Aquat. Living Resour. 21, 265–273 (2008)

DOI: 10.1051/alr:2008035
www.alr-journal.org

Aquatic Living Resources

Linking catchability and fisher behaviour under effort management

Hans J.A.E. van Oostenbrugge[1,a], Jeff P. Powell[1], Jos P.G. Smit[1], Jan-Jaap Poos[2], Sarah B.M. Kraak[2] and Erik F.C. Buisman[1]

[1] LEI (Agricultural Economics Research Institute), Fisheries Unit, PO Box 29703, 2502 LS The Hague, The Netherlands
[2] Wageningen IMARES, Wageningen UR, PO Box 68, 1970 AB IJmuiden, The Netherlands

Received 13 September 2007; Accepted 13 March 2008

Abstract – Catchability is crucial for the economic performance of fisheries and their management. However, in many bio-economic simulation models it is assumed to be either constant or it is largely ignored, despite the fact that it is known to vary due to technical, environmental and behavioral factors. Such variation can cause the relationship between effort and fishing mortality to be nonlinear. This paper provides evidence for the possibility of nonlinear optimizing behavior from the Dutch beam trawl fishery, provides a methodology for estimating the curvature of the resulting relation, and a simple way of implementing these processes within a bio-economic model. Moreover, it shows the influence of a nonlinear relationship between effort and fishing mortality in a model of effort management (EU long-term flatfish management plan).

Key words: Non-linearity / Bio-economic modeling / FLR framework / North Sea flatfish fishery

1 Introduction

In fisheries management, catchability is the link between fishing effort and the resulting fishing mortality. Catchability is defined as the proportion of available fish in a population that would be captured by a unit of effort. Because of this relationship, catchability is crucial to the economic performance of fisheries and their management. However, in many bio-economic simulation models catchability is assumed to be either constant or it is largely ignored, despite the fact that it is known to vary due to technical, environmental and behavioral factors (Overholtz et al. 1995; Anon. 2006a). Ignoring the variability of catchability is likely to bias the results of these models and lead to flawed management decisions (Pascoe et al. 2001; Ulrich et al. 2002).

The aim of this paper is to begin to address this shortcoming in the literature by proposing a model that allows catchability to vary. We do so by: (1) estimating the potential effect of the optimization of fishing behavior on catchability in a situation in which effort (total number of sea days) is restricted and providing empirical evidence for the possibility of optimization behavior by fishers within an effort regulated fishery; and, (2) showing the effect of such behavior on catchability and, as a consequence, on fleets and stocks within a long-term management program.

[a] Corresponding author: Hans.vanOostenbrugge@wur.nl

Variation in catchability has been studied extensively, generally for purposes other than bio-economic modeling, namely to standardize catch per unit of effort (CPUE) data as an indicator of fish abundance (e.g. Addisson et al. 2003; Bishop 2006; Marchal et al. 2003; Olin et al. 2004). Many experimental studies provide information about the effects of technical gear characteristics, environmental factors and fish behavior on catchability, and this knowledge is incorporated in the use of fish surveys. Data from commercial fisheries can provide an inexpensive alternative to these surveys. However, the value of such data is limited by the targeting behavior of fishers. For example, Ellis and Wang (2007) showed for the Australian northern prawn fishery that targeting behavior increased catchability in some areas by 10%. However, in these studies no link was drawn to management measures and the effects changes in catchability can have on their results.

Fisher behavior has been taken into consideration in management evaluations, but is most often concerned with the effects of spatial management measures, such as marine protected areas (Pelletier and Mahevas 2005). The main assumption in these models is that fishers optimize their behavior in order to maximize their utility (Hutton et al. 2004). However, with a few exceptions, these models only simulate short-term effort reallocation and do not assess the effects on catchability (Pelletier and Mahevas 2005).

Article published by EDP Sciences

Certain processes underlying the variation in catchability of commercial fishing fleets have been studied. It has been found that technical developments in the fishing fleet may increase catchability over time (technical creep) which may bias assessments that use catch data and predictions of bio-economic models (e.g. Pascoe et al. 2001; Ulrich et al. 2002 and Rijnsdorp et al. 2006). Also, management measures such as the introduction of exclusion zones affected the cacthability of the fleet, partly through reallocation of fishing effort (Pascoe et al. 2001). Both Ulrich et al. (2002) and Rijnsdorp et al. (2006) studied technical creep in relation to restrictions in fishing effort. Using a bio-economic simulation model, Ulrich et al. (2002) showed that the outcomes of the total allowed effort limits (TAE) were especially sensitive to variability in catchability, while incorrect catchability parameters in the model resulted in underestimation of the fishing mortality and overestimation of the spawning stock biomass (SSB). Rijnsdorp et al. (2006) studied effort and fishing mortality to fine-tune management regulations, noting that through the optimization behavior of fishers, fishing mortality could be affected less than proportionally by effort reductions.

Since the introduction of management plans, effort limitations have become more popular in EU Atlantic fisheries. Insight into how fishers can be expected to react and thereby change catchability will be of critical importance to the success of these plans. The main goal of these effort limitation plans is to reduce excess fishing and the resulting discards caused by the misbalance in single species TACs.

One of the models that takes changes in catchability into account is the EIAA model which was developed to evaluate the economic effects of TAC restrictions in the EU (Anon. 2005). The model calculates fishing activity using a Cobb-Douglas type inverse production function, and it uses information on all relevant TACs, SSBs, prices and historical landings of non-TAC species. The model assumes that all TACs can be taken and that landings of non-TAC species will not change. The price by species is included in the activity function and assumes that fishers have an incentive to first use fishing effort on species with the highest value. The weighing procedure results in an average and less than proportional change of activity compared to changes of the TACs. The EIAA model tends therefore to produce lower catchability rates. Thus it is not a very suitable tool for the evaluation of effort restrictions when one would expect that the optimization behavior of fishers would result in increased catchability (Anon. 2006b).

The starting point of our analysis of the fishing process is that as effort becomes more restrictive, fishers have to drop fishing trips. Because they want to optimize their utility, which we assume to be economic utility, they will drop those trips that they perceive to have the lowest expected economic benefit; the least efficient trips are thereby omitted from the fisher's portfolio. The sequence of events outlined applies to individual fishers as well as to the total fishing fleet if fishing rights can be easily transferred from one vessel to another thereby enabling fishers to redistribute fishing opportunities. Because of this desire to optimize, the average annual catchability of species will change: The catchability of target species, from which the catches are positively correlated with the total value of the catch, will increase (Fig. 1). The catchability of non-target species might increase or decrease, depending on the co-occurrence of the species with the target species.

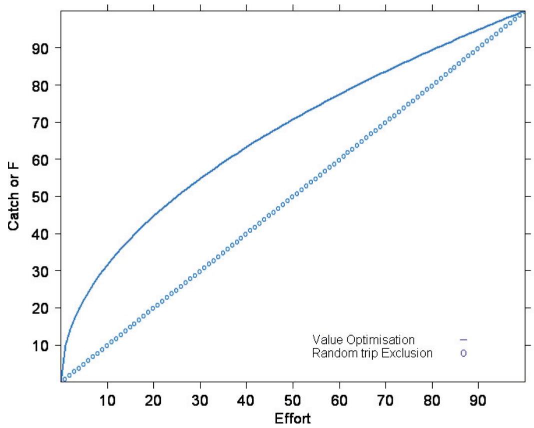


Fig. 1. Relationship between catch of a target species and effort (both as the percentage of the initial value) in the case of random exclusion of fishing trips and catch value optimization.

Our analysis is divided into two sections. The first section uses historical data to estimate the relationship between cumulative effort and catch. The second section incorporates the findings into a simulation model. We use the case of the Dutch North Sea flatfish fishery to conduct our analysis. This fishery is the most important fishery for plaice and sole, contributing to 39% of the total plaice and 70% of the total sole catch from the North Sea in 2006 (ICES 2007). More than 80% of the plaice and 90% of the sole landings of these species are realized by vessels with engines greater than 1500 hp and over 24 m (Anonymous, 2006c). The two main target species make up more than 82% of the total value of the landings of these vessels. Since 2002, effort has been increasingly restricted for these vessels due to the cod recovery plan (EC, 2004). In addition, in 2007, a flatfish recovery plan (EC, 2005) with effort restrictions was introduced. The aim of the plan is to reduce fishing mortality by half over the coming years by reducing fishing mortality by 10% each year until values of 0.2 for sole and 0.3 for plaice are achieved. These goals are to be reached through both TAC and effort reductions.

2 Material and methods

2.1 Historical analysis

The possibilities for optimization were analyzed by means of a cross-sectional analysis of landings data from large Dutch beam trawlers (>1500 hp) from 2001–2006. Catch and effort data were analyzed at the trip level and taken from official logbook data gathered by the Dutch ministry of Agriculture, Nature and Food Quality. These data include catch and effort data per trip and species, the date and time at which ships depart and return from a trip, the name of the ship, the power of the main engine, and the ICES rectangle in which fish were caught.

Total value per unit of effort (VPUE) was used as a proxy for the utility of a trip, where value is defined in terms of revenues and effort is defined as hp-days. Values were calculated using logbook catch and effort information. Prices of the species in a trip were based on the monthly average price statistics from Dutch fish auctions.

$$VPUE_t = \frac{\sum_i C_{it} \times p_{im}}{f_t} \tag{1}$$

where

$VPUE_t$	= Value per unit of effort of the t^{th} trip,
C_{it}	= Catch of i^{th} species in the t^{th} trip,
p_{im}	= Average auction price of i^{th} species in m^{th} trip,
f_t	= Effort of the t^{th} trip expressed in hp-days.

It was assumed that given a reduction in effort fishers will skip those trips which they believe will add the least to their total utility. Fishers are not expected to incorporate the share of the value of a trip which derives from random variation into their decisions of which trips to take. Therefore, an analysis of variance (ANOVA) was used to provide estimates for the VPUE for each trip based on general spatial and temporal patterns and differences among ships. We assumed that the estimated VPUE from the ANOVA resembled the "true" value of a trip which fishers then use to rank trips, as random variation is averaged out. The catches were $\log_{10}$-transformed to meet the conditions for parametric analysis of variance. The model used was:

$$LVPUE_{ijk} = \mu + v_i + m_j + a_k + \varepsilon_{ijk} \tag{2}$$

where

$LVPUE_{ijk}$	= $\log_{10}$ Value per unit of effort,
μ	= overall mean,
v_i	= effect of i^{th} vessel,
m_j	= effect of j^{th} month,
a_k	= effect of k^{th} area,
ε_{ijk}	= error.

Non-significant terms were removed from the model. Residuals were tested for normality and 95% confidence limits were calculated to compare main group means in case of significant effects.

The estimated values from the ANOVA were used as a proxy for the expected value of a trip and, in turn, to estimate the relationship between effort and the catchability of plaice and sole. The procedure used was to sort trips in descending order based on their estimated VPUE. Hereafter, catches of plaice and sole and effort were accumulated over the trips and the relationship between cumulative effort and cumulative catch was estimated for both species using a simple regression analysis. In the analyses the catchability (q) is assumed to depend on the effort (f) in the following way:

$$q = a \times f^b. \tag{3}$$

Where b is a constant between –1 and 0, indicating the non linearity of the relationship and a is a constant relating to the average level of the catchability. The functional form of this relationship follows from the need to have a continuous, non-linear increasing relationship between catches and effort. Based on a Cobb-Douglas production function, it reflects diminishing returns to scale. This standard production function has been widely used to model the relationship between inputs and outputs in the economic literature (see e.g., Varian 1992).

Assuming a constant exogenous stock abundance within a year, the relationship between cumulative catch and cumulative effort can be used to estimate the beta by using the following regression model:

$$C_i = \alpha \times f^{\beta} \times \varepsilon_i \tag{4}$$

where C_i is cumulative catch of plaice or sole, f is cumulative effort expressed in hp-days, α and β regression are coefficients and ε_i is the error term. The regression coefficient β is an estimate for the constant b in formula 3 **plus 1**, as all terms in equation (3) are multiplied by f to come to equation (4). This methodology was similar as in Kraak et al. (2004).

2.2 Model simulations

To demonstrate the effect of the non-linear relationship between effort and catches (and thereby fishing mortality), the estimated relationship between effort and catchability was incorporated into a dynamic simulation model for the North Sea flatfish fishery built using the FLR framework which is a collection of tools programmed in the computer language R that facilitates the construction of bio-economic simulation models of fisheries and ecological systems (Kell et al. 2007).

The model was built to evaluate the effects of the long-term flatfish management plan as evaluated by STECF (Scientific, Technical and Economic Committee for Fisheries, Anon. 2006) in September 2006. Later changes to the management plan have not been taken into consideration in this study. In its basic form, it was designed to simulate the impact of the management plan on stock size and landings over a number of years. In the model, ICES stock assessments and advanced biological relationships of, for instance, stock recruitment and growth, are combined to create age-structured models of sole and plaice populations. These biological components are combined with management procedures including the harvest control rules specified in the EU management plan. For the purposes of this paper, an important assumption of the IMARES model (Wageningen IMARES) is that there is a linear relationship between effort and fishing mortality. A main contribution of the model in comparison with standard ICES work is that it provides an approach to combine management and assessment of two stocks.

On the basis of the EU management plan, the harvest control rule within the model calculates fishing mortality rates using Article 4 to set a TAC for plaice, Article 5 to set a TAC for sole, and a complementary effort limit specified in Article 6. The model simulates the stock dynamics for plaice and sole, multiple fleets, and the fisheries management, including assessments and management decisions over a specified period of years. For the simulation years under consideration, 2006 to 2012, the model links effort reduction (Article 6) directly to a reduction of fishing mortality, which means that the effort multiplier is reduced by 10% per year and results in a reduction in effort from 21,255 in 2006 to 11,296 in 2012. More information on the model features can be found in Machiels et al. (2007).

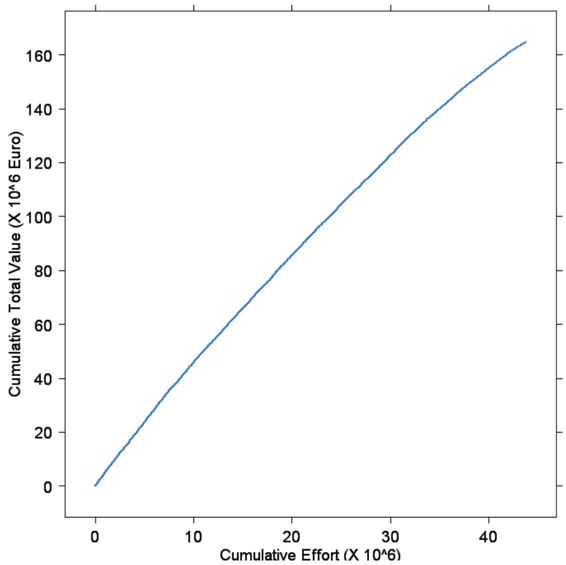


Fig. 2. Relationship between the cumulative value of landings and cumulative effort for 2006. Sorting of trips is based on estimates of an ANOVA (see text).

The approach taken was to adjust the catchability for each year using the following Formula based on formula 3:

$$q_j = q_0 \times \left(\frac{f_j}{f_0}\right)^b. \tag{5}$$

Where

q_j = catchability in year j,
q_0 = catchability in year 0,
f_j = fishing effort in year j,
f_0 = fishing effort in year 0.

Resulting catches and fishing mortalities were calculated using the adjusted catchability for each year of the simulation period. Simulations over a period of 6 years (2006–2012) were conducted for 3 values of the coefficient b: 0 (in the case of constant catchability) and, –0.2 and –0.4. Values of the coefficient were set equal for both species. Simulation results for each of the scenarios were compared with regards to their impact on spawning stock biomass, catch, total value of the catch, gross added value to the fishery.

3 Results

3.1 Historical analysis

Figure 2 was constructed using data from 9293 trips in 2006 and illustrates the relationship predicted in Figure 1; similar figures appear for the years 2001 to 2005. In short, using historical data and the behavioral assumptions specified in the previous section, it is possible to construct a plausible, *non-linear* relationship between ordered, cumulative value of the landings without random fluctuations and cumulative effort.

Table 1 shows the key variables that might allow a fisher to distinguish between the values of a trip. The ship, area and month variables together account for 61% of the variability of the value of a trip.

Table 1. Analysis of variation for the model including ship, quadrant and month variables.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Ship	105	319.84	3.05	79.520	$<2.2 \times 10^{-16}$
Area	91	64.76	0.71	18.577	$<2.2 \times 10^{-16}$
Month	11	159.66	14.51	378.902	$<2.2 \times 10^{-16}$
Residuals	9085	348.01	0.04		

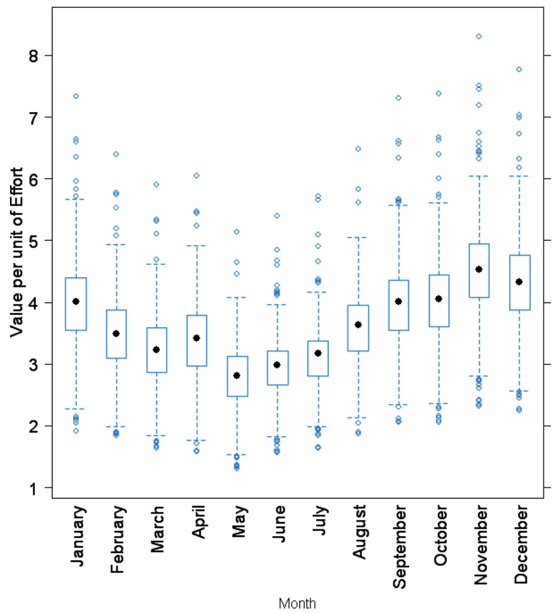
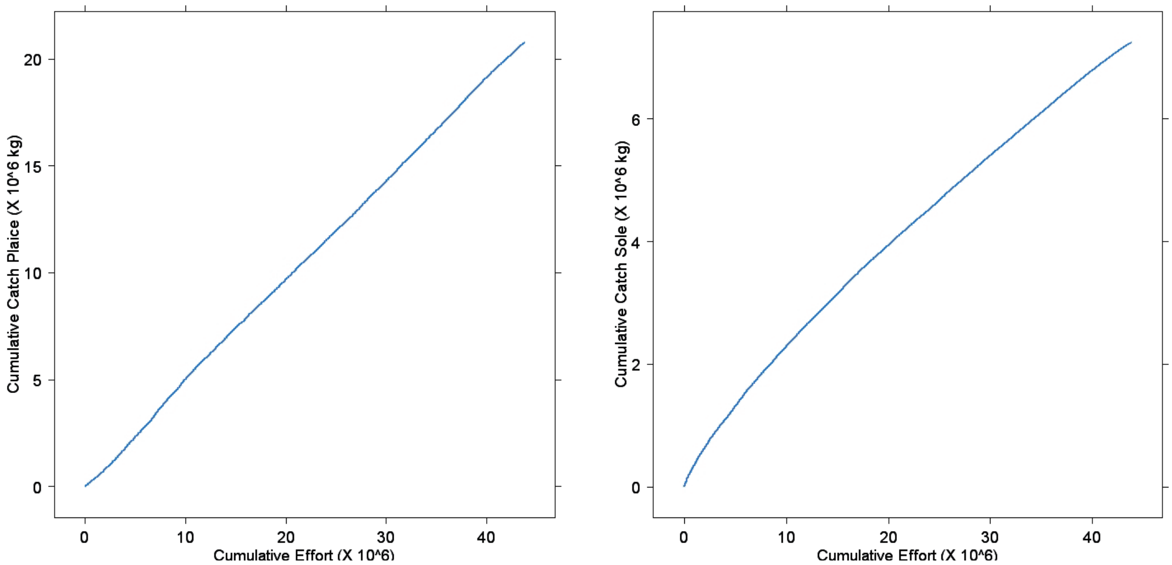


Fig. 3. Differences in total value per unit of effort (VPUE) per month over the year 2006.

The most important factor responsible for the variation in VPUE was the vessel, accounting for 36% of the total variability. Additional analysis of the average VPUE for 106 ships in the year 2006 shows a wide range in values among ships, from a low of 1.9 Euros per unit of effort to a high of 6.4 with a mean of 3.7. Some ships, whether because of differences in the physical characteristics of the ship or differences in the skills of captain and crew or some other characteristic, are consistently and predictably better than others at catching fish, implying that the implications of a reduction of effort will impinge on some owners more than others.

Similarly, differences in the average VPUE caused by differences in the month fished account for 18% of the observed differences in the value of a trip (Fig. 3). Average values range from a low of 2.8 Euros per unit of effort in May, to a high of 4.5 in November. Therefore, a reduction in effort, all else equal, will mean that less profitable trips in the month May should be dropped from the fisher's portfolio before those trips made in, say, November. Finally, the area variable accounts for a modest 7% of the variability in the value per unit effort over the year. The decision as to where to fish appears to have less of an impact on the variation in the value of a trip than the other two variables; a reduction in effort will therefore have relatively little influence on where fishers fish.



(a) (b)

Fig. 4. Relationship between the cumulative catch of plaice (left) and sole (right) versus cumulative effort for Dutch large beam trawlers for 2006.

Table 2. Estimations of regression parameters for relationship between cumulative catches for plaice and sole and cumulative effort for 2006. A smaller ß estimate value implies greater curvature in the relationship between catchability and effort and thereby catch and effort ($b = \beta$–1).

	Estimate	Std. Error	*t* value	Pr(> |*t*|)
Plaice[1]				
α	0.037335	0.011266	3.314	0.000923
β	0.957542	0.000679	1409.3	$<2\times10^{-16}$
Sole[2]				
α	1.31815	0.00526	250.8	$<2\times10^{-16}$
β	0.829385	0.00032	2616.1	$<2\times10^{-16}$

[1] Adjusted R-squared: 0.9956.
[2] Adjusted R-squared: 0.9987.

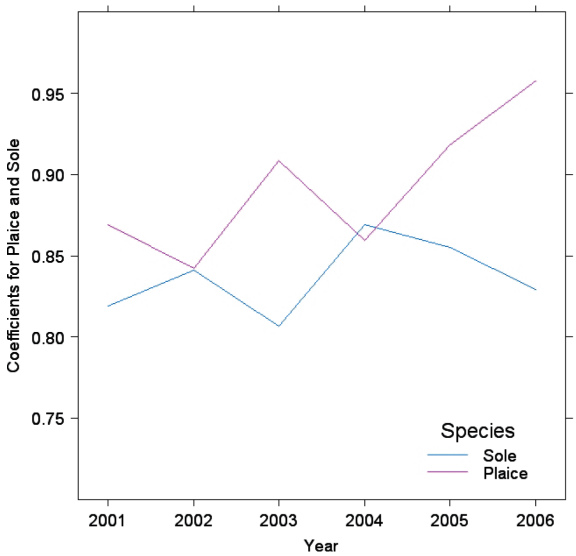


Fig. 5. Coefficients of curvature (β-estimates) for plaice and sole. A smaller coefficient, all else equal, results in greater curvature.

Figure 4 shows that, just as in the case of value, catch for both plaice and sole is decreasing per unit of effort expended. A reduction in effort will mean first dropping those trips with less expected catch. However, it is the difference between the figures of sole and plaice that is of real interest. Comparison of the two figures indicates a greater curvature for sole than that for plaice, perhaps, implying that sole was the species driving fisher behavior.

Regression results from running equation (4) (Table 2) confirm a preliminary examination of Figure 4 and indicate that the curvature of the relation between cumulative catch and cumulative effort is greater for sole than for plaice in 2006.

However, the greater observed curvature of sole in 2006 is not consistent over time. While the means of the coefficients that express the degree of curvature over the years are nearly identical (plaice = 0.89, sole = 0.84), they are negatively correlated over the period 2001-2006 (Fig. 5). The figure indicates that for years 2002 and 2004 the value of sole and plaice per unit effort could both have been of nearly equal importance in motivating the priority of fishing trips. In other years, the value of sole per unit of effort was the primary motivation behind decisions of when and where to fish, a motive that appears to be of increasing importance in recent years as shown by the fall in the coefficient for sole and the increase in that of plaice.

One straightforward explanation that accounts for the negative correlations observed in Figure 5 is the fact that our observations come from a mixed fishery. In years when variation in revenue per unit of effort is caused by highly variable sole landings per unit of effort, plaice landings per unit of effort have been more stable. Variability of landings per unit effort

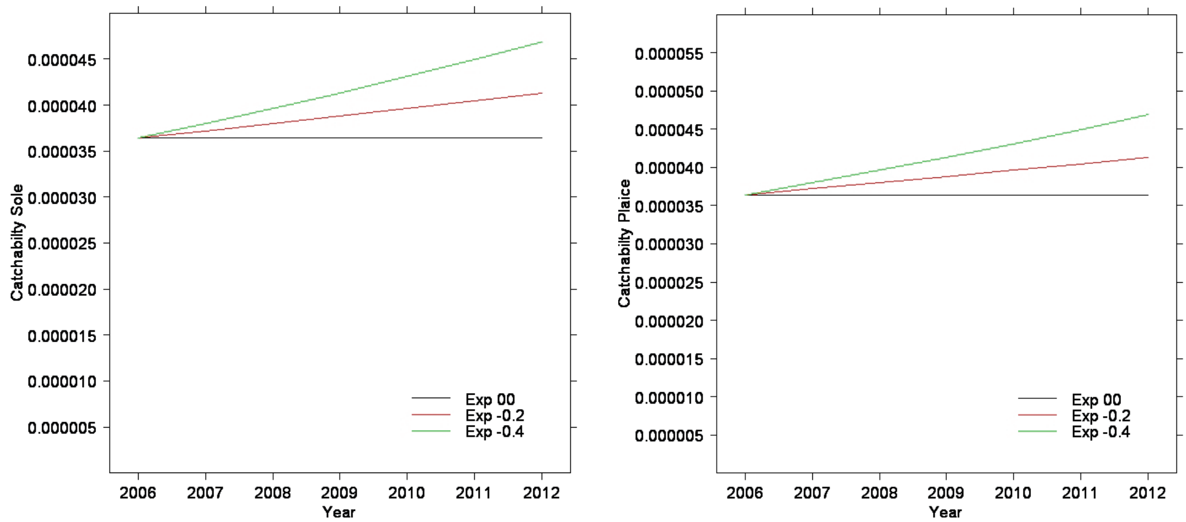


Fig. 6. Three exponents of curvature (b) and their respective impact on the catchability of sole and plaice.

may be caused by various reasons, for example, given effort limitation, fishers made their choices of which trips to conduct based primarily on the TAC they perceive to be less constraining. Other causes of variable landings per unit of effort are seasonal price changes and temporal closures of the fishery (in 2001 and 2003).

Our model for estimating the curvatures of catch is simplistic. However, adding terms, such as a non-linear variable for the month fished, did not appreciably change the results. Residuals from the model show a slightly periodic structure that should be better accounted for in further studies. The results were also skewed by data with a higher catch per effort. The decision was made to keep these data (less than 20 data points out of more than 8600 for year 2006) within the data set until there is positive evidence that they represent errors.

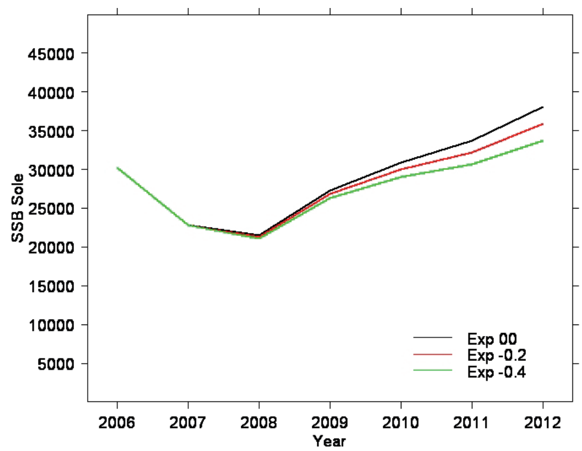


Fig. 7. Evolution of the spawning stock biomass (SSB) estimates of sole for model runs with different values of exponents of curvature (b). SSB will be lower given a smaller, more negative, exponent.

4 Simulation analysis

The parameters were implemented within the IMARES model by using Equation (5) above. Moreover, the model was adjusted to ensure that the fishing opportunities were only restricted by the effort reduction in the management plan (10% reduction each year). The following results compare three scenarios, the Exp 00 is the linear case, while the Exp –0.2 and Exp –0.4 represent non-linear cases when the coefficient b in Equation 5 are, respectively, –0.2 and –0.4. An effort that is smaller than the base year, raised to a negative power, will result in a larger catchability for the simulated year (Fig. 6).

As previously discussed, the EU harvest control rules implemented in the IMARES model resulted in a reduction in effort of 10% for each year of the simulation. That, along with the negative values for coefficient b we estimated, results in the continuous increase in catchability for both non-linear scenarios for both sole and plaice. This caused an increase in catchability of around 28% in 2012 in the case of the scenario for sole with coefficient $b = -0.4$ compared to the linear case, having both biological and economic implications. In comparison to the linear case, both non-linear cases result in larger fishing mortality rates than intended by the application of the HRC and hence smaller SSBs (Fig. 7). The figure shows the situation for sole, the impact on plaice is similar; for instance, in the last year of the simulation with an exponent of –0.4, the SSB for plaice was about 18% smaller than that of the linear case.

A higher catchability, all else equal, means that the chance that an individual fish will be caught by gear will increase, so that a lower SSB does not necessarily translate into a lower catch. In fact, the economic results predicted by the IMARES model show that the economic implications continue to be positive; the results for the non-linear cases are better than predicted by the linear case because the increase in catchability for a given amount of effort will more than offset the reduction in SSB (Fig. 8).

However, there appear to be limits to the ability of higher catchability to offset the lower SSB. Figure 7 shows that while landings for both non-linear cases are greater than the linear case for each year of the simulation; landings for the non-linear

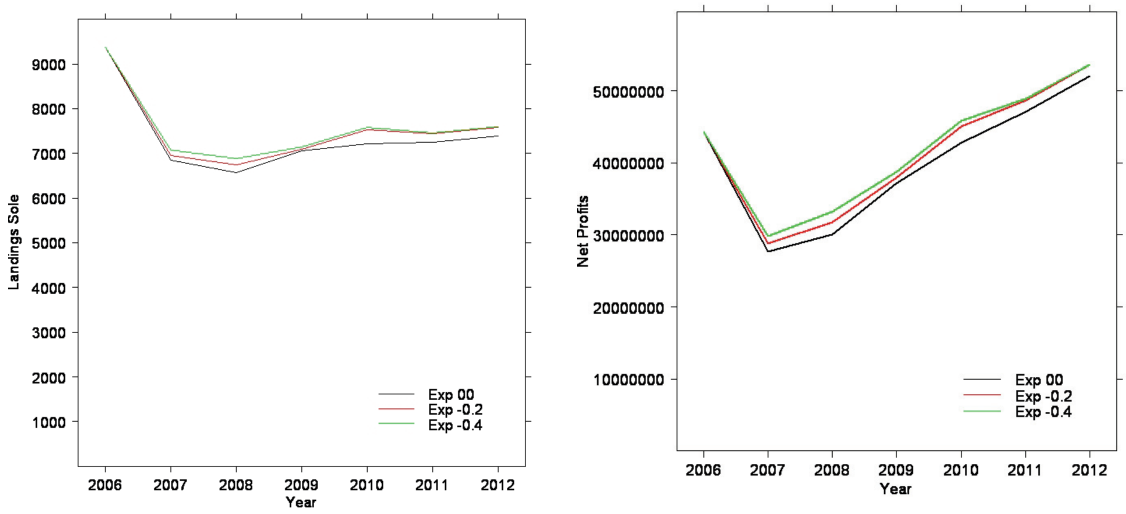


Fig. 8. Evolution of sole landing and net profits for model runs with different values of exponents of curvature (b). Higher catchability for a given effort means higher than expected landings and profits.

cases appear to converge. As simulation time progresses, landings when the exponent is equal to –0.4 fall toward the landings when the exponent is equal to –0.2. Eventually, a higher catchability reduces the increase in SSB to such a degree that resulting landings in both non-linear scenarios are nearly equal. As previously noted, landings in both non-linear scenarios never fall to those levels of the linear case and revenues in both scenarios remain above the linear scenario during this time horizon. However, it may be the case that if the simulation runs had been extended over a longer period beyond 2012, the landings and revenues of the non-linear cases may fall to, or even below, the levels of the linear case. Results for plaice were similar to those reported for sole. In the last year of the simulation landings for plaice of both non-linear cases converge, but remain above that of the linear case. Finally, as a direct result of the higher catches for both species in the non-linear cases, total revenues for those cases were above the linear case for each year of the simulation. Once again, revenues for the non-linear cases converged in later years as landings converged.

5 Discussion

Our results show it is theoretically possible for fishers to rank trips in terms of their utility, because they can be distinguished by the value they are expected to provide. This ranking can occur at the level of the fisher, and, given tradable fishing rights and a well-functioning market for those rights, across the entire fleet. Our contention is that a reduction in total allowed effort will cause average catchability to rise as fishers drop less profitable trips from their portfolios, a contention that is in agreement with conclusions drawn by Rijnsdorp et al. (2006). In turn, an increase in average catchability means that a reduction in effort will yield smaller reduction of the fishing mortality and have less of an impact on SSB than that implied by a linear relationship linking catch to effort. Results from the simulation model show that ignoring this effect and hence under-estimating catchability will result in a lower than expected SSB, a larger than expected catch, and higher than expected revenues for the years simulated. If the possibility of such behavior is accepted, then a policy intended to reduce the fishing mortality rate should take such behavior into account.

The results of the analysis underline difficulties which may arise when managing a fishery by attempting to control fishing effort. If fishing effort is defined by a simple index such as horse power-days at sea, even in the short-run non-linear responses to effort change might be expected due to the fact that inputs in the individual production function are substitutable, which implies that profit maximising fishers not only choose the most profitable trips, but also the most profitable combination of inputs. The results of this study indicate that such flexibilities are at least in the short run not very large for the fleet in question. This could be explained by the high degree of specialisation and the rules in place for the design of other inputs like engine and gear.

Our model assumes an exponential relationship between catchability and effort and between catches and effort. As stated in the material and methods section, the functional form of this relation is chosen because of the need to have a continuous, non-linear increasing relationship between catches and effort, and the economic background of this functional form. Other functional forms such as a linear relationship between catchability and effort might lead to a better fit of the data, in specific situations. However, changing the functional form does not change the principle that the optimization behavior of fishermen will increase catchability for target species in an effort limited situation and leads to higher fishing mortalities. Moreover, using, e.g., a linear functional form might lead to unrealistic negative revenues/landings in case of extrapolation.

Our measures are perhaps not as refined as we would like them to be. For instance, we use monthly data in the ANOVA when an analysis based on weekly data (Rijnsdorp 2006) would have yielded more variation and thereby greater curvature. However, initial analysis shows that the effects of such refinements are limited. Greater refinement in the differentiation of areas might also be possible and lead to better results. In addition, we are underestimating the ability of fishers to vary their behavior by only including the effects of the ship, area and season. Fishers undoubtedly have other means to change their behavior, our variables account for only around 60% of the calculated variation. These factors taken together mean that our *b* estimates, and therefore the resulting catchability variables, will be lower than the potentially achievable estimates.

In addition, our analysis is simplistic in that it only looks at the direct impacts of a reduction in effort, and not the resulting reactions of fishers. Two examples will help to illustrate the issue. First, in our analysis we assume that less valuable trips will be dropped, but price flexibilities may induce frequency dependence, where effort reductions cause price increases and incentives for increasing effort. The second example involves the changes in effort allocation as a result of fleet dynamics. Given the variation in economic performance, less profitable ships might be forced to withdraw from the fleet given a big enough reduction in effort. This will enable the remaining ships to extend their effort. The effect of exchanging the most profitable trips from less profitable vessels for least profitable trips of more profitable ships is not clear. A more complete model would take into account these reactions and interactions between the values of fishing trips after an effort reduction, but this would quickly become highly complex.

There are some other limits to the analysis used in this paper, some of which can be surmounted using more data and better analytical techniques, and some of which are less tractable. First, we are limited to six years of data from 2001–2006, and only during the last two years did effort become the limiting constraint. This analysis is limited to the reaction of fishers to changes in effort, making years 2005 and 2006 the most relevant years. The form of the data would ideally reflect effort restricted behavior. Second, we use only large beam trawlers (horsepower > = 1500). Although all sizes of ships could have been included in the analysis, the complexity required to account for technical and behavioral differences among the various classes of ships would make the analysis far too complex for current purposes. Third, the measure of utility is not ideal, we use the value of a trip, measured in terms of the total value of all fish caught during a trip, divided by effort, measured by the horsepower and the number of days at sea of a trip. A more thorough estimate of utility, for instance, one that included the major variable costs of a trip. Better data does exist for calculating profits for part of the fleet. In a related issue, we make the simplifying assumption that the behavior of fishers is expressed in their ability to choose among different seasons and areas, as well as those differences due to specific ship characteristics. There are undoubtedly other factors influencing utility, but we are limited in our ability to decipher those factors by a lack of data. Data Envelopment Analysis (DEA) (Fare et al. 2001) could be used in future studies to identify these factors.

Despite these drawbacks, the method used can be used to get an idea of the changes in catchability resulting from effort restrictions. These can be very important in impact assessments of management plans which include effort limitations as a means to reduce fishing mortality. In addition, our method of valuing and ranking trips has the advantage of being easy to implement and understand while the general approach can be applied across fleets.

Acknowledgements. This study was carried out as part of the EU co-funded projects COMMIT and EFIMAS. The commission is acknowledged for their financial contribution. We want to thank M.A.M. Machiels (Wageningen IMARES) for his contribution to the implementation if the simulation model used. We thank our EFIMAS and COMMIT colleagues for their valuable comments and discussions. Also, we thank the two anonymous reviewers for their useful comments. The Dutch Ministry of Agriculture, Nature and Food Quality is thanked for the use of the logbook data base.

References

Addison J.T., Lawler A.R., Nicholson M.D., 2004, Adjusting for variable catchability of brown shrimps (*Crangon crangon*) in research surveys. Fish. Res. 65, 285–294.

Anonymous, 2005, Economic performance of selected European fishing fleets in 2004. The potential economic impact on selected fishing fleet segments of TACs proposed by ACFM and reviewed by SGRST for 2006 (EIAA-model calculations). No FISH/2005/12. http://stecf.jrc.cec.eu.int/sgeca/eaef/2005.php.

Anonymous, 2006a, Commission Staff Working Paper: Report of the joint SGECA - SGRST sub-group meeting on bio-economic modeling, ISPRA 4-6 October 2005 and 7–9 March 2006, 92 p. + annexes.

Anonymous, 2006b, Commission staff working paper, Impact assessment: plaice and sole long-term management SGECA-SGRST-06-05 Brussels, 26-29 Sept. 2006 http://fishnet.jrc.it/c/portal/layout?p_l_id=PUB.1013.20.

Anonymous, 2006c, Economic performance of selected European fishing fleets. Annual report 2005, March 2006.

EC, 2004, Council Regulation (EC) No 423/2004 of 26 February 2004 establishing measures for the recovery of cod stocks, Off. J. Eur. Union 9.3 pp. 8–11.

EC, 2005, Proposal for a council regulation establishing a management plan for fisheries exploiting stocks of plaice and sole in the North Sea. COM(2005) 714 Final, 2006/0002 (CNS).

Bishop J., 2006, Standardizing fishery-dependent catch and effort data in complex fisheries with technology change. Rev. Fish Biol. Fish. 16, 21–38.

Ellis N., Wang, Y.-G., 2007, Effects of fish density distribution and effort distribution on catchability. ICES J. Mar. Sci. 64, 178–191.

Fare R., Grosskopf S., Kirkley J.E., Squires D., 2001. Data envelopment analysis (dea): a framework for assessing capacity in fisheries when data are limited. IFFET 2000 Proc. 10th Biennial Conference of Fisheries Economics and Trade Oregon State University, July 10–14, Corvallis.

ICES, 2007, Report of the ICES Advisory Committee on Fishery Management, Advisory Committee on the Marine Environment and Advisory Committee on Ecosystems. ICES Adv. Books 1, pp. 10–16.

Hutton T., Mardle S., Pascoe S., Clark R.A., 2004, Modelling fishing location choice within mixed fisheries: English North Sea beam trawlers in 2000 and 2001. ICES J. Mar. Sci. 61, 1443–1452.

Kell L.T., Mosqueira I., Grosjean P., Fromentin J.M., Garcia D., Hillary R., Jardim E., Pastoors M., Poos J.J., Scott F., Scott R.D., 2007, FLR: an open-source framework for the evaluation and development of management strategies. ICES J. Mar. Sci. 64, 640–646.

Kraak S.B.M., Buisman F.C., Dickey-Collas M., Poos J.J., Pastoors M.A., Smit J.G.P., Daan N., 2004, How can we manage mixed fisheries? A simulation study of the effect of management choices on the sustainability and economic performance of a mixed fishery. ICES Doc. CM 2004/FF, 11.

Machiels M.A.M., Kraak S.B.M., Beek F.A. van, 2007, Evaluation of a management plan as proposed by the European Commission in 2006 for fisheries exploiting stocks of plaice and sole in the North Sea. Wageningen IMARES Rep. C011/07.

Marchal P., Ulrich C., Korsbrekke K., Pastoors M., Rackham B., 2003, Annual trends in catchability and fish stock assessments. Sci. Mar. 67, Suppl. 1, 163–73.

Olin M., Kurkilahti M., Peitola P, Ruuhijärvi J., 2004, The effects of fish accumulation on the catchability of multimesh gillnet. Fish. Res. 68, 135–147.

Overholtz W.J., Edwards S.F., Brodziak K.T., 1995, Effort control in the New England groundfish fishery: a bio-economic perspective. Can. J. Fish. Aquat. Sci. 52, 1944–1957.

Pascoe S., Andersen J., Wilde J.W. de, 2001, The impact of management regulation on the technical efficiency of vessels in the Dutch beam trawl fishery. Eur. Rev. Agr. Econ. 28, 187–206.

Pelletier D., Mahévas S., 2005, Spatially explicit fisheries simulation models for policy evaluation. Fish Fish. 6, 307–349.

Rijnsdorp A.D., Daan N., Dekker W., 2006, Partial fishing mortality per fishing trip: a useful indicator of effective fishing effort in mixed demersal fisheries. ICES J. Mar. Sci. 63, 556–566.

Taal C., Bartelings H., Klok A., van Oostenbrugge J.A.E, Vos B. de, 2006, Fishery in figures 2006 (in Dutch). Agricultural Economics Research Institute, LEI Rep. 06-04, LEI The Hague.

Ulrich C., Pascoe S., Sparre P.J., De Wilde J.W., Marchal P., 2002, Influence of trends in fishing power on bioeconomics in the North Sea flatfish fishery regulated by catches or by effort quotas. Can. J. Fish. Aquat. Sci. 59, 829–843.

Varian H., 1992, Microeconomic Theory. 3rd edition, W.W. Norton.