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## Disentangling the effects of capture efficiency and population abundance on catch data using random effects models

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**Abstract:** We propose a random effects model for disentangling population abundance and capture efficiency effects on bottom-trawl catches. The spatial distribution of individual fish is assumed random leading to a Poisson distribution for the number of individuals in the trawl path (no schooling). Capture efficiency, i.e. the proportion of individuals in the trawl path being retained by the gear, is modelled as a random variable. We propose model extensions that include the effects of body size on haul efficiency. We applied the models to several species from the Celtic Sea groundfish community based on small-scale repetitive hauls. The resulting abundance estimates allowed us to study population abundance ratios; the estimated capture efficiencies were comparable between species and showed that generally gear efficiency increases for larger species with the exception of haddock (*Melanogrammus aeglefinus*), which had low estimated gear efficiency despite its large body size. Model identifiability was studied using simulations and an independent trawl data set from the same area.

**Keywords:** abundance; catchability; Celtic Sea; Poisson distribution; trawl survey

## Introduction

Abundance of fish stocks is often inferred from catch information from commercial fisheries or scientific trawl surveys. Selecting the correct probability distribution of catches is important for choosing the correct estimator for survey derived population abundance indices (Pennington, 1983; Myers and Pepin, 1990; Terceiro, 2003) or the correct error distribution in a stock assessment model. The distribution of catch numbers per trawl haul is commonly characterised by many zeros and some extreme values, resulting in a rather skewed distribution. This shape is not unique to trawl catch data and occurs in many studies of animal distribution. Welsh *et al.* (1996) summarised the different model classes that have been employed to deal with data that feature "extra zeros". In two stage models the probability of obtaining a non-zero observation is modelled separately from the distribution of the number of animals observed or caught conditional on it being non-zero. The distribution of non-zero observations might be truncated Poisson (Terceiro, 2003) or truncated negative binomial (O'Neill and Faddy, 2003) or even Gamma (Stefánsson, 1996). This class of models is known as conditional models or more commonly in the fisheries literature as the delta approach (Stefánsson, 1996). The probability of non-zero catches as well as the mean catch per haul is then modelled using generalised linear models with explanatory variables such as area or depth (Stefánsson, 1996). A slight modification of this leads to considering the observations to follow a mixture distribution of a Poisson or negative-binomial distribution and a Bernoulli draw (finding/observing animals or not) (Welsh *et al.*, 1996). Applied to catch data, the first component of this model can be interpreted as the spatial distribution of fish abundance and the second as the probability of the gear catching a particular fish.

Two biological processes underlie trawl catches: the abundance and spatial distribution of fish populations and capture (trawl) efficiency. The first component determines the number of fish in the trawl path (swept area) and the second describes how many of these will end up in the codend. Capture efficiency is primarily influenced by fish reactions such as herding, escapement and net selectivity (see Wardle, 1993; Engås, 1994 for reviews). Traditionally in stock assessment models capture efficiency, or more generally catchability has been described by a parameter, which might vary among ages or from year to year but which is generally regarded as constant (e.g. XSA, Shepherd, 1999). Dickson (1993a) proposed a deterministic model for trawl efficiency that takes account of the effects of sweeps, otterboards and the trawl net. Harley and Myers (2001) have used selectivity curves with the parameters for a particular species coming from a common distribution. Recently, Fryer *et al.* (2003) extended this approach and introduced the concept of random selectivity curves, which vary among hauls. Using this idea, we regard haul catchability as a random process.

In this paper we propose an approach for estimating population abundance separately from trawl catchability based on catch numbers per haul. We assume that fish capture is a random process which causes catchability to vary from haul to haul. We develop a model for catch numbers per haul including species catchability as a random effect. In fisheries science, the concept of random effects is best known from generalised linear mixed models (Venables and Ripley, 2002). The model is tested using a data set of repetitive bottom trawl hauls carried out in a single statistical rectangle within the Celtic Sea taken over a short time interval. We then deal with the identifiability of such a model. The crucial question is whether it is actually possible to disentangle the catch process, and the local population abundance and estimate all parameters reliably. Parameter identifiability is addressed using simulations and an independent data set from the same area but a different year. Finally, some model extensions

are considered that take into account explanatory variables for both the capture process and the abundance distribution.

## Catch process

### Model development (Model 1)

We model the distribution of catch data as a mixture of population abundance and random capture efficiency. If individual fish were randomly distributed in space, considering the two-dimensional fish distribution once fish from a certain water layer were projected onto the sea floor, then the number of individuals encountered in a given area would follow a Poisson distribution. Consequently, the distance between (projected) individuals along a transect line would be described by an exponential distribution. Few studies have looked at the spatial distribution of fish at the scale of a fishing haul. Some information comes from a study on Greenland halibut where using videos from a system mounted on the trawl headline Albert *et al.* (2003) found that the distance between individuals followed an exponential distribution. Data derived from video observations obtained with an ROV suggest that a number of deep-sea species are randomly distributed on a small scale (Trenkel unpublished). Hence it might be reasonable to assume that demersal and benthic fish species are randomly distributed in an area with homogeneous substrate and depth conditions. This assumption implies that individuals do not form (big) schools, though a few individuals might occur together without violating the assumption. The effect of schooling will be further considered in the discussion.

Let us turn now to the capture process which we view as a random process. For each species a given fishing haul has a particular capture efficiency and all capture efficiencies are described by a common parametric distribution. Differences in efficiency among hauls might be due to gear properties, environmental or biological factors. If we take the swept area over a wide enough scale, capture efficiency can be interpreted as the proportion of animals caught which takes values between zero and one.

In summary, the model assumptions are that 1) individual fish are randomly distributed in space (ignoring the vertical component) and do not form large schools; 2) capture efficiency is a random variable in the range (0,1); 3) the width of the swept area is the same for all hauls, but trawled distance can vary. We can now write down this simple capture model.

For the  $i$ th haul, denote by  $n_i$  the number of individuals present in the trawl path of which a certain proportion  $q_i$  was caught, where  $i=1, \dots, m$ , and the capture efficiencies  $q_i$  are independent random variables. Modelling the number of individuals in the trawl path by a Poisson distribution, we have

$$n_i \sim \text{Poisson}(\lambda) \quad n_i = 1, 2, \dots \quad (1)$$

The capture efficiencies  $q_i$  are modelled through normally distributed random variables  $p_i$  which a logistic transformation puts into the appropriate range  $q_i \in (0,1)$ .

$$p_i \sim N(\mu, \sigma^2) \quad (2)$$

$$q_i = \exp(p_i) / (1 + \exp(p_i)) \quad (3)$$

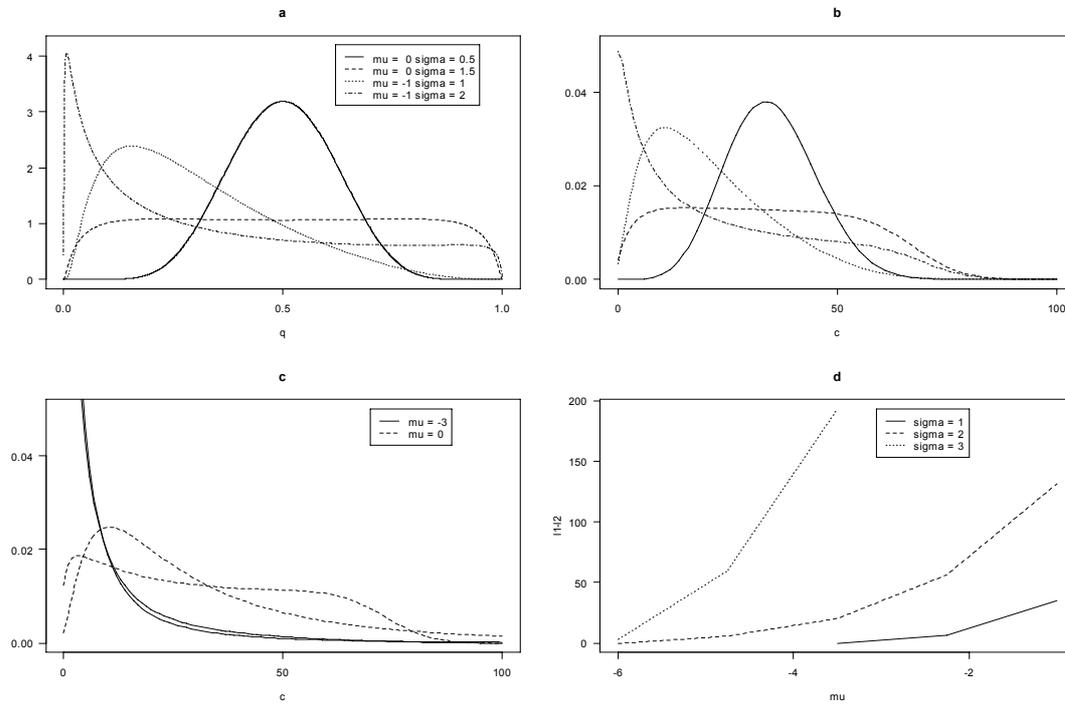
The probability density of  $q_i$  is shown in Figure 1a) for different combinations of the parameters  $\mu$  and  $\sigma$ . It is seen that the two-parameter family of densities is flexible, and can accommodate the same shapes as the beta-distribution.

This formulation corresponds to a random effects model for catchability. The resulting model of catch numbers is

$$C_i \sim \text{Poisson}(q_i \lambda D_i/2) \quad i=1, \dots, m, \quad (4)$$

where  $D_i$  is the distance trawled by haul  $i$ , such that  $D_i/2$  is a factor for standardising to the nominal trawl distance of 2 nm in the Celtic Sea study. Figure 1b) shows the probability distributions of  $C_i$  corresponding to the random effects distributions in Figure 1a) when  $\lambda=70$ . Given the flexibility of the distribution, its shape can resemble that of a negative binomial distribution.

**Figure 1. Illustration of the different distributional shapes that can be accommodated by capture model 1. a) probability density of the capture efficiency  $q$  for different parameter values; b) corresponding probability functions for catch numbers  $C$  ( $\lambda = 70$ ); c) comparison of the two- and three-parameter families of probability densities for two values of  $\mu$  ( $\sigma = 2$ ); d) Kullback-Liebler distance between the two- and three-parameter families as a function of  $\mu$  for different values of  $\sigma$ .**



## Parameter estimation

We estimate the three model parameters  $\lambda$ ,  $\mu$ ,  $\sigma$  by maximum likelihood. To this end, we need to calculate the marginal probability distribution for the catch  $C_i$  of haul  $i$ :

$$f(C_i | \lambda, \mu, \sigma) = \int_{-\infty}^{\infty} f_p(C_i | q(p_i), \lambda) \phi(p_i; \mu, \sigma) dp_i, \quad (5)$$

where  $f_p$  is the probability function corresponding to eq. (4),  $q(p_i)$  is given by eq. (3) and  $\phi(p_i; \mu, \sigma)$  is the Gaussian probability density distribution. The log-likelihood function is then given as

$$l(\lambda, \mu, \sigma) = \sum_{i=1}^m \log \{ f(C_i | \lambda, \mu, \sigma) \} \quad (6)$$

The likelihood function is maximized using the random effects module of the software package AD Model Builder (Fournier, 2005), which uses the Laplace approximation to evaluate the integral in eq. 5 (Skaug and Fournier, <http://bemata.imr.no/laplace.pdf>). AD Model Builder automatically calculates uncertainty estimates based on the observed Fisher information matrix. It should be noted that the Laplace approximation provides only an approximation of the integral (5), which may lead to biased estimates of parameters in some situations (Breslow and Lin, 1995). One should therefore always attempt to assess the accuracy of the Laplace approximation. We carry out a simulation study to investigate the finite sample properties of the approximate maximum likelihood estimates.

## Model properties

The proposed model has three parameters:  $\lambda$ ,  $\mu$ ,  $\sigma$ , and the only information available for estimating these is the empirical distribution of  $C_i$ ,  $i=1, \dots, m$ . Depending on the shape of the distribution, the parameters will be confounded to a varying degree, and as an extreme it may be impossible to estimate all three parameters simultaneously. What happens then is that the model collapses during the estimation process to a two-parameter family:  $\lambda \cdot \exp(\mu)/(1+\exp(\mu)) \rightarrow \alpha$  as  $\lambda \rightarrow \infty$  and  $\mu \rightarrow -\infty$ . Here,  $\alpha$  is a single parameter replacing the two parameters  $\lambda$  and  $\mu$ . The resulting two-parameter model is a Poisson-lognormal mixture distribution for catches  $C_i$ , i.e. a Poisson distribution where the mean follows a lognormal distribution.

In practical terms, the phenomenon described above means that the two-parameter family fits the catch numbers  $C_i$  equally well as the three-parameter family. To illustrate this point we simulate a large dataset (1000 realizations of  $C_i$ ) and fit both the two-parameter and three-parameter families by maximum likelihood. Technically speaking, we obtain the two-parameter family from the 3-par family by fixing  $\mu$  at the very low value -7. We generate data for two different parameter settings:  $\mu = -3$  and  $\mu = 0$ . It is seen from Figure 1c) that when  $\mu$  is small ( $\mu = -3$ ) the two probability distributions lie close to each other, and hence will yield approximately the same fit to data. For a given value of  $\mu$ , the closeness of the two- and three-parameter families depends on the value of  $\sigma$ . So, at which point does the three-parameter family collapse to the two-parameter family? To investigate this, we plot the likelihood ratio between the two models as a function of  $\mu$ , for three different values of  $\sigma$  (Figure 1d). To eliminate simulation error we use a large sample size ( $m=1000$ ). The figure shows that the ‘breakdown point’ (the value of  $\mu$  below which the likelihood ratio is zero) depends on  $\sigma$ .

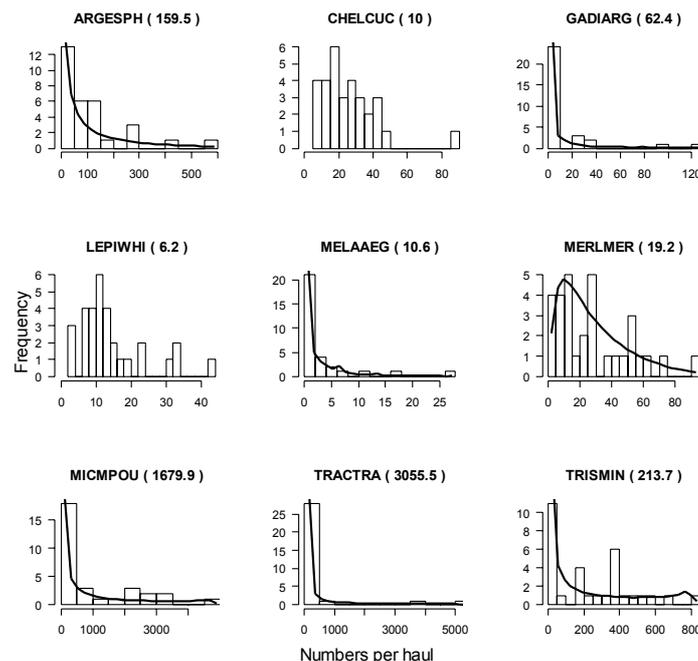
Let us now consider the case where the model (eqs. 1-4) is fitted separately for several species. One of the model assumptions is that the width of the area swept by a haul is the same for all hauls but not the trawled distance. This width is also the same for all species and as a consequence the values for the capture efficiencies are directly comparable between species. Similarly the population abundances can be compared. Of course this is only the case if model assumptions are true, in particular that individuals are randomly distributed in space. However, estimates would not be comparable for two species if one of them responded to the trawl by herding behaviour, which in our model would imply a larger swept area (due to assuming capture efficiency  $<1$ ) compared to a species which would disperse or scatter at the approach of the trawl and for which the implied swept area would be smaller.

## Case study

In October 1994 the Mirec study consisting of small scale bottom trawling was carried out in the Celtic Sea using the standard survey gear (36/47 GOV) equipped with rubber bobbins. Within six days (day time only), 31 hauls of 30 minutes duration at 4 knots were performed in an area one degree wide and half a degree high centred on 48N 45 and 8W 30. All hauls but two were carried out at depths 140-160 m; the two other hauls were located around 120 m. Overall 25 species were caught, counted and their length measured. Nine species were caught in sufficient numbers and in enough hauls to attempt fitting the capture model (model 1).

Figure 2 shows the distributions of observed numbers per haul which all have long right hand tails. Empirical dispersion factors (variance/mean of catch numbers) ranging from 6.2 for megrim (LEPIWHI) to over 3000 for horse mackerel (TRACTRA) confirmed the strong overdispersion for all species. The expected distributions (obtained by parametric bootstrapping from the fitted model 1) are plotted as continuous lines for all but two species. Based on visual inspection the model seemed to provide a good description of the shape of the catch data. The two species for which no estimates were obtained were red gurnard (CHELCUC) and megrim. The estimation procedure did not converge for these two species as the estimated values for the capture efficiency most likely were below the critical value for which the three-parameter model becomes a two-parameter model (see section on Model properties), hence the model was not identifiable. For the remaining species population abundances ( $\lambda$ ) were estimated with variable precision (Table 1, model 1); the estimate for haddock (MELAAEG) was particularly unreliable but also the smallest value. The ratios of estimated population abundance and mean observed catch (standardised to 2 nm haul length) varied between around 3.3 for poor cod (TRISMIN) and 20 for haddock.

**Figure 2. Mirec case study, histograms of numbers per haul, numbers in brackets are dispersion indices (var/mean). Continuous lines are expected histograms obtained by parametric bootstrap from fitted model 1.**



**Table 1. Mirec case study, estimates of average population abundance ( $\lambda$ ) and ratio population abundance/mean catch per haul ( $\lambda/\bar{C}$ ) for capture model 1 and capture model 2 (capture efficiency is a function of body length). Standard deviations in brackets.**

Code	English name	Species	Model 1		Model 2
			$\lambda$	$\lambda/\bar{C}$	$\lambda$
ARGESPH	argentine	<i>Argentina sphyraena</i>	655.4 (112.8)	6.0 (1.3)	657.4 (114.2)
GADIARG	Silvery cod	<i>Gadiculus argenteus</i>	134.1 (21.6)	10.4 (4.1)	133.2 (20.5)
MELAAEG	haddock	<i>Melanogrammus aeglefinus</i>	66.5 (109.4)	20.0 (7.6)	67.1 (112.1)
MERLMER	hake	<i>Merluccius merluccius</i>	129.7 (56.3)	4.4 (0.7)	125.6 (49.0)
MICMPOU	blue-whiting	<i>Micromesistius poutassou</i>	4829.7 (155.4)	4.6 (1.0)	4884.5 (214.1)
TRACTRA	horse mackerel	<i>Trachurus trachurus</i>	5137.3 (236.7)	13.6 (7.4)	5170.8 (298.5)
TRISMIN	poor cod	<i>Trisopterus minutus</i>	806.2 (35.0)	3.3 (0.5)	808.7 (36.42)

**Table 2. Mirec case study, comparison of estimates of the mean ( $\mu$ ), log-transformed standard deviation ( $\log(\sigma)$ ) of the random capture variable and mean capture efficiencies for capture model 1 and model 2 (population abundance is a function of age). Standard deviations in brackets.**

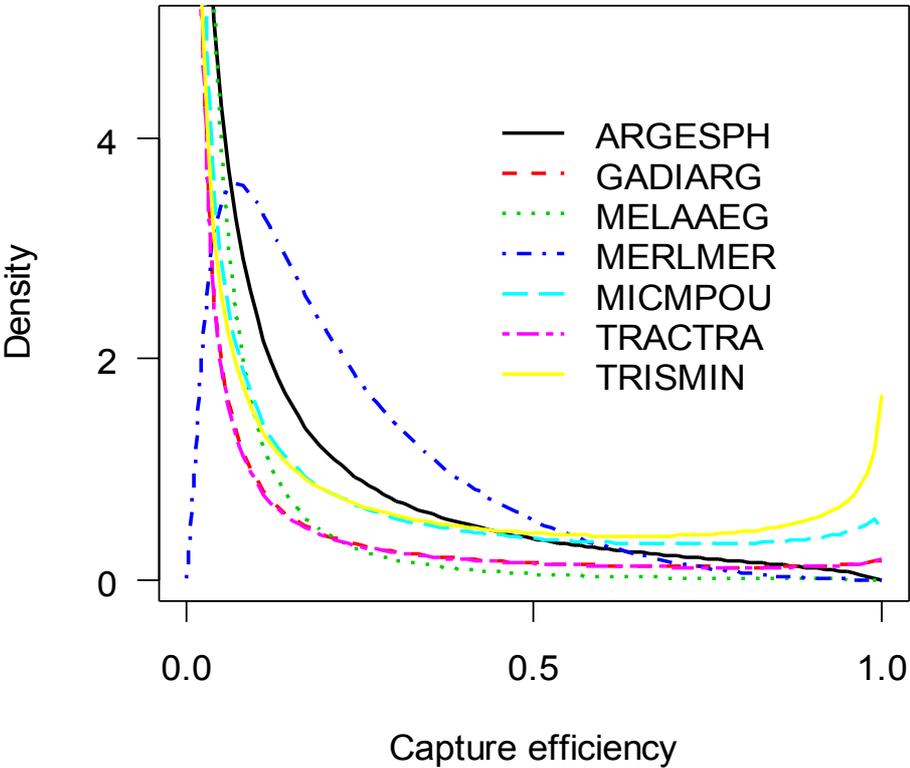
Code	Model 1			Model 3		
	$\mu$	$\log(\sigma)$	$\bar{q}$	$\mu$	$\log(\sigma)$	$\bar{q}$
ARGESPH	-2.41 (0.41)	0.60 (0.16)	0.17	-2.37 (0.41)	0.57 (0.16)	0.17
GADIARG	-5.10 (0.81)	1.20 (0.23)	0.09	-4.29 (0.88)	1.27 (0.24)	0.14
MELAAEG	-4.04 (1.68)	0.51 (0.29)	0.05	-4.0 (1.64)	0.51 (0.29)	0.05
MERLMER	-1.55 (0.62)	0.08 (0.21)	0.22	-0.45 (0.51)	0.25 (0.23)	0.42
MICMPOU	-2.59 (0.52)	1.03 (0.14)	0.22	-1.64 (0.47)	0.91 (0.15)	0.29
TRACTRA	-5.21 (0.63)	1.21 (0.16)	0.08	-4.6 (0.62)	1.12 (0.18)	0.10
TRISMIN	-2.06 (0.57)	1.11 (0.16)	0.28	-1.97 (0.57)	1.12 (0.16)	0.29

The estimates of the mean  $\mu$  of the random capture variables were all in the range -5.21 to -1.55 (Table 2, model 1). The smaller the value the smaller is the capture efficiency  $q$  (eq. 3). However, this effect can be counterbalanced by large variances  $\sigma$ , estimates of  $\ln(\sigma)$  are given in Table 2. Note that the estimates of  $\ln(\sigma)$  were rather imprecise for small values. Haddock had the smallest average capture efficiency  $\bar{q}$  of 0.05, while poor cod had the largest of 0.28 (Table 2). The full distributions for the capture efficiency  $q$  are shown in figure 3. Note how the distributions for blue-whiting (MICMPOU) and poor cod have larger values for  $q$  close to 1 compared to the other species. This explains the large average capture efficiency for poor cod and the relatively large value for blue-whiting although their respective distributions had most of the mass close to zero.

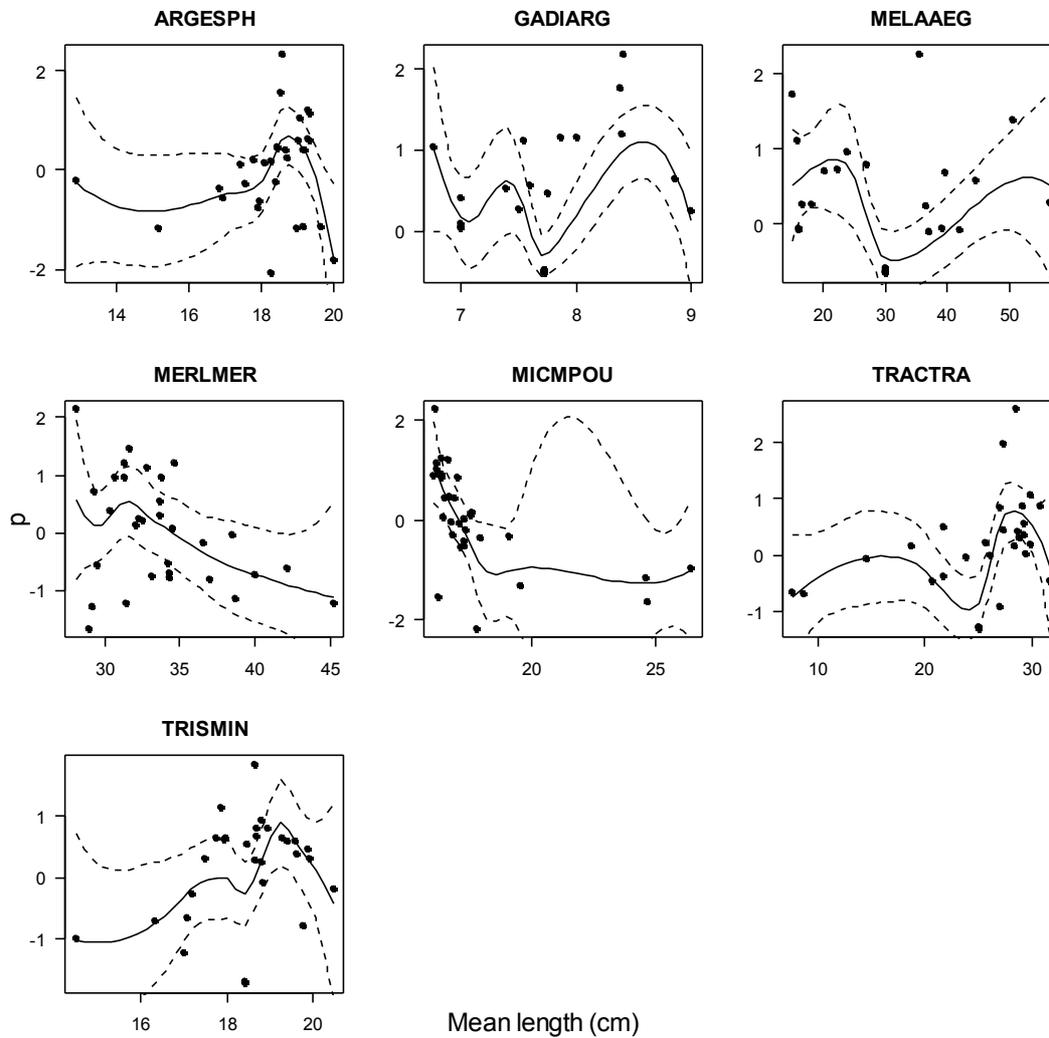
In order to check the appropriateness of the normal distribution for the random effect  $p_i$ , the histograms of estimated random effects were plotted (results not shown). These histograms looked rather symmetric and a comparison with the assumed normal distributions confirmed this impression. However, there were two cases silvery cod (GADIARG) and haddock, which showed a somewhat heavy right hand tail. Thus there might be some factor with respect to

which the estimated random effects exhibit a relationship and which could explain the non-Normal distribution of the random effects. An obvious candidate would be fish length. Hence to investigate this further, the estimated random effects were plotted against the mean length of the species in the catch (Figure 4). These figures suggested that indeed mean fish length in the catch might be an important factor in determining the capture efficiency of a given haul. We will come back to this later when we consider possible model extensions but we will first consider the issue of model validation for this simple model.

**Figure 3. Mirec case study, comparison of the estimated probability density distributions of capture efficiency (model 1) for different species.**



**Figure 4. Mirec case study, estimated random effects (model 1) plotted against mean length in the catch. Continuous lines are smoothed nonparametric estimates (with 95% confidence bands).**



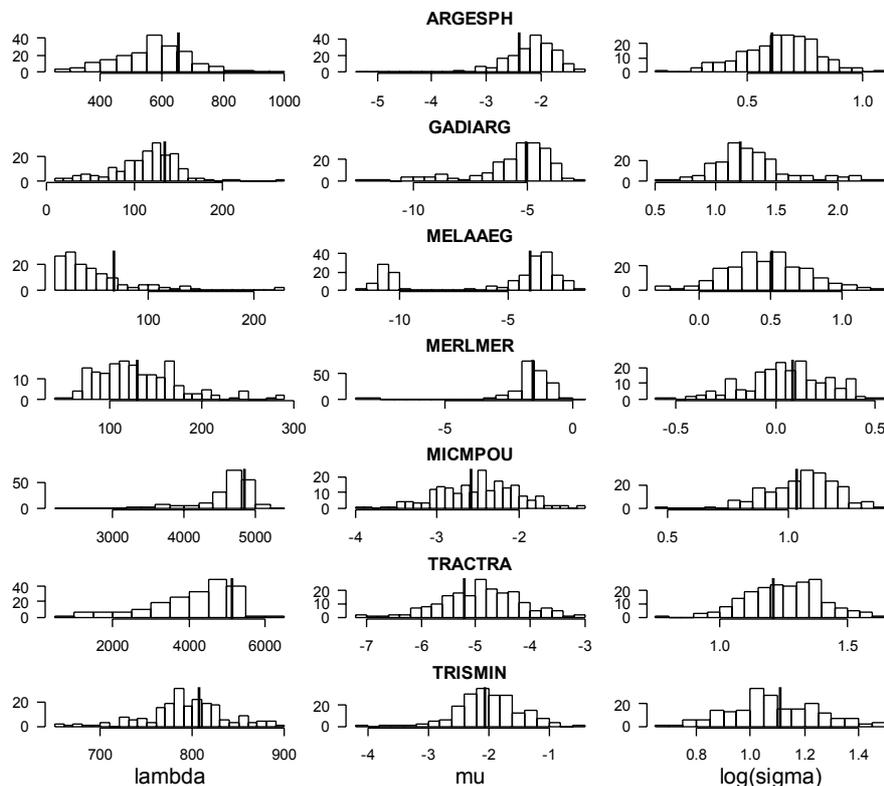
## Model validation

### *Simulation study*

We carried out a simulation study in order to assess the identifiability of our capture model for the Mirec catch data. The two yardsticks we used were bias and precision of parameter estimates. The questions are: can we on average get correct estimates for all model parameters for all species, and are precision estimates provided by AD Model Builder of the right size?

The estimated parameter values (Table 1 and 2) and the model (eqs. 1-4) were used in a parametric Monte Carlo approach to simulate catch data (200 data sets). The data simulations were carried out separately for all species. The capture model was then fitted to each simulated catch data set. For all three model parameters, true parameter values lay within the 10 and 90 percentiles of the distribution of simulated estimates (Figure 5). The average relative bias over all seven species (mean of estimates from simulated data minus true value divided by true value) was 1% (range -20 to 40 %) for population abundance estimates ( $\lambda$ ), 6% (range -9 to 38%) for the mean  $\mu$  of the random capture variable and -4% (range -38 to 9%) for its standard deviation ( $\ln(\sigma)$ ). Thus, the parameter estimates in Table 1 and 2 were not likely to be severely biased. In order to assess whether the estimates of precision of parameter estimates were correct, we compared the sample standard deviations of the parameter estimates obtained from the simulated data with the original standard deviation estimates from the Mirec data set. The sample standard deviations for population abundance estimates were larger than the Mirec values for all species ( $\lambda$ : average 226 %, range 26 to 484%). For the parameters of the random capture variable, the difference was less striking ( $\mu$ : average 47%, range -8 to 119%;  $\ln(\sigma)$ : average 6%, range -9 to 48%). This indicates that the variance of all population abundance estimates for the Mirec case study might have been severely underestimated as would the other two parameters, but to a lesser degree. It seems likely that the quadratic approximation to the maximised likelihood function used by AD Model Builder to obtain standard deviations for parameter estimates was not completely satisfactory for this model. We will have to bear this in mind when comparing parameter estimates in the next section.

**Figure 5. Simulation study, histograms of estimated parameter values of capture model 1. The catch data was simulated from model 1 fitted to the Mirec case study. True parameter values are given by vertical lines.**

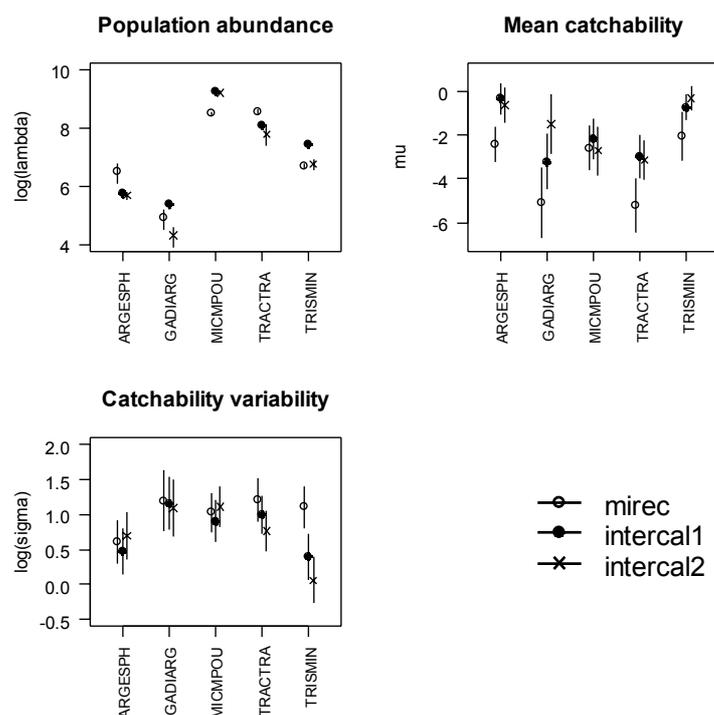


## Test data set

Another way of validating the model estimates and the appropriateness of the capture model more generally comes from using an alternative data set. In 1996 an intercalibration study was carried out between the old research vessel *Thalassa 1* and the new one *Thalassa 2* (see Pelletier 1998 for a description of the study). One of the sites selected for this intercalibration study was the same as for the Mirec study. Thirty parallel hauls were carried out leading to two data sets: Intercal 1 (*Thalassa 1*) and Intercal 2 (*Thalassa 2*). These data sets provide the opportunity to firstly compare capture efficiency estimates for two data sets (Mirec vs. Intercal 1) obtained using exactly the same gear and the same vessel but coming from different years (1994 vs. 1996). This leads to the null hypothesis  $H_{0q}: q(\text{Mirec}) = q(\text{Intercal 1})$ . Secondly, to compare abundance estimates for the same time (1996) and area obtained using the same gear but different vessels (Intercal 1 vs. Intercal 2). The null hypothesis for this comparison is  $H_{0\lambda}: \lambda(\text{Intercal 1}) = \lambda(\text{Intercal 2})$ .

The comparison of model estimates was possible for five species. For three out of the five species, the shapes of the distributions of capture efficiency ( $q$  in eq. 3) were nearly identical for all three data sets (figure not shown). For the other two species, silvery cod and poor cod, the distributions were more similar for the same year (Intercal 1 vs. 2) compared to different years (Intercal vs. Mirec). The comparison of model estimates however showed, that the values of the mean ( $\mu$ ) of the random capture variables were not significantly different for Silvery cod and poor cod due to low estimation precision (Figure 6). Significant differences were found for argentine and horse mackerel for which the shapes of the capture efficiency distributions were similar. Thus,  $H_{0q}$  is rejected for two out of five species.

**Figure 6.** Mirec and Intercal 1 & 2 case studies, comparison of estimated parameter values (model 1). Mirec study in 1994 with *Thalassa 1*. Intercal 1 in 1996 with *Thalassa 1* and Intercal 2 in 1996 with *Thalassa 2*. Vertical lines indicate 95% confidence intervals.



Comparing the two population abundances estimates ( $\lambda$ ) for 1996 (Intercal 1 vs. 2), significant differences were found for Silvery cod and poor cod leading to rejecting  $H_0$  for two out of the five species tested. It might be hypothesised that the precision of population abundance estimates was underestimated, which in turn would have led to significant differences though there were none in reality. In the simulation study it was found that the precision of abundance estimates of these two species was underestimated by 74 and 27% respectively. Thus the estimates remain significantly different even if the standard deviations were increased by these amounts.

## Model extensions

### *Selecting explanatory variables*

The catch process model (model 1) can be extended by including the effects of explanatory variables. An obvious candidate is body length which affects net selectivity and fish reactions directly. If individuals occur together by length or age, population abundance present in the path of a given trawl haul might be "explained" by body length indirectly. Thus body length can either be used as an explanatory variable for the capture efficiency (eq. 2) or the population abundance (eq 1).

In order to study the impact of body length on capture efficiencies, the mean estimated capture efficiency  $\bar{q}$  (model 1) was plotted against the average body length in the catch (Figure 7a). The relationship was a clearly increasing function with two exceptions, haddock and horse mackerel. Both had low average capture efficiency despite having large average body size.

### *Capture efficiency as a function of body size (model 2a & b)*

Modelling the mean of the random capture variable as a linear function of the average body length ( $l_i$ ) in haul  $i$ , we get

$$\mu_i = a + b l_i \quad (7)$$

$$p_i \sim N(\mu_i, \sigma^2) \quad (2a)$$

This means that the capture efficiency  $q_i$  (eq. 3) is a logistic function of body length, which corresponds to a classical selectivity model. The model for population abundance remained as before (eq 1). We used average body length in a haul to represent the length effects of a given species. Hauls with no observations (zero hauls) pose a problem, as no mean length is available. The question is whether this is a case of randomly or non-randomly missing information. To put it differently, is the fact that no individuals were observed in a given haul caused by small local abundance, in which case the information would be randomly missing, or is it caused by the individuals present being too small to be retained in the net, which would mean non-randomly missing information? It might also be a mixture of both. But given the rather large body size of the species in the Mirec study, in most cases zero-hauls were more likely to be due to low local abundance. Support for this hypothesis comes from the observation that for all species zero hauls were surrounded by small hauls. Thus we decided to estimate the covariate for zero-hauls by the mean of the average haul length from all non-zero hauls.

Assuming the same relationship between the capture variable (species independent  $b$  in eq. 7 but separate intercepts  $a$ ; referred to as model 2a), we obtained mean capture efficiencies which decrease with average body length (Figure 7b). If we assumed however that the

relationships differed (species specific  $b$  in addition to  $a$ , model 2b), we obtained three classes of species (Figure 7c). Mean capture efficiency clearly increased with body size for argentine, silvery cod, poor cod and horse mackerel, it decreased for hake and blue-whiting and remained constant for haddock. Table 3 summarises the signs of these relationships. Thus the form of the length specific selectivity function differed between species.

*Population abundance as a function of age (model 3)*

**Table 3. Mirec case study, sign of slopes for capture efficiency as a function of body length (Model 2) and abundance as a function of age (Model 3).**

Code	Model 2	Model 3
ARGESPH	+	+
GADIARG	+	+
MELAAEG	0	+
MERLMER	-	-
MICMPOU	-	-
TRACTRA	+	+
TRISMIN	+	+

Modelling population abundance as a decreasing function of age, we obtain

$$\lambda_i = d \exp(-c \text{ age}) \tag{8}$$

$$n_i \sim \text{Poisson}(\lambda_i) \tag{1a}$$

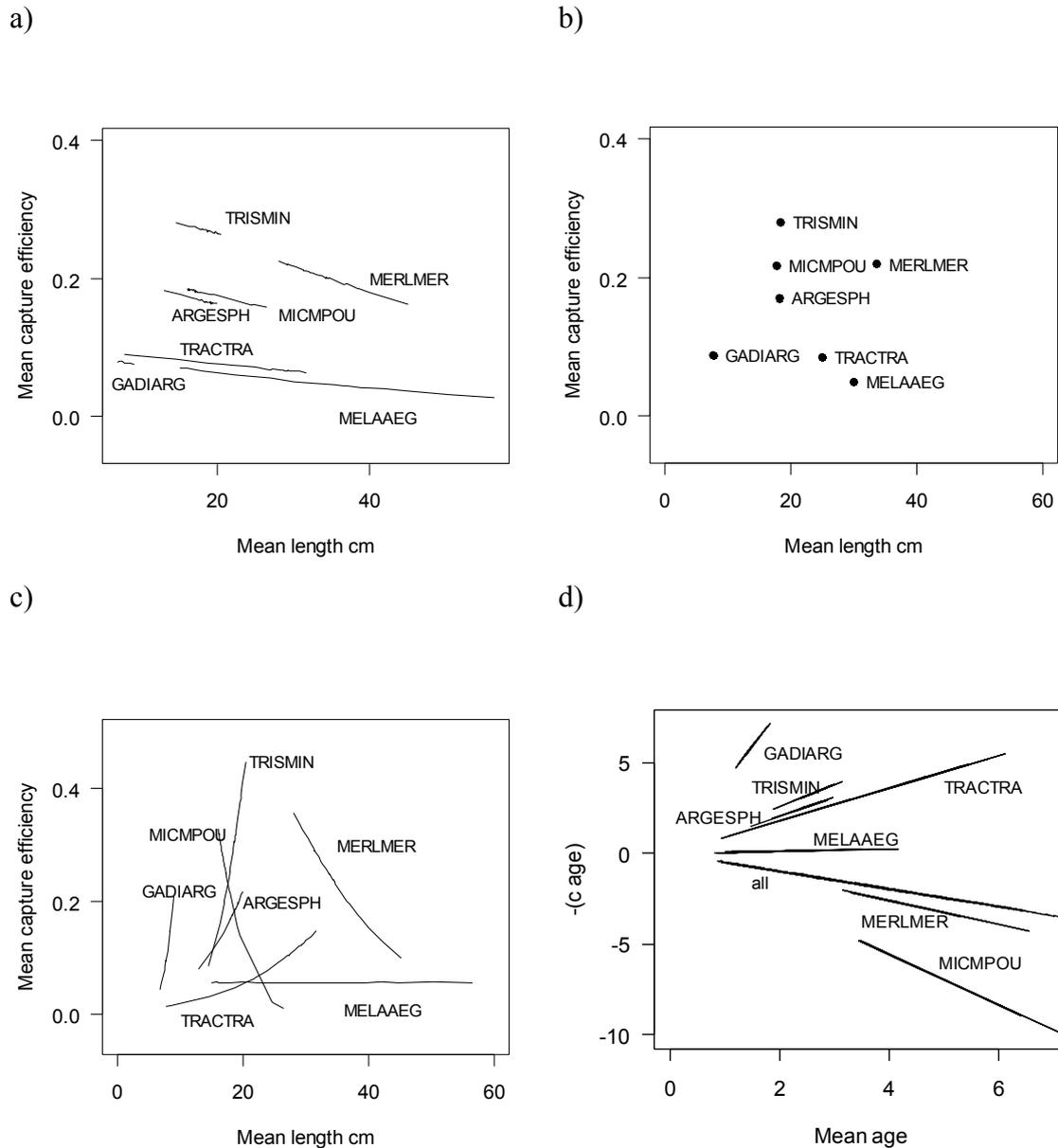
This model corresponds to a classical population dynamics model where  $c$  is total mortality and  $d$  average recruitment. The random effects catchability model remained as in model 1 (eqs. 2 & 3). Age can be estimated from body length assuming a growth function. Using the inverted von Bertalanffy growth model, we estimated mean age in a haul by first estimating the age of all individuals using growth parameters as in Trenkel and Rochet (2003, appendix). For the species not present in that study, we derived values from FishBase ([www.fishbase.org](http://www.fishbase.org); GADIARG  $k=0.5$ ,  $L_{inf}=15$ ; MELAAEG  $k=0.2$ ,  $L_{inf}=100$ ).

Estimating separate mortalities  $c$  for all species, only two species (blue-whiting and hake) had positive mortalities (negative slopes in Figure 7d and Table 3). These were the same species that had decreasing capture efficiencies with body length (negative slopes for model 2). Thus only for blue-whiting and hake was there evidence that population dynamic effects might have been more important in determining catch numbers per haul compared to gear efficiency effects.

*Model comparison*

We have now fitted three different capture models to the Mirec catch data. We used Akaike's information criteria (AIC) to compare the goodness-of-fit of the different model (Table 4). The simple model (model 1) had the smallest AIC for argentine and haddock, while the model with capture efficiency as a positive function of length (model 2b) was best for poor cod. For hake and blue-whiting the model with abundance as a negative function of age (model 3) had the smallest AIC. For horse mackerel both model 2 and 3 had identical fits and were better than the simple model. The best fitting model for Silvery cod was model 3 with population abundance increasing with age, which does not make much sense biologically unless older individuals immigrated into the survey area.

**Figure 7. Mirec case study. a) Mean estimated capture efficiency (model 1) vs mean length in catch; b) Mean estimated capture efficiency vs mean length in the catch with separate relationships for each species (model 2a); c) Mean estimated capture efficiency vs mean length in the catch with common relationship for all species (model 2b), d) Mean estimated abundance vs mean age in the catch (model 3).**



**Table 4. Mirec case study, comparison of model fits (AIC). Best fitting model in bold.**

Code	Model 1	Model 2	Model 3
ARGESPH	<b>-28687.60</b>	-28687.40	-28687.40
GADIARG	-2236.72	-2236.66	<b>-2239.40</b>
MELAAEG	<b>-162.80</b>	-160.91	-160.91
MERLMER	-4676.70	-4681.56	<b>-4686.12</b>
MICMPOU	-433356.00	-433366.00	<b>-433368.00</b>
TRACTRA	-154091.60	<b>-154093.20</b>	<b>-154093.20</b>
TRISMIN	-74288.00	<b>-74290.00</b>	-74289.60

## Discussion

The estimated capture efficiencies for all species in the Mirec study were all rather low with a mean below 0.3. Poor cod had the highest estimated mean capture efficiency (0.28 followed by blue-whiting 0.22 and hake 0.22 (model 1 in Table 2). In comparison haddock had a low mean capture efficiency (0.05) although it is of similar body size as hake. The estimated standard deviation of the capture random variable (Table 2) was larger for haddock compared to hake but still only about half the value for the other species. Both haddock and hake are living close to the sea floor and hence it seems unlikely that a variable vertical distribution in the water column contributed to the difference in mean capture efficiency. Thus the difference must be either due to differences in the reaction to the trawl or non-random spatial distributions of one or both species. The effect of vertical avoidance of haddock in front of the approaching vessel can be excluded, as all hauls took place at depths below the mark of 100 m, below which only weak and irregular reactions have been observed for this species (Ona and Godø, 1990).

Let us first consider the available evidence on capture efficiency and reaction behaviours. For Barents Sea haddock, overall capture efficiency of a survey trawl equipped with bobbins (as used here) was estimated to be 0.05 for individuals <20 cm and to increase up to 0.37 for individuals >50 cm (Dickson 1993b). Our estimates are somewhat low compared to these. However, Engås and Godø (1989) noted that escape of small haddock under the ground gear depended much on the sweep lengths, with longer sweeps leading to more escapes. Other gear parameters also impact capture (Reeves *et al.*, 1992). Furthermore, Glass and Wardle (1989) found that haddock reactions increase with increasing light level (artificial light). Using population estimates derived from catch-at-age data, Harley and Myers (2001) estimated length specific survey (IBTS) catchability for North Sea haddock. Catchabilities were around 0.6 and 0.2 (25 cm individual) in autumn and winter respectively. Again, our values for haddock appear low. Closely linked to reaction behaviour is maximum fish swimming speed which actually allows individuals to escape the approaching trawl. A recent laboratory study found that a 42.0-cm haddock could maintain a swimming speed of about  $0.92 \text{ m s}^{-1}$  for up to 15 mins (at  $10 \text{ }^{\circ}\text{C}$ ) with larger burst swimming speeds (Breen *et al.*, 2004). No information is available for hake, so that it is not possible to establish whether haddock might be a better swimmer.

We now turn to the second explanation for the estimated difference in mean capture percentage for haddock and hake. Given that the survey area was rather small, the substrate homogenous and the depth range small, horizontal abundance gradients seem unlikely. Hence schooling might have been a factor. Indeed by using videos on the trawl headline haddock have been observed to form schools occasionally (Aglen *et al.*, 1997). This hypothesis is supported by the observation that estimated horse-mackerel capture efficiency was low given its body size. Horse-mackerel is well known to form schools (Massé *et al.*, 1996). Let us now consider the effects of schooling on our capture model.

If schooling occurs in some species, the proposed capture model does no longer hold for those species. Assuming constant school size  $\tau$  and a random spatial distribution of schools, the distribution of the number of individuals in the trawl path (eq. 1) becomes  $n_i \sim \tau \cdot \text{Poisson}(\lambda)$ , where  $\lambda$  is now the expected number of schools. Note that the variance of  $n_i$  under this model is  $\tau^2 \lambda$ , which is larger than  $\tau \lambda$ , the variance under the assumption  $n_i \sim \text{Poisson}(\tau \lambda)$ . In contrast the expectations of both models are identical ( $E[n_i] = \lambda \tau$ ). As a consequence, if our (wrong) capture model (model 1) is fitted, the population abundance ( $= \lambda \tau$ ) estimated under this model

should be an approximately unbiased estimate of the true population abundance, while the distribution of the capture efficiency will be inflated by the extra variance. This situation can be expected to lead to higher values for capture efficiencies close to one. Indeed both blue-whiting and poor cod show this feature of upwards bending curves on the right hand side, to a lesser degree also horse mackerel but not haddock (Figure 3). Thus in this case average capture efficiencies are overestimated and the median might be a more robust measure for obtaining interpretable capture efficiencies. Thus given that schooling is expected to lead to an overestimate rather than an underestimate of the average capture efficiency, the most convincing explanation for the low haddock estimate is its capability to avoid capture.

Having established that point estimates of abundance estimates should be more or less valid even if schooling occurred, we can now discuss the comparison of our population estimates to the average catch numbers. Given we do not know the width of the swept area, we can only compare relative abundances and abundance/catch ratios between species. These ratios were found to vary between 3 and 20, with most species below ten (see table 1 col 4). Thus if we were to use our model based abundance estimates instead of the average catch per haul to produce a survey abundance index, our perception of the community species composition would be somewhat different. The species with the highest estimated abundance was horse mackerel while blue-whiting was most abundant in the catch. On the other end of the spectrum haddock was in either case the least abundant species but the order of the remaining species differed.

The proposed capture model was shown to be identifiable (simulation study) and to some degree repeatable (test data set) which means that the two stochastic processes capture efficiency and population abundance distribution could be disentangled conditional on all model assumptions being true. While assuming random capture efficiency might appear reasonable, the fundamental assumption of a random spatial fish distribution (Poisson distribution) needs further verification. One approach would be to use a split-beam echosounder, track individual fish and then determine their spatial distribution (Pedersen, 1996). An alternative is to use videos either fixed on the trawl headline (Albert, *et al.*, 2003) or on underwater vehicles (Trenkel *et al.*, 2004). The advantage of videos is that species identification is much easier. Further model extensions are also envisageable by including additional environmental explanatory variables or trawl gear parameters. Correlations between species occurrences could also be included.

In conclusion, the proposed capture model offers a method for disentangling the effects of species abundance and catchability on trawl catches. This provides abundance indices that are comparable between species and which give true species capture efficiencies. It furthermore allows comparing capture efficiency for different species.

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## References

- Aglen, A., Engås, A., Godø, O. R., McCallum, B., Stansbury, D. and Walsh, S. 1997. Density dependent catchability in bottom trawl surveys. ICES CM 1997/W:16. 8 pp.
- Albert, O. T., Harbitz, A. and Høines, Å. S. 2003. Greenland halibut observed by video in front of survey trawl: behaviour, escapement, and spatial patterns. *Journal of Sea Research*, 50: 117-127.
- Breen, M., Dyson, J., O'Neill, F. G., Jones, E. and Haigh, M. 2004. Swimming endurance of haddock (*Melanogrammus aeglefinus* L.) at prolonged and sustained swimming speeds, and its role in their capture by towed fishing gears. *ICES Journal of Marine Science*, 61: 1071-1079.
- Breslow N. E. and Lin X. H. 1995. Bias correction in generalized linear mixed models with a single-component of dispersion. *Biometrika*, 82: 81-91.
- Dickson, W. 1993a. Estimation of the capture efficiency of trawl gear. I Development of a theoretical model. *Fisheries Research*, 16: 239-253.
- Dickson, W. 1993b. Estimation of the capture efficiency of trawl gear. II: Testing a theoretical model. *Fisheries Research*, 16: 255-272.
- Engås, A. 1994. The effects of trawl performance and fish behaviour on the catching efficiency of demersal sampling trawls. *In Marine Fish Behaviour in Capture and Abundance Estimation*, pp. 45-68. Ed. by A. Fernö and S. Olsen. Oxford, Fishing News Books, Oxford. 221 pp.
- Engås, A. and Godø, O. R. 1989. The effect of different sweep lengths on the length composition of bottom-sampling trawl catches. *Journal du Conseil pour Exploration de la Mer*, 45: 263-268.
- Fournier, D. 2005. An introduction to AD MODEL BUILDER version 7.0.1 for use in nonlinear modeling and statistics. Available from <http://otter-rsch.com/admodel.htm>.
- Fryer, R. J., Zuur, A. F. and Graham, N. 2003. Using mixed models to combine smooth size-selection and catch-comparison curves over hauls. *Canadian Journal of Fisheries and Aquatic Sciences*, 60: 448-459.
- Glass, C. W. and Wardle, C. S. 1989. Comparison of the reactions of fish to a trawl gear, at high and low light intensities. *Fisheries Research*, 7: 249-266.
- Harley, S. and Myers, R. A. 2001. Hierarchical Bayesian models of length-specific catchability of research trawl surveys. *Canadian Journal of Fisheries and Aquatic Sciences*, 58: 1569-1584.
- Massé, J., Koutsikopoulos, C. and Patty, W. 1996. The structure and spatial distribution of pelagic fish schools in multispecies clusters: an acoustic study. *ICES Journal of Marine Science*, 53: 155-160.
- Myers, R. and Pepin, P. 1990. The robustness of lognormal-based estimators of abundance. *Biometrics*, 46: 1185-1192.
- Ona, E. and Godø, O. R. 1990. Fish reaction to trawling noise: the significance for trawl sampling. *Rapp. P.-v. Reun. Const. int. Explor. Mer*, 189: 159-166.
- O'Neill, M. and Faddy, M. 2003. Use of binary and truncated negative binomial modelling in the analysis of recreational catch data. *Fisheries Research*, 60: 471-477.

- Pedersen, J. 1996. Discrimination of fish layers using the three dimensional information obtained by a split-beam echo-sounder. *ICES Journal of Marine Science*, 53: 371-376.
- Pelletier, D. 1998. Intercalibration of research survey vessels in fisheries: a review and an application. *Canadian Journal of Fisheries and Aquatic Sciences*, 55: 2672-2690.
- Pennington, M. 1983. Efficient estimators of abundance, for fish and plankton surveys. *Biometrics*, 39: 281-286.
- Power, J. A. and Moser, E. B. 1999. Linear model analysis of net catch data using the negative binomial distribution. *Canadian Journal of Fisheries and Aquatic Sciences*, 56: 191-200.
- Reeves, S. A., Armstrong, D. A., Fryer, R. J. and Coull, K. A. 1992. The effects of mesh size, cod-end extension length and cod-end diameter on the selectivity of Scottish trawls and seines. *ICES Journal of Marine Science*, 49: 279-288.
- Shepherd, J. G. 1999. Extended survivors analysis: An improved method for the analysis of catch-at-age data and abundance indices. *ICES Journal of Marine Sciences* 56: 584-591.
- Stefánsson, G. 1996. Analysis of groundfish survey abundance data: combining the GLM and delta approaches. *ICES Journal of Marine Science*, 53: 577-588.
- Terceiro, M. 2003. The statistical properties of recreational catch rate data for some fish stocks off the northeast U.S. coast. *Fishery Bulletin*, 101: 653-672.
- Trenkel, V. M. and Rochet, M.-J. 2003. Performance of indicators derived from abundance estimates for detecting the impact of fishing on a fish community. *Canadian Journal of Fisheries and Aquatic Sciences*, 60: 67-85.
- Trenkel, V.M., Francis, R.I.C.C., Lorange, P., Mahévas, S., Rochet, M.-J. and Tracey, D. 2004. Availability of deep-water fish to trawling and visual observation from an ROV. *Marine Ecology Progress Series*, 284: 293-303.
- Venables, W. N. and Dichmont, C. M. 2004. GLMs, GAMs and GLMMs: an overview of theory for applications in fisheries research. *Fisheries Research*, 70: 319-337.
- Wardle, C. S. 1993. Fish behaviour and fishing gear. *In Behaviour of Teleost Fishes*, pp 607-643. Ed. by T. J. Pitcher, Chapman & Hall, London. 2<sup>nd</sup> edition, 740 pp.
- Welsh, A. H., Cunningham, R. B., Donnelly, C. F. and Lindenmayer, D. B. 1996. Modelling the abundance of rare species: statistical models for counts with extra zeros. *Ecological Modelling*, 88: 297-308.