Fishing location choice and risk preferences among small fishers – Implications for fisheries management policies

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Abstract

The study provides evidence for how risk preferences determine fishing location choices by artisanal fishers on the south-west coast of the island of Mauritius. Risk preference is modelled using a random linear utility framework defined over mean-standard deviation space. The study estimates expected revenue and revenue risk from the Just and Pope production function and applies the random parameter logit model to account for fisher-specific and location-specific characteristics. The findings are consistent with utility-maximising fishers, whereby the likelihood to choose a fishing location is positively associated with expected revenue and negatively related to revenue risk. Distance from fishing station to fishing grounds affects the choice of fishing location negatively. The estimated model allows heterogeneity in risk preferences and concludes that 51% of fishers can be classified as risk averse, 31% as risk seekers and the remaining as risk neutral. The study also estimates the degree of substitutability and complementarity between fishing locations based on the risk preferences of fishers and discusses the relevance of this for fisheries management policy.

Key words: risk preferences; location choice; two-moment decision models; Just-Pope production

1. Introduction

Fisheries embody biological and economic heterogeneities, and fishers, as decision makers, continuously face a range of choices over different fishing sites in an uncertain environment (Eales & Wilen 1986; Smith & Wilen 2005; Girardin *et al*. 2017). An understanding of fishers' behaviour and their decisions about their fishing locations is essential to predict fishing mortalities and assess the effectiveness of fisheries management practices (Smith 2005; Hunt *et al*. 2019; Murphy *et al*. 2019). Fishers' location choices are influenced by several factors, including fish abundance and target species (Pet-Soede *et al*. 2001); trip duration (Dabrowksa *et al*. 2017); site-specific experience and knowledge (Lopes & Begossi 2001); information sharing (Curtis & McConnell 2004); technical considerations (Eales & Wilen 1986); tactical decisions (Salas & Gaertner 2004; Christensen & Raakjaer 2006); distance between home port and fishing ports (Buracam *et al*. 2013); weather conditions (Lopes & Begossi 2011)' and social factors such as rules, institutions, local traditions, culture and habits, among others (Daw 2008; Van Putten 2012).

A key characteristic of a fishery is risk and uncertainty (Smith & Wilen 2005; Holland 2008). Risk is interpreted as measurable uncertainty, associated with probabilities or chances of loss (Peterson & Smith 1982). Uncertainty may arise due to bad weather, imperfect information about resource abundance (size, composition and spatial distribution of stocks), dynamic changes in prices, and stochastic and unpredictable variation in growth of the fish stock, among others (Smith & Wilen 2005; Eggert & Lokina 2007; Holland & Herrera 2009). In fisheries characterised by multiple species, fishers may do more than only maximise expected returns because they face varying degrees of uncertainties in relation to the trip and thus have to deal with a considerable level of risk[1] (Eggert & Tveterås 2004). Fishers therefore respond to the entrenched uncertain environment by allocating effort to specific fishing grounds to minimise the risk involved and to maximise expected returns (Salas & Gaertner 2004). The risk preference of fishers is therefore a major determinant of fishers' behaviour in their choice of fishing ground (Mistiaen & Strand 2000; Eggert & Lokina 2007; Eggert & Martinsson 2009; Girardin *et al*. 2017). While individuals' economic decisions are significantly influenced by their risk attitudes (Saha 1997), risk sensitivity in small-scale fishers' decision making is poorly understood (Dowling *et al*. 2015), and this may substantially alter the level of economic incentives required to influence their behaviour (Holland 2008).

The behavioural responses of fishers, with an emphasis on their risk preferences and location choices, have been the subject of economic inquiry for various reasons. Firstly, the analyses focus on the microeconomic decision environment that fishers face and shed light on the extent to which fishers respond to economic incentives as rational agents, at least in the short run (Eales & Wilen 1986; Eggert & Tveterås 2004). Studies on behavioural supply responses eventually provide evidence for the theoretical prediction that fishers will redistribute fishing effort with respect to differential returns across fishing grounds, as postulated by Gordon (1954). Secondly, behavioural analysis, given the critical role of risk preference, assists in understanding fishers' reactions to the change in choice sets following changes in fishing conditions, management practices and regulatory regimes, such as quotas and area closure (Wilen 1979; Larson *et al*. 1999; Scheld *et al*. 2020). A management strategy in a particular fishing ground to restore fisheries that leads to a fall in catch variability but a slight increase in fish stock would reinforce risk-averse fishers decisions to choose that location (Eggert & Lokina 2007). In this respect, risk averseness may also have serious implications for the effectiveness of fishery policy in the long run by decreasing catch over time (Symes & Hoefnagel 2010). Thirdly, risk preference is a key factor for estimating the welfare gain/loss due to fishery management. In case a management policy such as area closure or closed season for targeted species forces fishers to relocate to other fishing locations, the welfare loss will be overstated if fishers are risk seekers and will be understated if they are risk averse (Mistiaen & Strand 2000; Eggert & Tveterås 2004). Fourthly risk attitudes can also compel fishers towards sub-optimal behaviour by choosing a location with low expected returns and relatively lower variance. For instance, risk aversion can lead to substantial distortions among fishers, given that they are more likely to use resources less intensively compared to risk-neutral use (Eggert & Lokina 2007). Risk-averse fishers may choose to fish at an unsustainable level, even though it may reduce their overall fish catch in the long run (Cinar *et al*. 2013). Another contribution to a study of fishers' risk preferences is that it helps to understand persistent non-compliance in many fisheries (Brick *et al*. 2012). Risk aversion is seen as a deterrent to criminal behaviour (Eisenhauer 2004, Brick *0*. 2012). Last but not least, fishing location choice modelling can also be used to forecast fishing choices in relation to changes in the economic, biological, climatic and oceanographic factors (Hutton *et al*. 2004; Bucaram *et al*. 2013).

The behavioural modelling of fisheries was initiated by Bockstael and Opaluch (1981), who incorporated risk preference into the behavioural motivations of fishers using a discrete choice model, specifically the McFadden (1974) random utility model. This was followed by other scholars, including Dupont (1993), Eales and Wilen (1986) and Mistiaen and Strand (2000), among others.

While there is increasing interest in measuring the risk attitudes of fishers, most of the studies focus on commercial fisheries (for instance Larson *et al*. 1999; Eggert & Tveterås 2004). Empirical evidence of risk attitudes among artisanal fishers, especially in developing countries, is scanty (Eggert & Lokina 2007). This study therefore examines the relationship between risk preferences and location

[1] There are different types of risk that are documented in the literature, such as natural risk – defined as the risk of the vessel incurring damage, social risk – in terms of meeting a financial obligation in order to be able to fish again, endogenous risk – which is the relationship between revenue/profit and utility (Dowling *et al*. 2015) and mortality (Smith & Wilen 2005). This study focuses on financial risk and risk preferences.

choices among artisanal fisheries in Mauritius. A survey with a sample of trap-based fishers was conducted repeatedly over a year to collect socio-demographic data and trip-related information. The conceptual framework assumes a utility function defined over mean standard deviation (MS) space, as initiated by Meyer (1987) and documented in Leathers and Quiggin (1991) and Eggert and Tveterås (2004). Following Eggert and Tveterås (2004) and Pradhan and Leung (2004), the study conducts a two-stage econometric analysis; in the first stage, the expected returns and variance are estimated by the Just and Pope (JP) production function and the results are used to calculate site-specific indicators of expected return and revenue risk. In the second stage, the measures of mean standard deviation, together with other site- and fisher-specific characteristics, are used in a discrete choice model of fishing location choice. The random parameters model, also known as the mixed logit model (Hole 2001) is applied in a mixed-model framework following the suggestion of Hoffman and Duncan (1988). The econometric method permits heterogeneity in risk preferences by assuming the coefficient of revenue risk to be randomly distributed. Therefore, the model allows an estimate of risk preferences for the sample of fishers. Fishers are therefore classified as risk seekers, risk neutral and risk averse. The study eventually discusses the relevance of its findings for fisheries management policy.

2. Conceptual framework

Research in this field can be differentiated according to the theoretical framework underlying risk attitudes, the survey design and the choice sets, an estimation of the expected returns and variance, and the econometric approach to analyse the data, such as the multinomial conditional logit, the nested logit and the random parameters logit models, among others.

Risk preference can be modelled using either the revealed preference method or stated preference methods (Nguyen & Leung 2009). The revealed preference models, as used in this study, attempt to analyse risk attitudes from the actual behaviour of fishers (Mistiaen & Strand 2001; Eggert & Tveterås 2004), while the stated preference models collect information on preferred choice between pairs of alternative outcomes characterising the different risk attitudes (Eggert & Martinsson 2004; Eggert & Lokina 2007; Brick *et al.* 2012). Different variations have been used within the two commonly used utility functions, namely the expected utility theory and the prospect theory framework (Holland 2008; Nguyen & Leung 2009).

The conceptual framework in this study is based on the random utility model, which leads to the two-stage estimation method. The random utility model assumes that a decision maker's utility function is deterministic, but contains some components that are unobservable (Pradhan & Leung 2004). Such unobserved components therefore are treated as random variables and could be specific characteristics of the decision maker, or attributes of the choices. The concept therefore combines a variation in tastes between individuals in a population and the idea of unobserved variables in the econometric model (Hanemann 1984).

2.1 Random utility model

The decision maker, i, is described as facing a choice between a finite and exhaustive set of mutually exclusive J alternatives within a choice set C, in relation to which he chooses an alternative, j, if and only if his utility $U_{ij} > U_{il}$ for $l \neq j$. Preferences are described by a well-behaved utility function, of which the arguments include a vector of exogenous constraints on current decision-making. The utility function can be decomposed into a systematic (deterministic) term (V_{ij}) and a stochastic, unobservable component (ε_{ij}), as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

The error term is assumed to be uncorrelated across choices, and this assumption leads to the independence of the irrelevant alternative (IIA) property in the choice model. This means that outcome categories can plausibly be assumed to be distinct in the eyes of each decision maker. The unobserved component of the utility is assumed to have a zero mean, while the observed part of the utility is the expected or average utility. The econometric model is driven by the probability that choice j is made as follows:

$$P_{ij} = P(V_{ij} - V_{il} > \mathcal{E}_{il} - \mathcal{E}_{ij}) \quad \forall \quad j \neq l \tag{2}$$

Since ε_{ij} and ε_{il} are random variables, the difference between them is also a random variable. The probability that the fisher will choose alternative j is given as

$$P\left(Y_i = j \middle| X_{ij,} W\right) = \frac{\mathrm{e}^{V_{ij}}}{\sum_{j=1}^{J} \mathrm{e}^{V_{ij}}} \tag{3}$$

V_{ij} can be specified as follows:

$$V_{ij} = \theta' Z_{ij}\left(X_{ij}, W_i\right) = X_{ij}\beta + W_i\alpha_j, \tag{4}$$

where X_{ij} are the attributes of the choices for which the variables vary across choices, W_i contains the characteristics of the individual or factors whose values are invariant to a choice a fisher makes, and θ', β and α_j are the vectors of coefficients providing information on the marginal utilities with respect to the attributes.

2.2 Measuring risk preferences in a mean-standard (MS) deviation space

The estimation of risk preferences depends on the functional form of the utility. Using the arguments of Eggert and Tveterås (2004), the linear utility function in the mean-standard deviation framework is assumed. The expected utility maximisation problem can be written as follows:

$$U = U\left[\mathrm{E}\left(\pi(.)\right), \mathrm{Var}\left(\pi(.)\right)\right], \tag{5}$$

where U is a continuously differentiable utility function defined on revenue or profit π. If fishers are risk neutral, then only the expected mean matters, while risk-averse and risk-loving fishers will make a trade-off between expected mean and the variance of expected mean or net revenue risk (Eggert & Martinsson 2004). In case of risk averse, $\frac{dU}{d\mathrm{Var}\left(\pi(.)\right)} < 0$, while for risk seekers, $\frac{dU}{d\mathrm{Var}\left(\pi(.)\right)} > 0$. The expected utility-maximisation problem is equivalent to the mean and standard (MS) deviation maximisation problem, that is

$$\max_X V(\mu, \sigma), \tag{6}$$

where $\mu = E(\pi)$ and σ is the standard deviation of expected revenue.

A linear representation of the utility function is given as follows:

$$V(\mu, \sigma) = b_1\mu + b_2\sigma \tag{7}$$

The linear functional form implies constant absolute risk aversion (CARA), which also leads to an increasing relative risk aversion. The constant absolute risk aversion utility function has the property that risk is independent of wealth.

The slope of the indifference curve is given as:

$$S(\mu, \sigma) \equiv -\left(V_\sigma / V_\mu\right) \tag{8}$$

Risk aversion, neutrality and seekers correspond to $S(\mu, \sigma) > 0, = 0\ and < 0$ respectively (Eggert & Tveretås 2004). The sign of b_2 reflects fishers' risk aversion. If it is assumed to be a random parameter, then the model allows for heterogeneous risk preferences among fishers. This means that the size of the risk premium, that is the wedge between risk-neutral and risk-averse decisions, is allowed to vary across fishers.

To operationalise the model, an estimate of expected return and standard deviation of revenue is needed. The framework outlined by Just and Pope (JP) (1979), which is further developed by Eggert and Tveterås (2004) and applied by Pradhan and Leung (2004), is used for this purpose. The JP production function is given by:

$$y = g(\mathbf{k}) + u = g(\mathbf{k}) + h(\mathbf{k})^{\frac{1}{2}}\,\epsilon, \tag{9}$$

where $\mathbf{k}$ is a vector of K inputs, $g(.)$ is the mean function, $h(.)$ is the variance function and ϵ is the exogenous production shock, with $E(\epsilon) = 0$ and $Var(\epsilon) = \sigma_\epsilon^2$. The variance function is expressed as follows:

$$h(\mathbf{k}) = exp[\tau\mathbf{k}] \tag{10}$$

Thus $\mu = E(\pi) = p.g(\mathbf{k}) - \mathbf{wk}$, and $\sigma = p.h(\mathbf{k})\sigma_\epsilon$. Further details on the estimation procedure are given in section 4.

3. Survey design, data and econometric method

3.1 Study site and survey design

The Republic of Mauritius is situated in the Indian Ocean, about 800 km east of Madagascar. It consists of two main islands, Mauritius and Rodrigues, and their outer islands, namely the St. Brandon group of islands, Agalega, Chagos Archipelagos and Tromelin. The Exclusive Economic Zone of the Republic of Mauritius extends over an area of 1.9 million km^2. The study was done to the south east of the main island of Mauritius and covered an area of roughly 90 km^2.

The site is one of the biggest lagoon areas of the islands where most fishers prefer to fish (40%). The area also hosts the Blue Bay Marine Park (see Figure 1). A questionnaire was prepared to collect data on the fishers' socio-economic characteristics, fishing technology (e.g. size of boat) and trip-related information. There were about 400 trap fishers in the region, and the questionnaire was administered to a sample of 100 of them in the period from February to October. For each fisher, information was collected on 10 trips.

Fishers were shown a map similar to that in Figure 1. After their trips, they were asked to show on the map the location of their trip, as well the route they took to reach their destination from their home ports. The interviewers recorded their path on the map. The questionnaire recorded the following, among other data: (i) total catch in kg; (ii) weight of individual fish species; (iii) number of basket traps used during that trip; (iv) size of the basket traps; (v) number of hours fished; and (vi) number of fishers on the boat.

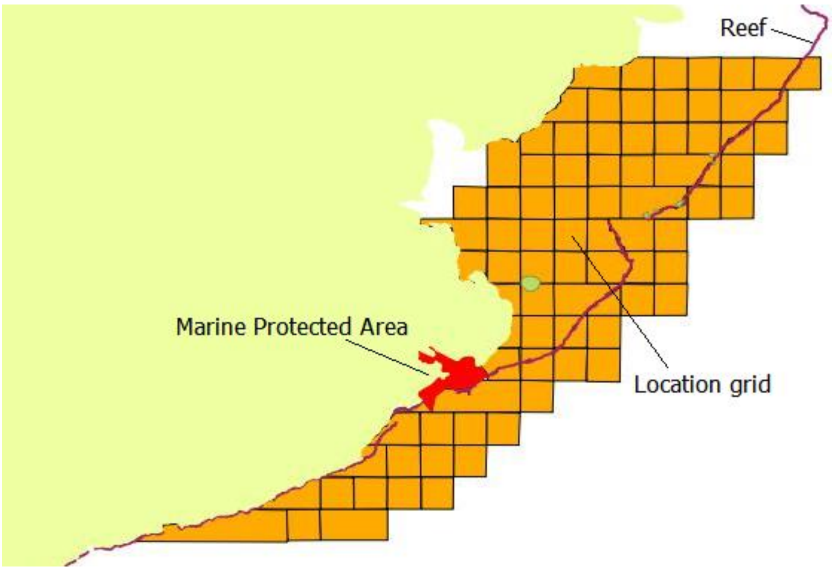

Figure 1: Study site and location grid
Source: Author, using QGIS software

The first survey, which was conducted in February 2015, collected data on boat characteristics and the socio-economic profiles of the fishers, including age, household size, etc.

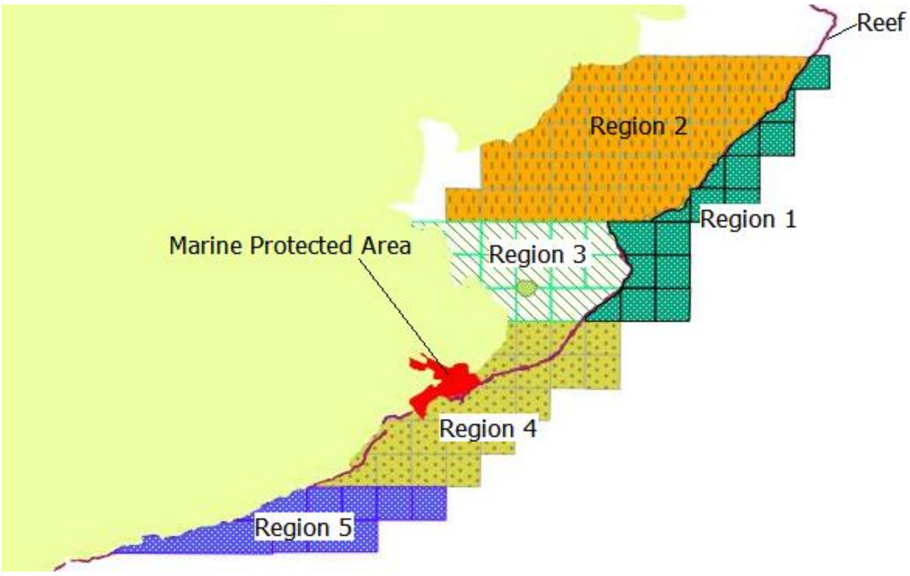

Figure 2: Fishing locations
Source: Author, using QGIS software

Figure 2 shows the fishing ground classified into five different regions. The criteria to divide these regions are based on the characteristics of the fishing areas (inside and outside the reef) and on the fish species that are targeted by the fishers. Region 1 is located to the east and lies in the off-lagoon area, where the water is very deep. Within the lagoon areas there are four regions that are classified on the basis on fishing intensity and targeted fish species. Regions 2 and 3 are adjacent to region 1, but lie in the lagoon area and are intensely fished, with region 3 having a lower catch rate than region 2. Region 4, located to the south, hosts the Blue Bay Marine Park within a 6 km radius, while region 5 is further to the south. Most fishers whose home ports are located in the north have to travel long distances to go there. The average revenue and standard deviation of revenue are shown in Table 1. There are sufficient differences in the mean-standard deviation of returns to analyse fishing location choices.

Table 1: Characteristics of fishing grounds

	Number of trips	Average revenue (Rs)	Standard deviation (Rs)	Minimum (Rs)	Maximum (Rs)
Region 1	217	3 213.49	1 218.11	0	6 567.5
Region 2	363	1 565.95	677.46	0	8 205
Region 3	250	1 202	596.24	0	3 450
Region 4	61	3 564.96	1 561.07	345	8 855
Region 5	49	4 579.75	918.36	1 980	6 815

Source: Survey

The actual revenue data from the survey suggests that regions 1, 4 and 5 have the highest mean revenue, with relatively higher standard deviation, while regions 2 and 3 have lower expected revenue and lower standard deviation. Fishers therefore face a trade-off between high expected revenue and high revenue risk, or they may sacrifice high expected revenue for lower revenue risk.

3.2 Estimation method

The first stage of the estimation method is to construct a measure of expected returns and revenue risk to be used as choice- or region-specific attributes of fishers. The second stage is an estimation of a random parameter logit (RPL) model to model and predict these choices. A detailed explanation of RPL can be found in Train (2009). When the data consists of only choice-specific attributes of which the values vary across alternatives, the appropriate model is the conditional logit, with which a single parameter for the effect of the variable is estimated. When the data consists of only individual-specific information and the value of a variable does not differ across outcomes, the appropriate model is the multinomial (unordered) logit. On the other hand, when the data consists of choice- and individual-specific attributes, an interesting possibility is combining the conditional and multinomial logit (unordered) model in a single model, referred to as the random parameter or mixed logit model, which is estimated by modifying the conditional logit model. The mixed model could avoid specification error, if any, due to the omission of relevant variables. The relevant test statistics are the likelihood ratio statistic, which is similar to an R^2 in a standard least-squares application (Pradhan & Leung 2004).

The data structure in the RPL model follows the study of Hoffman and Duncan (1988) and Pradhan and Leung (2004). To explain the covariates used in the regression, an attempt is made to differentiate between region-specific attributes and fisher-specific attributes.

Hilborn and Ledbetter (1979) argue that a fisherman optimises the difference between the value of his catch and his operation costs, rather than his catch per unit of effort. The importance of revenue as a determinant of site choice is well documented (Smith 2005). According to Curtis and Hicks (2000), who use revenue to derive expected returns at a site, revenue depends on the price paid for the catch, which is invariant to location choice, while harvest is dependent on oceanographic conditions. These oceanographic conditions do not change suddenly, but are more likely to follow food-source migration patterns and spatially continuous changes in ocean conditions. Thus, the estimation method considers expected revenue and its variance as a measure of revenue risk.

3.2.1 Region-specific attributes

Each fisher is faced with five choices but chooses only one per trip. For the chosen one, the choice-specific attributes take the expected revenue as perceived by the fisher. The mean revenue $(MREV_j)$ and revenue risk $(SDREV_j)$ are calculated using the Just-Pope production function. This therefore comprises stage 1 of the estimation. The mean function is estimated using ordinary least squares, as follows:

$$REV_{it} = \alpha_0 + \alpha_1 HRS_{it} + \alpha_2 HRS_{it}^2 + \alpha_3 NBAS_{it} + \alpha_4 NBAS_{it}^2 + \sum_{m=1,4} \alpha_m DUM_m + \sum_{i=1,99} \alpha_i DUM_i + e_{it} \quad (11)$$

REV_{it} is the revenue per trip for fisher i at time t, HRS_{it} is hours fished for fisher i at time t, and $NBAS_{it}$ is the number of basket traps for fisher i at time t. DUM_m is a dummy variable representing specific month and DUM_i is a dummy variable for each fisherman.

The parameters of the variance function are estimated using the predicted residuals from equation 11, as follows:

$$\mathrm{var}(u_{it}) = \exp\,(\delta_1 HRS_{it} + \delta_2 HRS_{it}^2 + \delta_3 NBAS_{it} + \delta_4 NBAS_{it}^2 + \sum_{m=1,4} \delta_m DUM_m + \sum_{i=1,99} \delta_i DUM_i + \vartheta_{it} \quad (12)$$

The second stage is to operationalise the mixed logit model. Individual fishers' revenue and revenue risk are calculated from equations 11 and 12. However, the expected values of the covariates must be assigned to the non-chosen alternatives, assuming that those alternatives were also available to the fishers (Pradhan & Leung 2004). For those sites that were not chosen by the fisher, the predicted values from equation 11 were taken as proxies for the expected revenues. Fishers in a particular region share the same characteristics in relation to boat size and basket size, and hence the mean revenue is consistent for all those choosing the same site. Pradhan and Leung (2004) use the means of expected values of similar size and trip type.

The third region-specific attribute is the depth of the water at the fishing site, measured in metres. Each region's depth is taken into account in constructing the covariate.

An important region-specific is the distance travelled from home port to the fishing location (Campbell & Hand 1999). Data on the home port was collected for each fisher during the survey and this variable is constructed by measuring the distance between the home port and the fishing site. An important consideration is that fishers take different routes to reach their chosen location. Care is thus taken to measure the distance properly according to the route followed by each fisher to the destination. In case a fisher did not choose a particular location for the period, the route identified by another fisher with a similar home port is taken as proxy.

3.2.2 Fishers-specific attributes

The construction of individual specific attributes follows Hoffman and Duncan (1988). Consider an attribute, W_i, of fisher i, which is invariant across choices, such as age, boat size or number of basket traps. Let DUM_2, DUM_3, DUM_4 and DUM_5 be the dummy variables for regions 2, 3, 4 and 5 respectively. The attribute enters in the mixed logit model as follows: W_2DUM_2, W_3DUM_3, W_4DUM_4, and W_5DUM_5, for the four regions respectively. Region 1 is the base category. The coefficients give the effect of each attribute in each region relative to the omitted category.

4. Results

4.1 Random parameters logit model

Table 2 provides a summary of the variables and their definition to facilitate interpretation.

Table 2: Variables and definitions

Variable	Definition	Mean	Standard deviation	Minimum	Maximum
REV_{it}	Total revenue per trip for fisher i at time t (Rs)	2 089.97	1 375.34	0	8 855
HRS_{it}	Hours fished by fisher i at time t	5.61	0.78	0	8
$NBAS_{it}$	Number of basket traps used by fisher i at time t	8.187	1.70	1	13
$MREV_j$	Mean revenue in region j using the Just-Pope estimation (Rs)	2 089.97	1 119.58	178.35	5 789.99
$AVEREV_j$	Average revenue in region j using revenue per trip from fishers	2 360.554	824.15	1 202.18	3 233.27
AGE_i	Age of fisher i	52.57	10.18	25	78
$BOCA_i$	Boat capacity of fisher i (m^3)	7.81	2.12	4.10	15
DIS_{ij}	Distance travelled by fisher i to region j (km)	6.79	2.72	1	17.8
$DEPTH_j$	Depth in region j (meters)	12.09	11.012	0	35
$SDREV_j$	Standard deviation of revenue in region j using the JP estimation	412.07	197.78	86.99	1 216.89
$SDCAR_j$	Standard deviation of catch in region j	2.07	1.00	0.36	6.10

Tables 3, 4 and 5 show the regression estimation. The log likelihood chi-square is large and statistically significant in all the regressions, suggesting a reasonable fit. Model 1includes mean revenue and revenue risk; the latter is treated as a random variable. The coefficient of mean revenue is highly significant and positive. It indicates that the logs of the probability ratio of two alternatives are affected by a change in expected revenue per trip. The coefficient of revenue risk is also statistically significant and has the expected sign. A negative coefficient implies that a rise in revenue risk reduces the log of probability between two alternatives. This finding is consistent with Curtis and Hicks (2000), Mistiaen and Strand (2000), Eggert and Tveretås (2004) and Smith and Wilen (2005). The coefficient indicates the degree of risk aversion (Eggert & Tveretås 2004; Pradhan & Leung 2004). The standard deviation of revenue risk is also statistically significant, implying that the hypothesis that risk preferences are heterogeneous cannot be rejected.

Table 3: Mixed logit regression – JP expected revenue and revenue risk with site-specific attributes

Variables	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
	Model 1	**Model 2**	**Model 2**
$MREV_j$	0.000212 (0.0000788)***	0.00602 (0.0000849)***	0.000897 (0.000112)****
DIS_{ij}		-0.305 (0.02939)***	-0.289 (0.0295)***
$DEPTH_j$			-0.046 (0.011)***
Random parameter			
$SDREV_j$	-0.0104 (0.00341)***	-0.0099 (0.0032)***	-0.00970 (0.00321)***
SD of $SDREV_j$	0.0315 (0.003)***	0.029 (0.00324)***	0.0295 (0.00329)***
Number of observations	4 995	4 995	4 995
LR $Chi^2(1)$	1 361.94	1 187.44	1 179.69
Prob > Chi^2	0.0000	0.0000	0.0000
Log likelihood	-862.169	-795.525	-786.505

SE = standard error; *** = significant at 1%, ** = significant at 5% and * = significant at 10%

Model 2 includes distance (DIS_{ij}) from home port as covariate, and the coefficient is negative and highly significant ($p < 0.05$). This is consistent with studies such as those by Campbell and Hand (1999), Holland and Sutinen (2000), Wilen *et al*. (2002), Andersen *et al*. (2012) and Bucaram *et al*. (2013), to mention a few. It can be predicted that profit-maximising fishers will also take into account the opportunity cost of travel time and the cost of travelling in choosing where to fish.

Table 4 shows the regression models when individual attributes are taken into account, that is age, size of boat and number of baskets. From model 4, it is clear that fishers in higher age brackets are more likely to choose region 3 rather than region 1 (region 1 is the omitted category). The other coefficients are statistically insignificant. Boat size decreases the probability to fish in regions 3, 4 and 5 compared to region 1. A higher number of baskets reduces the likelihood to choose region 2 and 3 relative to region 1.

Table 4: Mixed logit regression – JP expected revenue and revenue risk with individual-specific attributes

Variables	**Coefficient (SE)**	**Coefficient (SE)**
	Model 4	**Model 5**
$MREV_j$	0.00126 (0.00143)***	0.00136 (0.002)***
DIS_{ij}	-0.511 (0.056)***	
$DEPTH_j$	-0.196 (0.068)***	-0.154 (0.076)**
$DUM_2 \times AGE_i$	-0.00006 (0.0163)	-0.01937 (0.0178)
$DUM_3 \times AGE_i$	0.0356 (0.0175)**	0.009362 (0.0197)
$DUM_4 \times AGE_i$	0.00295 (0.0140)	-0.03226 (0.019)*
$DUM_5 \times AGE_i$	0.0142 (0.018)	0.010456 (0.0203)
$DUM_2 \times BOCA_i$	-0.087 (0.086)	-0.05118 (0.101)
$DUM_3 \times BOCA_i$	-0.220 (0.096)**	-0.08237 (0.126)
$DUM_4 \times BOCA_i$	-0.187 (0.103)*	-0.2325 (0.134)**
$DUM_5 \times BOCA_i$	-0.192 (0.113)*	-0.27578 (0.126)**
$DUM_2 \times NBAS_{it}$	-0.241 (0.096)**	-0.10915 (0.102)
$DUM_3 \times NBAS_{it}$	-0.518 (0.100)***	-0.49935 (0.112)****
$DUM_4 \times NBAS_{it}$	-0.0986 (0.102)	0.112506 (0.129)
$DUM_5 \times NBAS_{it}$	-0.0855 (0.120)	-0.00307 (0.123)
Random parameter		
$SDREV_j$	-0.00913 (0.003)***	-0.00832 (0.00211)***
DIS_{ij}		-0.686 (0.0968)***
SD of $SDREV_j$	-0.0289 (0.00351)***	-0.0313 (0.00324)***
SD of DIS_{ij}		0.539 (0.0737)***
Number of observations	4 695	4 695
LR $Chi^2(1)$	879.82	964.23
Prob > Chi^2	0.000	0.000
Log likelihood	-639.952	-597.750

SE = standard error; *** = significant at 1%, ** = significant at 5% and * = significant at 10%

Model 5 treats distance as a random variable whose coefficient is allowed to vary among fishers, as in Holland and Sutinen (2000) and Andersen et al. (2012). The coefficient is highly statistically significant. One way to interpret the coefficient of this covariate is by the value that a fisher is willing to sacrifice to reach the destination.

In order to analyse the consistency of the estimation results from the JP production function, models 6 and 7 use the average revenues per trip of all fishers in that particular site as a proxy for fishers' knowledge of expected return. This is consistent with Holland and Sutinen (2000), who argue that, since the information flow among individual fishers cannot be determined accurately, the average revenues for the entire fleet can be used as a proxy for individuals' knowledge of average profit rates. As can be observed, the results are consistent with models 1 to 3.

Using model 5, an increase of Rs100 ($2.94) in average revenue will increase the likelihood of that fishing choice by 0.13%. The negative sign of the risk revenue indicates that, on average, fishers are risk averse. If the expected standard deviation of the expected revenue per effort increases by Rs100, the probability to choose that region reduces by 0.83%. The results show that utility-maximisation fishers respond positively to increases in expected revenue and negatively to revenue risk by choosing a region that maximises the best return. All models show that expected revenue and revenue risk determine the choice of fishing location.

Table 5: Mixed logit regression – average revenue and standard deviation

Variables	Coefficient (SE)	Coefficient (SE)
	Model 6	Model 7
$AVESREV_j$	0.00369 (0.0018)**	0.006 (0.0023)***
DIS_{ij}	-0.414 (0.042)***	
$DEPTH_j$	-0.399 (0.172)**	-0.0589 (0.215)***
$DUM_2 \times AGE_i$	-0.0431 (0.018)**	-0.0546 (0.0198)***
$DUM_3 \times AGE_i$	-0.00583 (0.0215)	-0.0206 (.0235)
$DUM_4 \times AGE_i$	0.0724 (0.0317)**	0.0458 (.0316)
$DUM_5 \times AGE_i$	0.054 (0.0387)	0.0269 (.0385)
$DUM_2 \times BOCA_i$	-0.178 (0.092)*	-0.200 (0.112)*
$DUM_3 \times BOCA_i$	-0.277 (0.108)**	-0.248 (0.141)*
$DUM_4 \times BOCA_i$	-0.011 (0.151)	0.186 (0.194)
$DUM_5 \times BOCA_i$	-0.165 (0.176)	0.0433 (0.199)
$DUM_2 \times NBAS_{it}$	-0.148 (0.0701)**	-0.125 (0.0725)*
$DUM_3 \times NBAS_{it}$	-0.372 (0.0772)***	-0.301 (0.0835)***
$DUM_4 \times NBAS_{it}$	-0.1987 (0.116)*	-0.0281 (0.125)
$DUM_5 \times NBAS_{it}$	-0.0386 (0.137)	0.0403 (0.138)
Random parameter		
$AVESREV_j$	-0.007 (0.003)**	-0.008 (0.0036)**
DIS_{ij}		-0.513 (0.0766)***
SD of $AVESREV$	0.0031 (0.0004)***	.0033 (0.0005)***
SD of DIS_{ij}		0.514 (0.0722)***
Number of observations	4 695	4 695
LR $Chi^2(1)$	228.58	328.42
Prob > Chi^2	0.000	0.000
Log likelihood	-995.812	-945.89

SE = standard error; *** = significant at 1%, ** = significant at 5% and * = significant at 10%

4.2 Elasticities of fishing effort

Following Eggert and Tveterås (2004), the study proceeds with an estimate of the elasticities of fishing effort with changes in expected return and revenue risk. Elasticities were calculated as follows: a change made to one of the covariates to modify the sample (e.g. a 1% change in expected revenue and revenue risk) and the predicted probabilities are calculated using observations from both the original sample and the modified sample. The difference between the two predicted probabilities provides the change in probability of choosing an alternative (Hole 2007). The percentage change in probabilities for each fisher in a particular location is then averaged.

Table 6 shows the elasticities of fishing effort with respect to changes in expected revenue. A 1% increase in expected revenue in region 1 will increase the log likelihood of choosing that fishing site by 1.4%. The same reasoning applies for regions 2, 3, 4 and 5, and the corresponding elasticities are 0.1, 1, 3.1 and 3. Fishing effort is highly elastic in regions 4 and 5, and relatively moderate in region 1. An inelastic response was observed for region 2.

Fishers in regions 4 and 5 are more likely to shift to region 1 than those fishing in regions 2 and 3. A possible explanation is that regions 4 and 5 are situated in the south and fishers have to travel long distances. From this perspective, a rise in expected revenue in region 1, where distance travelled is relatively less, leads to a significant fall in participation in regions 4 and 5.

Table 6: Elasticities with respect to changes in expected revenue

A 1% increase in expected revenue	% change in probability				
	Region 1	**Region 2**	**Region 3**	**Region 4**	**Region 5**
Region 1	1.380	-0.522	-0.522	-1.632	-1.115
Region 2	-0.360	0.090	-0.706	-0.373	-0.580
Region 3	-0.138	-0.307	0.962	-0.213	-0.179
Region 4	-0.327	-0.165	-0.196	3.128	-0.407
Region 5	-0.287	-0.226	-0.143	-0.440	2.945

Source: Author's calculation from model 5

As expected, the likelihood of fishing in other regions falls as expected revenue rises in a particular region. Regions 4 and 5 are highly responsive to changes in expected revenue.

Table 7 describes the elasticities with respect to changes in revenue risk. An increase in revenue risk in region 1 attracts more fishers to this region and lowers participation in regions 4 and 5. In contrast, an increase in revenue risk in regions 4 and 5 lowers the likelihood of fishing in region 1.

From the analysis, fishers have a tendency to substitute among regions 1, 4 and 5. It is not a coincidence that these regions are all located in the off-lagoon areas. However, substitutions vary between risk lovers and those who are risk averse. An increase in revenue risk is more likely to attract risk-seekers than risk-averse fishers.

Table 7: Elasticities with respect to changes in revenue risk

A 1% increase in standard deviation	% change in probability				
	Region 1	**Region 2**	**Region 3**	**Region 4**	**Region 5**
Region 1	0.927	0.133	0.037	-3.821	-0.961
Region 2	0.077	-1.879	2.514	0.107	1.167
Region 3	-0.010	1.426	-2.621	0.0135	0.488
Region 4	-0.885	0.014	-0.008	4.465	-0.637
Region 5	-0.185	0.253	0.194	-0.338	-0.427

Regions 2 and 3, which are both located in the lagoon area, are found to be substitutes. An increase in revenue risk by 1% of standard deviation in region 2 lowers participation in that region by a probability margin of 1.9%, but increases the number of fishers in region 3 by 2.5%. The same conclusion is derived if standard deviation increases in region 3, which leads to a rise in participation in region 2. It therefore can be concluded that risk-averse fishers shift between region 2 and region 3. Most of fishers who are risk lovers prefer region 1 and, since the latter is adjacent to regions 2 and 3, an increase in standard deviation increases the likelihood of fishing in regions 3 and 4. From these findings, it appears that region 1 and region 2 or 3 are complementary if the preferred region is 1.

4.3 Risk preferences of fisheries

The random parameter logit model assumes that the coefficient on revenue risk has a family of distribution functions that arise from assumed randomness (Mistiaen & Strand 2000). Using the coefficient of the random parameter revenue risk, an attempt was made to classify fishers according to risk-averse fishers and risk seekers. Figure 3 shows the density distribution. About 35% of fishers' trips can be categorised as risk seeking, while the remaining are risk averse. The results can be compared to the work of Eggert and Lokina (2007), who use an experimental approach to study the risk preferences of small-scale fishers in the Tanzanian waters of Lake Victoria. The experiment concerns pairwise comparisons of hypothetical fishing trips that vary in expected mean and spread of net revenue. The results show that about 34% of the fishers can be considered as risk neutral, 32% as risk averse, and 34% as risk seekers.

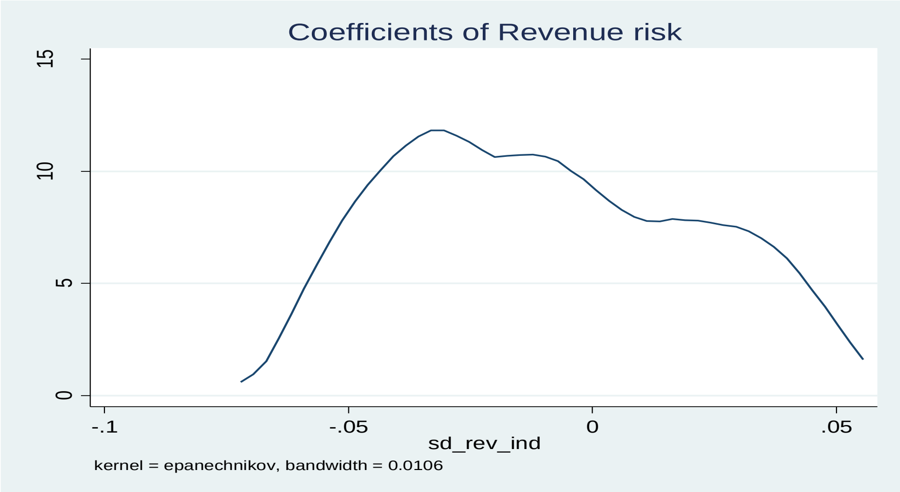

Figure 3: Density of heterogeneous preferences for revenue risk
Source: Author, from Stata 13

Using the 95% test of significant, and assuming that the coefficients are normally distributed, with a mean of -0.009 and a standard error of 0.003 (based on the skewness test statistics at the 5% level of significance), it is estimated that 15% of fishers can be classified as risk neutral, while 54% are risk averse. The remaining are risk seekers (31%). This compares to Mistiaen and Strand (2000), who observed that 5% of trips fall in the risk-loving category.

5. Discussion and conclusion

Spatial fishing intensities, and hence fishing mortality, may shift under future management scenarios, and hence it has become imperative to understand the factors that influence fishers' behaviour to avoid unintended effects in fisheries. The utility theoretic model and random parameter model (a combination of conditional and multinomial logit (unordered)) assume that decisions of individual fishers on their location choices contain a great deal of information about their attitudes towards risk, and therefore applies a revealed preference method to provide insights into their risk preferences.

In modelling choices over three regions that exhibit high expected returns and high standard deviation in revenue, and two regions that exhibit relatively lower expected return and lower standard deviation, fishers are observed to exhibit utility-maximising behaviour by choosing a trip in a region with higher expected relative revenue. Differential expected returns and their variation at fishing sites can be attributed to biological, oceanographic, fisher-related and economic factors. The biological processes of the different fish species, and the geographical location, such as on-shore versus off-shore, exhibit different environmental characteristics that affect the abundance of fish species and therefore influence catch rates. Catch rates also vary according to fishing intensities, and the technology used by fishers in relation to the sites they wish to fish. Prices of the target species would also affect expected returns and variance. More importantly, catch rates may differ spatially following changes in fisheries conditions and spatial management practices.

Travel distances from home ports are found to negatively affect the likelihood of choosing a location. The influence of revenue risk, as shown by the mixed logit regression analysis, on average affects the choice probability negatively, but this depends on risk preferences. The decision-making – while being complex – can be simplified as one in which fishers maximise utility in relation to expected returns and revenue risk, taking into account distance travelled and other factors, such as the depth of the waters.

Revenue risk has an ambiguous impact on the choice of different locations, depending on whether fishers are risk seekers, neutral or risk averse. Faced with similar expected returns at different fishing sites, an increase in the variation of the revenue in a particular region would attract risk seekers, as they perceive such wider variation as welfare enhancing. Risk-averse fishers, in turn, are less likely to choose fishing grounds with higher revenue risk when faced with a similar expected return elsewhere, and therefore shift to regions that exhibit lower variation. This behaviour can cause over-exploitation at fishing sites with a stable catch, and with species that are more evenly distributed and with more consistent prices (Holland 2008). The attitudes towards risk also make some fishing sites substitute each other, while others are complementary.

Regulatory changes and spatial fisheries management need to take into account the various factors that may influence fishers' decisions to choose their fishing sites and, among these, include the expected return from a trip, the associated revenue risk and fishers' attitudes towards risk. Thus, the sensitivities of effort with respect to these factors are key aspects of information to assess the effectiveness of management practices in relation to the health of the fisheries and the welfare of fishers. Management practices such as marine closure, which may influence fisheries conditions (e.g. abundance of target species), may have unintended effects, as they may redistribute fishers' efforts and affect fishing mortalities in an unplanned manner. For instance, when a marine closure mitigates variations in the catch in adjacent areas, it is more likely to attract risk-averse fishers, and this may lead to 'fishing-the-line' and over-exploitation

The findings of the study also emphasise that fisheries management policies should take into account the potential variation in fishers' preferences and heterogeneity in their attitudes towards risk so as to predict the directionality and magnitude of spatial fishing intensities. Future research may provide better insights into risk attitudes and specific characteristics of the fishing population, such as experienced and specialised fishers, women and poorer fishing communities with technological constraints, among others.

This study is based on trip-related information collected through a survey among fishers. The research design can be replicated straightforwardly in other artisanal fisheries to predict fishers' location choices and to determine fishing intensities at different fishing sites. In this respect, the analysis can help to better design fisheries management policies, which can improve both the state of the fishing sites and the welfare of fishers.

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