Intern Summary

Name: Lisette van Noord
University: Wageningen University
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Internship/Thesis Research title:
Do fishers fish randomly or directed? An analysis of the influence of operational factors on the variance in catch in the handline fisheries of Ambon and Lombok

Introduction:
The Indonesian tuna fisheries mainly capture tuna by angling, trolling, pole and line, long line and purse seine fishing methods. Around 90% of the vessels that are used in Indonesia are smaller than 5GT (Sunoko and Huang, 2014). Often they are used for coastal fisheries and need skilled fishermen for operation. Since most of the vessels operate on a small-scale the catch per vessel is low. Still, the Indonesian tuna production (also encompassing large scale purse-seining), continued to grow and is now considered to be the number one tuna producer worldwide (Sunoko and Huang, 2014). Although these fisheries need skilled fishermen, their knowledge on where to fish to obtain the highest catch rates might be limited due to high levels of uncertainty in the catch per day. For example, the purse-seine and liftnet fisheries on small pelagics in Ambon, fishermen return without catch in around 50% of the fishing trips. Although this sounds extreme, this type of uncertainty is not rare for small-scale pelagic fisheries (van Oostenbruge, 2003). Uncertainty is directly linked to random fishing. For fishermen to fish directed (non-random) they need accurate data on catch rates in relation to their effort applied to different areas and seasons. However, when there are high fluctuations in catch rates (and thus a high level of uncertainty) these patterns are hard to observe (van Oostenbrugge et al. 2001).

In this research, random fishing is defined as having little relation between the operational factors and the Catch Per Unit of Effort (CPUE). When this is the case, the fishermen do not use operational factors to maximise the catch. This concept is related to the Ideal Free Distribution (IFD), according to which the fishermen will allocate their effort to the locations where they will get the highest catch rates. To do this, fishermen need (among other things) perfect information on the location of the target species and the ability to move freely among the fishing grounds (Gillis, 2003). In this research we will not only look into the spatial effort allocation (i.e. the distance to the home port) but also in ice and fuel usage and days spent fishing per fishing trip. Including other factors besides spatial effort allocation will allow us to study a broader perspective of the behaviour of fishermen. These factors, distance to the home port, ice and fuel usage and days spent fishing, are related to daily operations and can easily be altered, sometimes even during the trip. For ease they are referred to as short-term operational factors. The engine power and the size of the boat are referred to as long-term operational factors.

Research question:

Main research question:

- Are Ambon and Lombok fishing activities random or directed?

Sub-questions:

- Which operational factors partially explain the variance in catch?
- Can we predict CPUE based on operational factors?
- Is the fishery in Lombok, that uses Fish Aggregating Devices (FAD), more directed than the fishery on Free Swimming schools (FS) in Ambon?

Methods:

The data was collected as part of the Fishing & Living and IMACS programs and provided by IFITT. The data contained information on the total amount of tuna caught per fishing trip, the amount of ice and fuel used per fishing trip, the distance travelled and the duration of a fishing trip in days. In the catch data, the different tuna species were differentiated and it was decided to only include yellowfin tuna (*Thunnus albacares*), since it is the target species.

Data analysis was done with the statistical programme SAS. First, the catch rates were standardized on the engine power and length of the boat used during the fishing trip, resulting in a Catch Per Unit of Effort (CPUE). The second step was to remove the effect of seasonality and year by running a generalized linear model with CPUE as response variable and year and month as explanatory variables. In step three a model was run on the residuals of step two with the following operation factors as independent variables; ice, fuel, distance and trip days. This model is shown in formula 1, where Y equals the residuals of step two.

$$Y = \beta_1 * trip\_days + \beta_2 * distance + \beta_3 * ice + \beta_4 * fuel + \varepsilon \quad (1)$$

A model containing all operational factors was developed, in order to assess their contribution to the total variance in relation to each other. The final model was made using the GLM-procedure. These steps were done on three different data sets; (1) the combined data from Ambon and Lombok, (2) the Lombok data only and (3) the Ambon data only. (We also performed an analysis on the zero-catches of Ambon since the fishers in Ambon often returned without a catch. The analyses and results of these analyses can be found in the full report).

Results:

Here in the results section we only show the results of step 3 (for the complete analysis, please refer to the full report). Table 1 and 2 show the models for the combined dataset. Approximately 3% of the variance is explained by distance, trip days and ice or fuel. Trip days have a significant negative effect on CPUE while fuel and ice have a positive effect. Distance is only significant when fuel is excluded and then has a positive effect.

	DF	Estimate	t Value	Pr > |t|
Intercept	1	-0.1652	-5.67	<.0001
distance	1	0.0003	1.56	0.12
trip days	1	-0.0352	-9.57	<.0001
fuel	1	0.0007	6.49	<.0001

Table 1; combined dataset. The model excluding ice.

	DF	Estimate	t Value	Pr > |t|
Intercept	1	-0.1848	-6.40	<.0001
distance	1	0.0006	3.44	0.00
trip days	1	-0.0399	-8.72	<.0001
ice	1	0.0001	5.08	<.0001

Table 2; combined dataset. The model excluding fuel

Table 3 shows the results for the Ambon dataset. It was not possible to make a significant model were all parameters were included. The closest was a model that includes ice, fuel and distance. The results suggest that even if the fishermen use more ice, spend more time at sea or travel further distances, this does not influence the CPUE. The explanatory value of the model including the parameters ice, fuel and distance is about 1%. The Ambon fishery tends to be a non-directed fishery.

	DF	Estimate	t Value	Pr > |t|
Intercept	1	-0.2454	-3.480	0.001
ice	1	0.0019	1.840	0.067
fuel	1	0.0026	2.330	0.020
distance	1	-0.0003	-0.780	0.436

Table 3: Ambon. Model excluding trip days

The results for Lombok are shown in Table 4. Approximately 3.5% of the variance is caused by the combined effect of the four operational factors. Distance is the only factor that is not significant. However, the parameter estimates of fuel and ice are low. It might be that each FAD has roughly the same amount of tuna and that the distance to the homeport does not really matter. Ice and fuel both have a positive significant effect although the parameter estimate is low. Compared to ice and fuel, trip days do have a significant negative effect, suggesting fishing continues until the desired catch is achieved (or fish until their resources run out).

	DF	Estimate	t Value	Pr > |t|
Intercept	1	-0.2793	-4.2	<.0001
ice	1	5.749E-05	3.14	0.002
fuel	1	0.0005	3.77	0.000
trip days	1	-0.0359	-6.45	<.0001
distance	1	0.0002	0.95	0.341

Table 4: Lombok. Model including ice fuel and trip days.

Discussion and conclusions:

Each operational factor was expected to follow a similar pattern across the four analyses. However, this was not the case. The lack of a pattern along the different analyses cannot be explained in this research, but most likely has to do with different tactics, priorities or attitudes towards the use of short-term operational factors between the two fisheries. For example, it might be the case that in Ambon the fishermen worry more about the duration of a fishing trip than in Lombok, causing the negative influence of trip days on the CPUE in Lombok.

Short-term operational factors cannot be used to predict the size of a catch. This can have a couple of different causes, of which the following three are deemed the most important: (1) the fishermen do not aim at obtaining the highest possible catch, but want to minimize the risk (Salas and Gaertner, 2004), (2) the fishermen do not have sufficient knowledge of the risks and profits in different fishing areas to maximise the catch rate due to high variance in catch rates (like in the case of the small scale purse-seine fishery in Ambon (Van Oostenbrugge et al., 2001)), and (3) the catch per effort was not representative of the true outcome of the effort. In this research only yellowfin tuna was used as representation of catch.

It was expected that the handline fisheries in Ambon and Lombok would not be completely directed. The fishermen in these fisheries have little resources and are therefore not likely to go on exploratory fishing trips, limiting their knowledge on the location of the fish. This also appeared from our analysis. We started with the model that combined the data on Ambon and Lombok and it was clear that the operational factors did not have a big influence on the catch rates.
For the model incorporating ice, fuel and distance, more of the variance was explained for Lombok than for Ambon. However, it is uncertain whether this is caused by the use of FADs in Lombok and not in Ambon. The boats in Ambon are smaller than in Lombok and therefore have a limited fishing area, making them less directed.

Follow-up steps for MDPI

- Conduct more research into factors influencing fishermen behaviour
- Discuss the results with fishermen for their input
- Assess the possibility of (dis)incentives for the behaviour in Indonesian regulations
- Understand the effect of FAD fishing on catches in small-scale fisheries