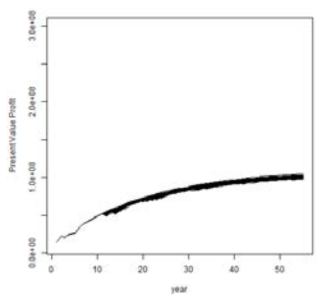
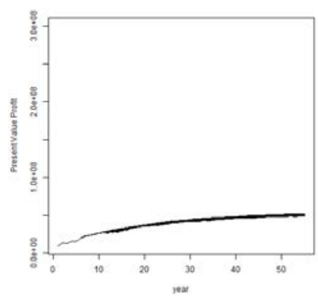
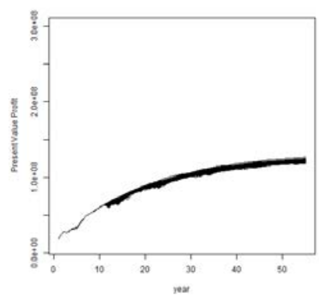
The highest contribution on fishing rent comes from LSF, followed by SSF and MSF (Figure 12). The LSF is low in number of vessels, but has the highest contribution of catch. While for SSF, the contribution of catch comes from the high number of vessels, comprising more than 80% of the tuna fishing fleet.

The comparison between combination 1A and 1B, and 2A and 2B shows the consequences of management actions when fisheries managers use imperfect information to make decisions about harvest control rules. Simulations with perfect information have higher effort than those with imperfect information, which means more jobs for fishers, but there is also more competition and therefore lower profits per vessel.

In the HCR 1 simulation, effort fluctuated a lot, both on combination 1A and 1B showing pulse fishing activity (Da-Rocha et al. 2012), alternating between increasing effort to the maximum level and freezing the fishery. The pattern of fishing effort in the HCR 2 simulation fluctuated in a narrower range (Figure 13). Therefore, despite higher fishing rent in HCR 1, the pattern of fishing effort in HCR 2 makes it a more reasonable rule for real-life application.

In many developing countries, fisheries serve as a poverty-reduction strategy to create employment in poor communities. The distribution of income per vessel in our model shows that the highest income per vessel is received by LSF, and then followed by MSF and SSF (Figure 14) in all rule combinations. We find that, if fisheries managers ignore unreported catch, it reduces the proportion of poorest fishers (Table 19). This is a result of low competition in simulation A, but also shows that employment is lower in simulation A than in simulation B.

Our results demonstrate that decisions made with perfect information yields higher fishing rents than those without additional information.

Combination	Small Scale Fishery	Medium Scale Fishery	Large Scale Fishery
1A			
1B			

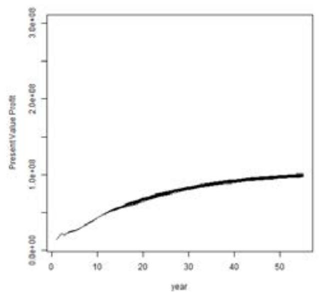
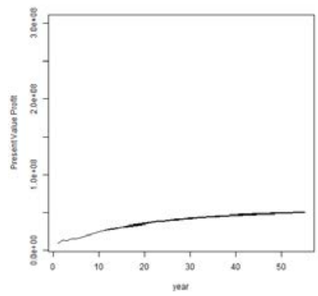
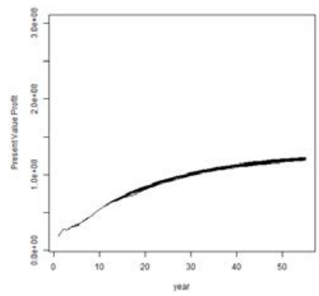
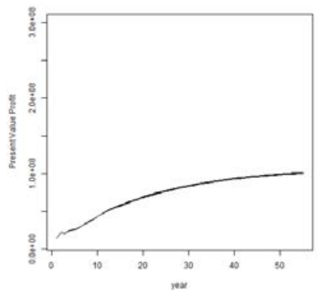
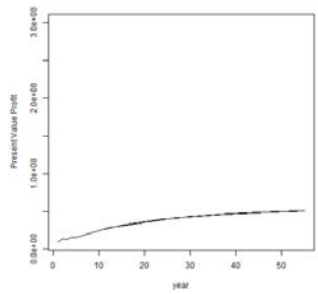
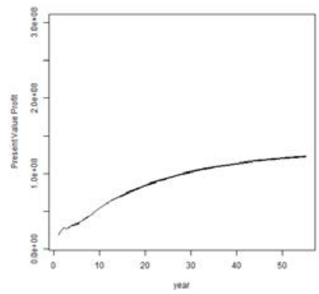
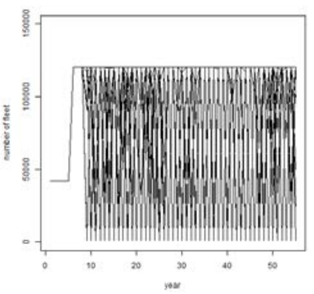
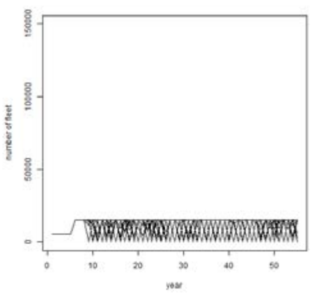
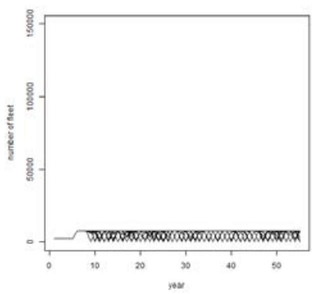
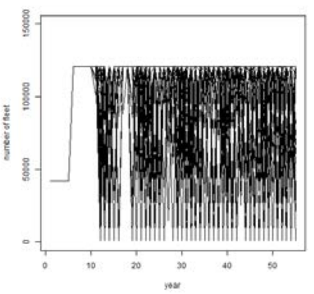
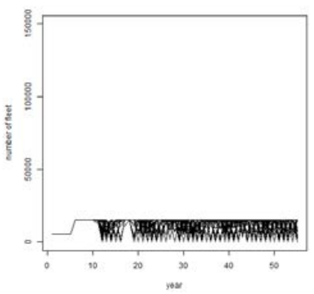
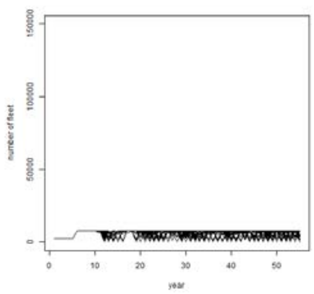
Combination	Small Scale Fishery	Medium Scale Fishery	Large Scale Fishery
2A			
2B			

Figure 12. Fishing rent in the projection years from selected scales

Table 19. Percentage of fishers earning less than 30×10[6] rupiah per year

Combination	Small Scale Fishery	Medium Scale Fishery	Large Scale Fishery
1A	96%	88%	0%
1B	96%	90%	0%
2A	96%	59%	0%
2B	96%	61%	0%

Combination	Small Scale Fishery	Medium Scale Fishery	Large Scale Fishery
1A			
1B			

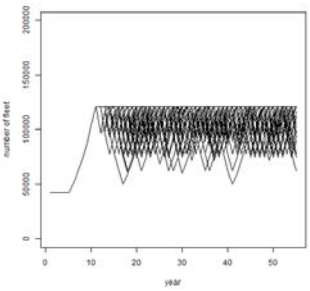
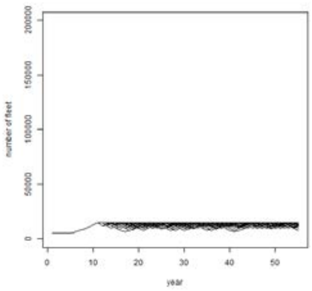
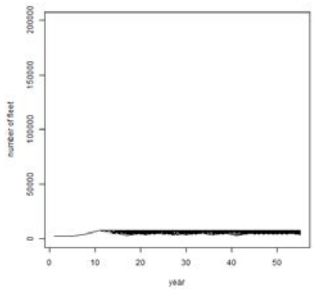
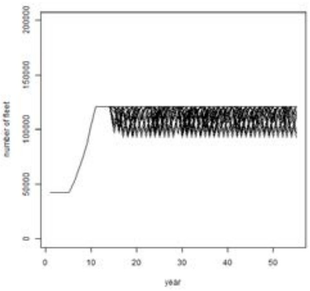
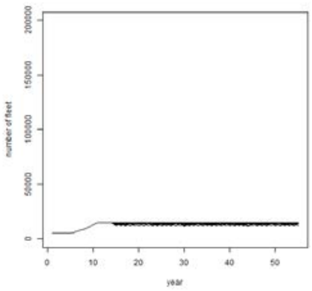
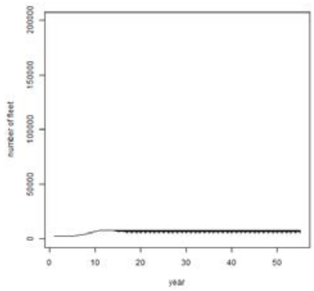
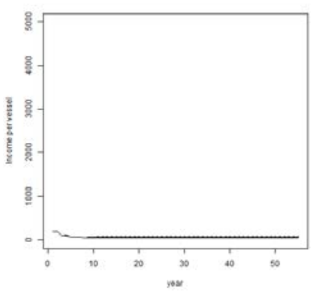
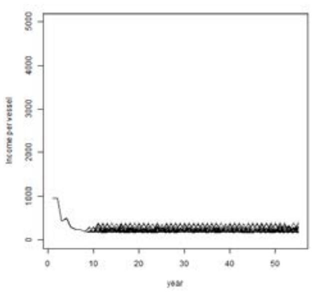
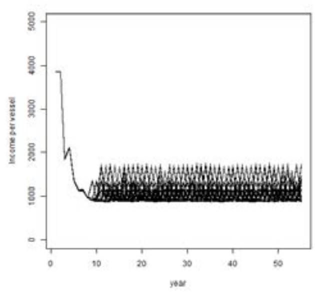
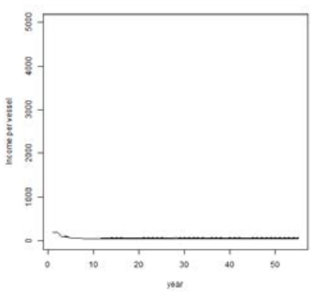
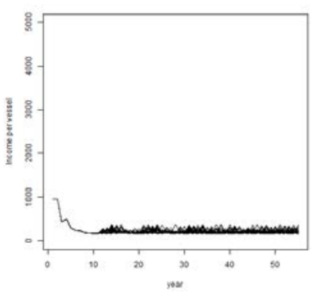
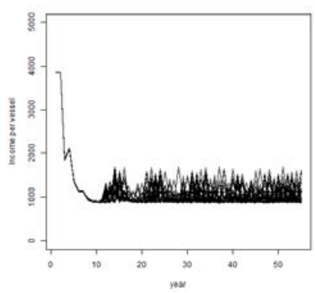
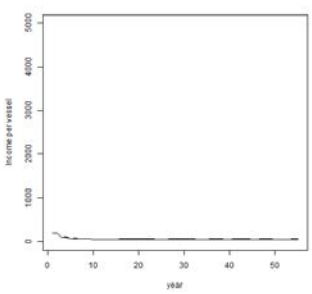
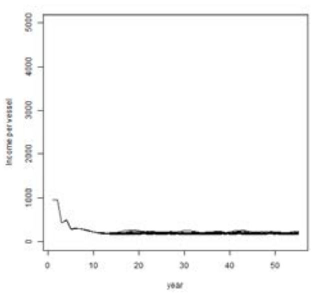
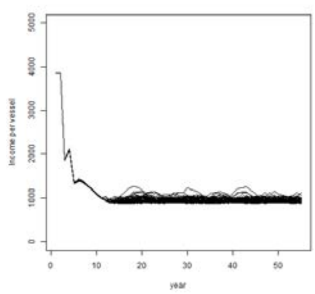
Combination	Small Scale Fishery	Medium Scale Fishery	Large Scale Fishery
2A			
2B			

Figure 13. Effort in the projection years of selected scales

Combination	Small Scale Fishery	Medium Scale Fishery	Large Scale Fishery
1A			
1B			
2A			

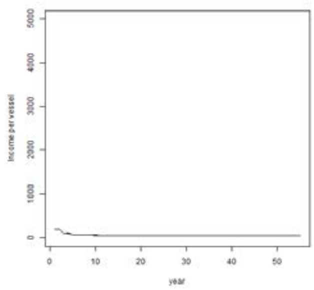
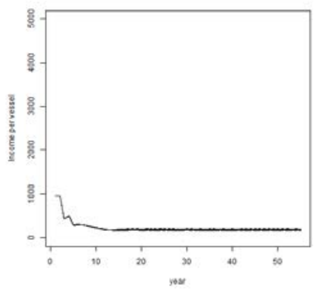
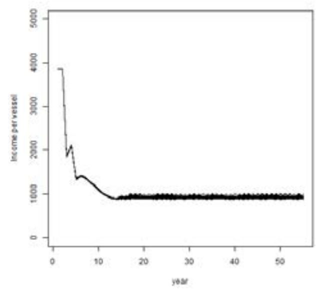
Combination	Small Scale Fishery	Medium Scale Fishery	Large Scale Fishery
2B			

Figure 14. Income per vessel in the projection years from selected scales with the highest fishing rent

6. Production function analysis of FADs-based tuna fisheries

This section identifies the key variables of tuna production in purse seine fisheries. Indonesian tuna fisheries rely on landing data, but we will offer an alternative approach in estimating production using on-board logbook data, particularly on the vessels using purse seine gear.

The Indonesian port authority has applied the logbook system since 2011. However, due to concerns about reliability, no analysis has been conducted using this database. Nevertheless, this database contains a wealth of information on operational variables such as the number of boats operating on FADs, the number of FADs visited, crew numbers, and the productivity of FADs on the basis of catch variability. Our findings will give an alternative option for managing FADs-based tuna fisheries by shedding light on some key variables of purse seines fisheries.

6.1 Analysis

We chose to use the port authority logbook data from the Bitung fishing port in 2013 because it contains complete documentation for all the months of that year, and has a minimum of entry errors. However, some data cleaning and filtering procedures were still needed.

Our production function of boats used independent and explanatory variables including: boat capacity in gross tonnage (GT), boat power (DK), crew numbers, and fishing position. We assumed that all purse seines set their net to fish on FADs. This information generates the total number of FADs visited:

$$
\begin{aligned}
Y\_K_i &= f(X1\_K_i) \\
Y\_K_i &= f(X2\_K_i) \\
Y\_K_i &= f(X3\_K_i) \\
Y\_K_i &= f(X4\_K_i)
\end{aligned}
$$

Where:

Y_K_i = Total catch per year from boat *i* (ton)
$X1\_K_i$ = Gross tonnage of boat *i* (GT)
$X2\_K_i$ = Number of FAD visits per year of boat *i*
$X3\_K_i$ = Boat power *i* (DK)
$X4\_K_i$ = Crew number of boat *i*
i = Boat

Our production function of FADs used several additional variables:

$$
\begin{aligned}
Y\_R_j &= f(X1\_R_j) \\
Y\_R_j &= f(X2\_R_j) \\
Y\_R_j &= f(X3\_R_j) \\
Y\_R_j &= f(X4\_R_j) \\
Y\_R_j &= f(X5\_R_j)
\end{aligned}
$$

Where:
Y_R_j = Total catch per year on FAD *j* (ton)
$X1\_R_j$ = Depth of FAD *j* (m)
$X2\_R_j$ = Net Primary Production (NPP) *j* ($mgCm^{-2}d^{-1}$)
$X3\_R_j$ = Distance of FAD *j* to the nearest seamount (km)
$X4\_R_j$ = Distance of FAD *j* to the nearest harbour (km)
$X5\_R_j$ = Distance of FAD *j* to the nearest land (km)
j = FAD

Data cleaning
We cleaned the data by removing all FAD positions that were outside the study area, located on the land, located in the shipping lane, and those less than 500 meters deep. A total of 3361 FAD positions were reduced to 2561 FADs, meaning there were 2561 fishing events on the FADs in 2013. The second step was filtering those FAD numbers based on boat name (the boat associated with each FAD position) and unique position of each FAD. This step left 79 unique boats (18 – 196 GT) and 877 unique FAD positions (145 FADs located in the Celebes Sea and 732 FADs in the Molucca Sea).

Model testing
The production function model used a linear regression, and we conducted normality, heteroscedasticity, and non-multicollinearity tests. Normality can be accepted if the plot of studendized residual has a normal distribution pattern. Heteroscedasticity will be accepted if the p value of the test > 0.05. On the non-multicollinearity test, independent and explanatory variables will be accepted if VIF value < 10. This test only applied to linear regressions with explanatory variables greater than 1.

Model selection
The process of identifying of variables that have effects on boats and FADs was gradual, with the best mode chosen by comparing the determination coefficient ($\boldsymbol{R^2}$) of each model.

6.2 Results

Production function of boats

Table 20. The test results, value of determinant signification, coefficient, and intercept variable of each model

Model Explanatory Variable	Normality test	Heteroscedasticity test	Multi-collinearity	$\boldsymbol{R^2}$	Significant	Coefficient	Intercept
$X1\_K_i$	Accepted	Accepted	-	0.06	*	1624.0	126399.0
$X2\_K_i$	Accepted	Accepted	-	0.20	***	4381.0	74524.0
$X3\_K_i$	Accepted	Accepted	-	0.01	-	229.1	159521.0
$X4\_K_i$	Accepted	Accepted	-	0	-	1482.0	185183.0
$X1\_K_i$, $X2\_K_i$	Accepted	Accepted	Accepted	0.36	$X1\_K_i$*** $X2\_K_i$***	2420.4 5362.7	-94786.2

On each explanatory and response variable, total catch was simulated using a linear regression. From those four linear regression models, the most significant explanatory variable was the total number of FADs visited per year ($X2\_K_i$) and gross tonnage (GT) ($X1\_K_i$). The next step was to apply both variables to the production function model of boats. Thus, there were five different models to be further tested.

Normality and heteroscedasticity tests of all five models were accepted. Only the last model (fifth) was the assumption of multi-collinearity also accepted. From those five different models, the highest determinant value was found on the last (fifth) model with explanatory variables being GT and the total number of FADs visited. Therefore, this model suggested that boat capacity (GT) and number of FAD visits or number of trips determined the total catch of purse seine fishers. This model explained 36% of the variation, with 67% explained by other variables.

Production function of FADs

The regression model of the explanatory variables in this case showed that the residual was not normally distributed, thus it needed to be transformed to log base 10.

Table 21. The test results, value of determinant signification, coefficient and intercept variable of FADs production model

Model Explanatory Variable	Normality test	Heteroscedasticity test	Multi-collinearity	R^2	Significant	Coefficient	Intercept
$X1\_R_j$	Accepted	Accepted	-	0.00	-	-2.94×10^{-5}	4.20
$X2\_R_j$	Accepted	Accepted	-	0.00	-	0.00	3.87
$X3\_R_j$	Accepted	Accepted	-	0.01	**	-0.002	4.18
$X4\_R_j$	Accepted	Accepted	-	0.01	**	0.0005	4.00
$X5\_R_j$	Accepted	Accepted	-	0	-	-0.0002	4.13
$X3\_R_j$, $X4\_R_j$	Accepted	Accepted	Accepted	0.03	$X3\_R_j$ *** $X4\_R_j$ ***	-0.0033 0.0006	4.05

The five production models of FADs showed that each explanatory variable could be accepted in the normality and heteroscedasticity tests. The analysis suggested that the most significant variables in the production model of FADs were distance to the nearest seamount, and distance to the nearest harbour. The determinant value showed that this model could explain only 3% of the variation. The main reason for this low percentage was the data did not cover all vessels that fished on FADs in the Celebes and the Molucca Seas.

6.3 Discussion and Summary

Identification of key variables on total catch provides information on catch efficiency in the tuna purse seine fisheries in Bitung fishing harbour. Focusing on the key variables could be one of the management options to control fishing pressure on FADs-based tuna fisheries.

Fisheries management in Indonesia has been focused on controlling inputs or the total number of vessels fishing. Management of the number of vessels operating in Indonesia is currently under the jurisdiction of the Directorate of Fishing Permit (DFP) – Directorate General of Capture Fisheries, Ministry of Marine Affairs and Fisheries. This institution only has the ability to control the total number of vessels in an area. By understanding the productivity of each individual vessel, DFP could estimate the capacity of vessels operating in the area. Knowing vessel capacity, DFP could more finely tune their adjustments of vessel numbers. Historically, the decision to control vessel numbers has not been transparent, but this method of control has an important role to play as a proxy for total catch.

Analysis of the production model of boats suggested that the key variable of total number of FADs visited has a significant influence on total catch per boat. Since there is no rule to limiting trip number or FAD visits, management could limit the duration of fishing permits. Thus each vessel would be limited to a certain amount of time spent fishing in Indonesian waters.

With regard to the production model of FADs, there is no doubt that controlling FAD numbers could be one of the main solutions to sustaining the tuna stock. Our model suggested that catch amount was associated with the distance of the FAD to the nearest seamount and harbour. Some fishers consider seamounts to be one of the environmental factors that attract tuna, and prefer to install their FADs in close proximity to them. Installing FADs near a harbour is likely in an effort to reduce the operational costs of travelling (fuel). Managing FADs based on location could have a significant effect on total catch.

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Appendix

Operating Model

The model uses an age-structure to simulate population and the dynamics of the fishery. Mathematical equations in the model are:

$$N_{a,t=1} = (im + em)N0_a \quad (1)$$
$$N_{1,t} = (im + em)R_t \quad (2)$$
$$N_{a=2,t}^{\max a} = (im + em)N_{a-1,t-1} \quad (3)$$

We use the Beverton-Holt stock-recruitment relationship:

$$R_t = \frac{SSB_t}{\alpha+\beta SSB_t}\sigma_R \quad (4)$$

Spawning Stock Biomass is the total biomass from age at the first length of maturity a_{lm} to maximum age in the same year. We divided the distribution of recruitment into two every year: pre-harvest (SSB1) and post-harvest (SSB2).

$$SSB1_t = (\%adult \times B_{a\ at\ LM,t}) + \sum_{a\ at\ LM+1}^{maxAge} B_{a\ at\ LM+1,t} \quad (5)$$

$$SSB2_t = (\%adult \times B_{surv_{a\ at\ LM,t}}) + \sum_{a\ at\ LM+1}^{maxAge} B\_surv_{a\ at\ LM+1,t} \quad (6)$$

The model estimates the distribution of recruitment over pre-harvest about 0.4SSB1 and post-harvest about 0.6SSB2.

$$SSB_t = 0.4 \times SSB1_t + 0.6 \times SSB2_t \quad (7)$$

Where:

em is emigration of fish to another region from region 4 (Skipjack) or region 7 (Yellowfin tuna)
im is immigration of fish to region 4 (Skipjack) or region 7 (Yellowfin tuna)
N is number of fish,
M is natural mortality,
F is fishing mortality,
SSB is spawning stock biomass,
R is recruitment,
t is year
a is age
α and β are spawning biomass-recruitment parameters,
σ_R is standard deviation of log normally distributed recruitment disturbance.

In the array of N, we combine length of period, age-structure, and number of draw (1000). N from age 1 to maximum age in year 1 is generated from the proportion of biomass in each region of the species.

For fishing activity, we use Baranov catch function:

$$C_{t,a} = N_{t,a}A\left(\frac{F}{Z}\right) \quad (8)$$

Where $C_{t,a}$ is catch in time t age a, N is abundance, A is annual mortality which equals to $(1 - e^{-Z_t})$, F is fishing mortality and Z is total mortality of fishing mortality (F) and natural mortality (M).

$$B_{t,a} = (N_{t,a} - C_{t,a}) \times w_a \qquad (9)$$

We use mean of weight of fish per age in the model. In order to have biomass in weight, we multiply average weight per age with the number of fish in each particular age.

Table 22. Sources of parameter estimation of Skipjack or SKJ (*Katsuwonus pelamis*) and Yellow fin tuna or YFT (*Thunnus albacares*)

Parameter	Source
Age	WCPFC (2016); (WCPFC 2017)
Weight per age	Estimated from WCPFC (2016); (WCPFC 2017)
Natural Mortality (M)	Estimated from Hampton and Fournier (2001), Hampton (2000)
Catchability (q)	Assumed constant
Selectivity (s)	Estimated from Hampton and Fournier (2001), Hampton (2000),WCPFC (2016); (WCPFC 2017)
α and β of spawning biomass-recruitment parameter for Region 4 of SKJ and Region 7 of YFT	Estimated from WCPFC (2016); (WCPFC 2017)
Proportion of SSB for Region 4 of SKJ and Region 7 of YFT	Estimated from WCPFC (2016); (WCPFC 2017)
Immigration and Emigration	Estimated from WCPFC (2016); (WCPFC 2017)
N0	Estimated from WCPFC (2016); (WCPFC 2017)
Mean Effort	Assumed
Minimum, normal and maximum unreported catch	Yuniarta et al. (2017)

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