



Causes and consequences of fleet diversity in fisheries: The case of the Norwegian Barents Sea cod fishery

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Abstract

Fisheries operate under fluctuating environmental conditions, targeting fish stocks that appear in varying densities in different areas, often with abrupt and unexpected local changes. Physical conditions, markets and management regulations constrain vessels in different and varying ways. These factors all contribute to forming the fleet diversity we find in most fisheries. Here, a simulation model of the Northeast Arctic cod fishery is used in order to investigate how this diversity is formed and maintained, assuming rational economic behaviour under varying combined constraints. The study also focuses on how the ability of vessels to find fish influences fleet diversity, profitability, stock development and seasonal profiles of the fishery. Results indicate that an increased ability to target the most profitable fishing grounds may influence fleet diversity positively or negatively, depending on overall exploitation level. High exploitation rates also increase the temporal fluctuations in fleet diversity and profits, which are amplified as the fish-finding ability increases.

Introduction

The seminal works of Scott Gordon and Anthony Scott in the mid-fifties (Gordon, 1954; Scott, 1955) introduced a modelling framework to analyse open access fisheries. The approach became extremely popular, with a vast number of later publications, textbooks, lectures, and talks showing the tremendous impact the two Canadian economists had on the development of fisheries economics and bioeconomic theories.

Highly simplified biological dynamics and simple economic models aimed to grasp some essential features of fisheries dynamics, but how useful the simplified approach has been in many of the studies that followed may be questioned. Unfortunately, it is fair to say that the effort put into this approach is not reflected in a corresponding influence in fisheries management; it never became a very successful tool in the management of real fisheries.

According to the simplified approach, assuming economically rational behaviour, only the most cost-efficient vessel units will survive in the long run in an open access fishery. The single-species, single-fleet Gordon-Schaefer model (G-S-model) therefore fails to explain how a diverse fleet develops and why it remains; more so, the basic assumptions are contradicted by the pure existence of diverse fleets in most all fisheries. It is with this background that one has to understand Wilen's (2000) statement: "the practical importance of most of this work over the period has been negligible, especially relative to the intellectual effort embodied".

Ironically, the only major contribution to practical fisheries management from the fisheries economists is probably the concept of individual transferable quotas, which bases its theoretical foundation on a modelling framework that assumes a homogeneous fleet to analyse the dynamics of a diverse fleet (Arnason, 1990). Terry Heaps (1993) pointed out this fallacy in logic and exemplified how the error would lead to significantly fewer vessels than what was socially optimal. In most cases, however, retaining a diverse fleet is seen as a socially desirable objective (Morgan, 1995), unintentionally correcting for this fallacy.

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However, there are other and perhaps even more serious problems related to the assumption of a homogeneous fleet in the analysis of the dynamics of fisheries. In a recent publication, Burgess and Rochet (2014) shows how fleet diversification creates opportunities for larger profits. The diversification relates to several dimensions, the most important being fishing technology, target species and spatial distribution (fishing grounds and homeports).

Even though the principles of the G-S-model provide the basis for the core modelling approach in most bioeconomics studies by far, an increasing concern for the importance of fleet diversity and spatial issues has emerged over the last decades, launching a number of different modelling ideas. This increasing concern is a general trend, particularly related to the growing interests in marine protected areas.

While Sanchirico and Wilen (2001) found it natural to retain the G-S-modelling principles of equilibrium harvest and also include spatial distributions, Seijo and Caddy (2008) used different modelling alternatives. Seijo and Caddy (2008) studied spatial management challenges when considering different ports in a simulation model where cost of fishing increases by distance. The biological part was age-structured and utilised a Beverton and Holt recruitment model (1957), while the distribution of fishing effort followed the distributions of profits in the previous period of time. Though using very different approaches, both Sanchirico and Wilen (2001) and Seijo and Caddy (2008) operated with highly diversified fleets in their models, driven by varying the spatial distribution of stock densities but also by economic factors.

Also, several biological studies have aimed to model the distribution of fishing effort, including density, dispersion or knowledge parameters. Three different applied perspectives are to: (1) develop statistical models to improve estimates of stock density distribution from survey data (Lewy and Kristensen, 2009); (2) investigate the weaknesses of catch per unit of effort (CPUE) as a stock density indicator (Saltaug and Aanes, 2003; Swain and Wade, 2003); and (3) focus on the effect fisher knowledge may have on catchability and stock size (Ellis and Wang, 2006).

In an empirical examination of fishing location choice in a shrimp fishery, Eales and Wilen (1986) concluded that fishers act according to well-known economic behavioural factors. Swain and Sinclair (1994) categorised three types of effort distribution: uniform, proportional to biomass distribution, and effort placed into the most fish dense area, while Swain and Wade (2003) indicated that fish density distribution alone does not explain the distribution of fishing effort even when full knowledge of fish distribution is available.

It is natural to assume that the difference between fleet distribution according to potential catch (as in Sanchirico and Wilen, 2001) and according to potential profits (as in the study by Seijo and Caddy, 2008) is caused by the cost associated with distance between port and fishing ground. In this study the effort distribution is related to densities of potential profits rather than stock densities, as described by Eide (2014). A smartness (embedded knowledge) parameter has also been included, as introduced by Eide (2011). This study employs a similar biological model as in Eide (2012) and focuses on the impact that varying spatial and temporal stock biomass distributions have on the distributions of fleet activities. The development and performance of a diverse fleet under varying environmental conditions is considered, where the environmental conditions include not only physical and biological constraints but also constraints caused by management regulations and the fish-finding capacity of the fleet.

As previously shown by Eide (2007, 2008), fleet diversity, combined with variations in stock size and age composition within and between years, may also be the origin of substantial quasi (temporary) rent. In the case of a pure open access fishery the amount of quasi rent may be quite high, in particular with large variations in stock abundances. Here, a fleet diversity index is introduced, following the setup of a standard Shannon Index (Spellerberg and Fedor, 2003), to identify changes in fleet diversity under different environmental conditions.

Model

The aim of the model presented here is to investigate the effects of profit-maximising behaviour in fisheries under varying constraints and possible spatial and temporal distribution of the Northeast Arctic (NEA) cod stock. The intention is not to predict the future distribution of the cod stock but rather to investigate how a given, and realistic, distribution of cod influences the fleet profitability and stock development under different assumptions of fish-finding ability and management regimes.

Physical conditions and biological dynamics

The NEA cod stock is shared between Norway and Russia and exhibits significant spatial and temporal variations. This study includes eight Norwegian fleet groups placed in four different homeports in the Northern part of Norway, while the Russian fishery is represented by catches equal to the total Norwegian harvest, distributed according to stock densities in the ocean area open for Russian vessels.

While the previously mentioned studies by Eide (2007, 2008) are based on the environmental development through the *SRES B2* scenario published by the Intergovernmental Panel on Climate Change (IPCC) in the Assessment Report 4 (AR4), the current study follows the climatic conditions from the *SRES A1B* scenario in the same report. Both scenarios are downscaled to the Barents Sea region by the *REMO5.1* model (Jacob

et al., 2001). The outputs of the *REMO5.1* model define the border conditions of simulations performed with the *SinMod* model (Slagstad and McClimans, 2005), providing this study with spatial and temporal distributions of physical and biological variables. While the *SRES B2* data utilised in Eide (2007, 2008) were not spatially distributed, the *SRES A1B* data utilised in this study are indeed.

The *SRES B2* scenario is based on local solutions to economic, social and environmental sustainability, while the possibly more realistic *SRES A1B* scenario within the A1 storyline family, describes a future of rapid economic growth where the energy use is balanced, not relying too heavily on any particular source of energy. As only *SRES A1B* scenario data were available at the required resolution level, it was outside the opportunity set by this study to include other scenarios.

The population dynamics of the NEA cod stock are represented by a cellular automata model set up and parameterised on the basis of empirical data from historical catches and research surveys (following Eide, 2014). The time resolution in the model is one month, and a homogeneous grid of 80 km x 80 km cells provides the spatial resolution. According to the findings of Rose et al. (1995), cod may have a range of 210 to 720 km over a period of 30 days, roughly corresponding to a Moore neighbourhood (Hogeweg, 1988) with a range of two cells per month in the cellular automata model. This range gives a distributional area of 5×5 cells of the biomass contained in the mid cell.

Following the set up in Eide (2014), zooplankton biomass is used as a proxy for cod food availability in the spatially distributed model. Other constraining factors for the spatial and temporal distribution of NEA cod are ocean temperature and ocean bathymetry.

The fully coupled discrete *SRES A1B/Remo 5.1/SinMod* model predicts that a significant change in the environmental conditions in the Barents Sea area will take place in the early 2030's. According to the changes in the physical environment and the corresponding impact on the lower trophic levels of the ecosystem, the environmental carrying capacity of NEA cod is calculated to increase by about 10% (Figure 1), slightly extending the distribution area of the stock eastwards (Figure 2). The simulation period is 45 years from the base year 2012.

The variations in carrying capacity distributions and the predicted increase are the combined effect of a number of factors. The results are partly linked to feedback mechanisms in the physical model (including precipitation dynamics, ice melting, ocean current dynamics, temperature changes in different layers, etc.), and partly caused by ecosystem responses to the physical changes, as in the species composition of zooplankton and their growth and distributions. The results are also based on the observed spatial distribution of cod from surveys and catch registrations. This information is provided for the period 2004–2010 by the *FishExchange*¹¹ project (see Eide, 2014, for more details).

Figures 1 and 2 present the combined effect of merging the observed spatial information with factors constraining the cod distribution. The results indicate restriction of the NEA cod distributions to areas with ocean depths less than 1000 m and to areas with an average temperature at a 50-m depth that is higher than -1.5 °C. Also, when zooplankton densities fall below 2 g C m^{-2} , estimated carrying capacities drop by 80%.

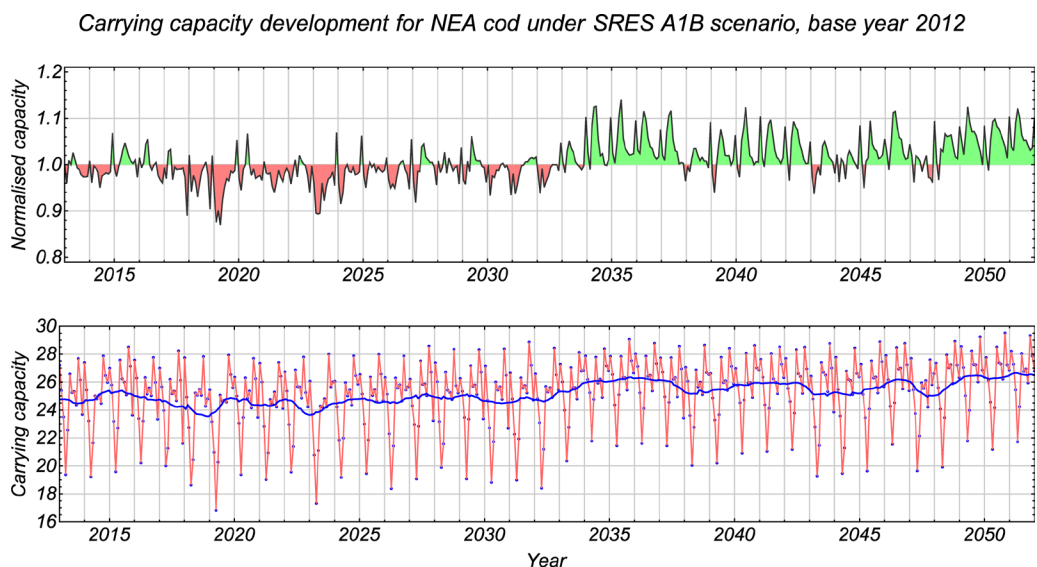


Figure 1

Carrying capacity development for NEA cod under *SRES A1B* scenario for base year 2012.

The upper panel shows monthly aggregates of normalised carrying capacities for NEA cod based on *SinMod* A1B simulations (Eide, 2014). The anomalies show percentage deviation from the corresponding month in 2012. The lower panel shows the monthly changes in terms of total carrying capacities of all cells (in million tonnes cod biomass). The red curve gives the monthly variation while the blue curve is the 12-month moving average of these numbers.

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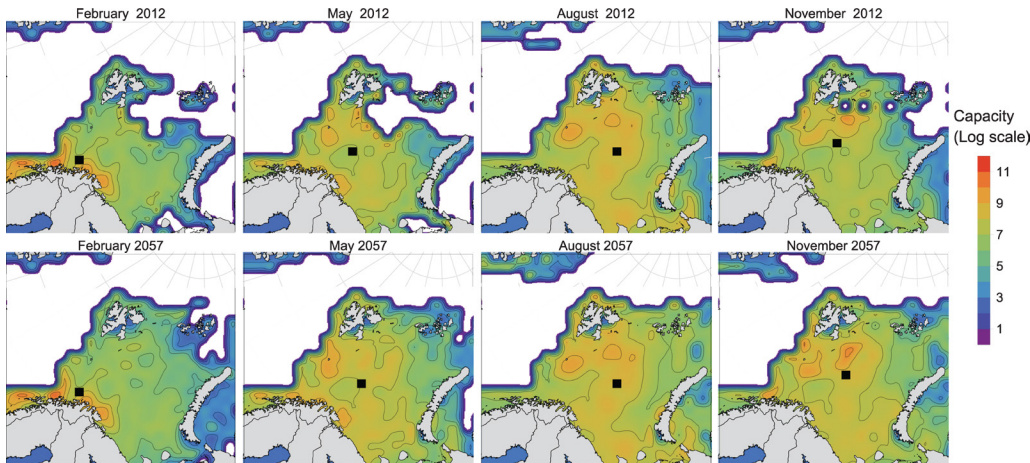


Figure 2
Spatial distribution of environmental carrying capacities for NEA cod in first and last model simulations.

The first of the performed simulations (2012) is shown in the upper panels; the last (2057) is shown in the lower panels. Distribution is based on different sources of spatial distribution of NEA cod during the period 2004–2010, on ocean temperature and zooplankton biomass from *SimMod* (A1B scenario runs) and on ocean depth. The monthly centres of gravity for the distributed levels of carrying capacities are shown as black squares. The size of the squares corresponds to the grid resolution (80 km times 80 km).

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The cellular automata rules were identified from the monthly biomass centres of gravity in the historical observations from 2004 to 2010. While running a rule-based biomass distribution and biological growth as shown in Eide (2012), the rules minimising the squared Euclidean distance between observed and modelled centres of gravity were chosen. A graphical illustration of the goodness of the fit between observed and modelled centres of gravity is shown in Figure 3, with more statistical information provided in Eide (2014).

Figure 4 illustrates the seasonal pattern in the model, another important property of this fishery. While the Box-Whisker chart represents values and variations during two of the first years (2014 and 2015) in the simulations presented in this paper, the thick red curve shows the catchability function in the NEA cod trawl fisheries. The function is parameterised on the basis of day catches in the trawl fishery during the unregulated fishery in 1971–1985 (the mathematical expression of the catchability function is given in Eide et al., 2003). The aim of the cellular automata model is to mimic a possible and realistic seasonal pattern of stock abundance in areas available for commercial fishing.

Harvest and fleet economics

A lattice with cell size 80 km x 80 km (Figure 5) is used to represent the spatial distribution of cod biomass and fishing activity. Each cell has its own environmental characteristics, being functions of physical and biological changes.

The model includes four North-Norwegian fishing ports (Svolvær, Tromsø, Hammerfest and Vardø) and two fleet types (small and large vessels) placed in each of these ports. The small vessels represent coastal fishing vessels with an assumed monthly range of four cells, while the large vessels may operate in the high sea, having a monthly range of eight cells (see Figure 5).

Previous studies (Hannesson, 1983; Eide et al., 2003) suggest that the stock-output elasticities in harvest production differ significantly between fleet groups in the NEA cod fishery. In order to accommodate different stock-output elasticities for coastal and high sea fishing vessels, a Cobb-Douglas product equation is used to express the monthly harvest (b) in a specific cell (cell i):

$$b_i(e_i, x_i) = q e_i x_i^\beta \quad (1)$$

where x_i is the initial cod biomass in cell i at the beginning of the month, q the catchability coefficient, e_i is the fishing effort by a given fleet (defined by homeport and vessel size) and β is the stock-output elasticity of the fleet, $0 \leq \beta \leq 1$.

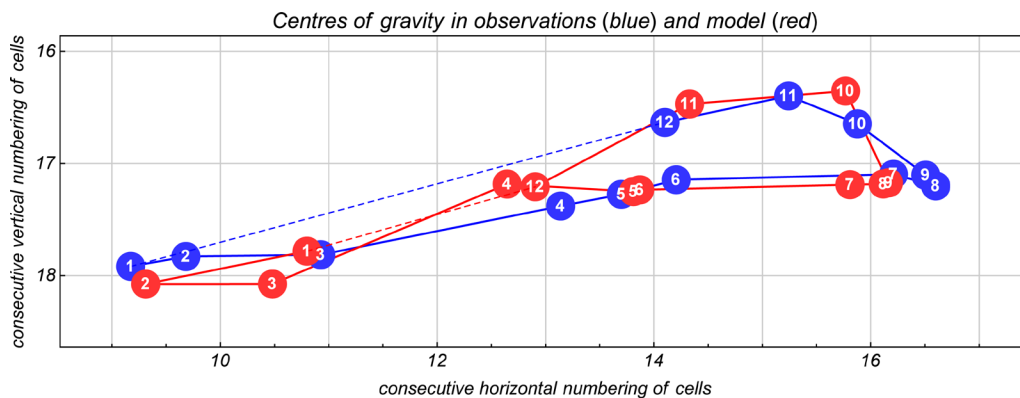


Figure 3
Model fit in terms of geographical placements of centres of gravity of NEA cod stock.

The observed monthly biomass centres are in blue and the modelled centres in red. The centres are marked with month numbers. For further details, see Eide (2014).

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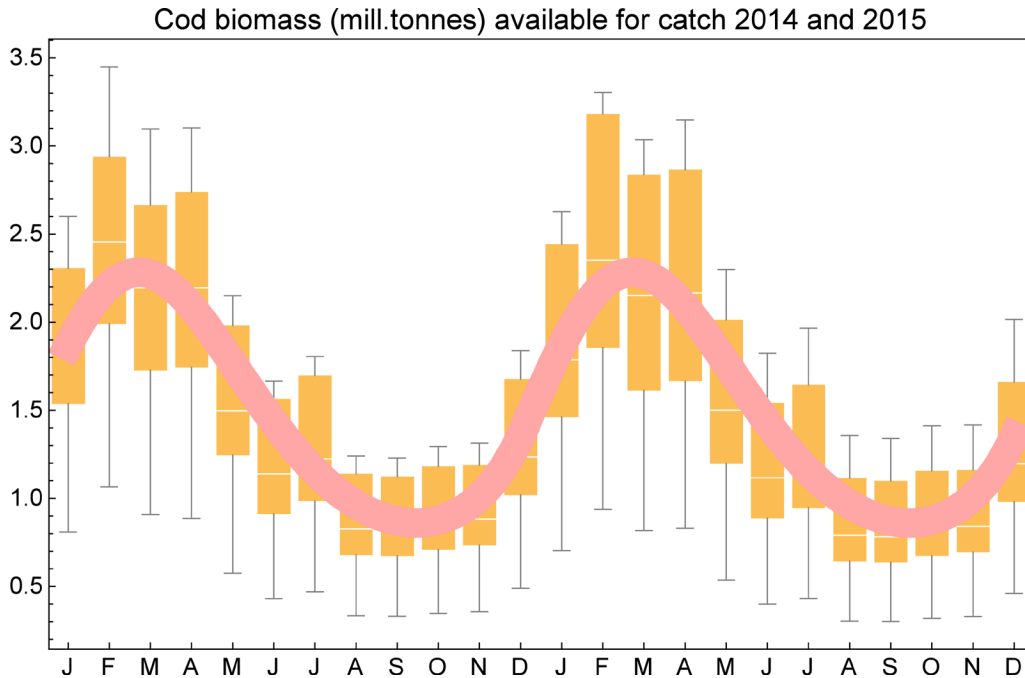


Figure 4
NEA cod biomass (million tons) available for catch in 2014 and 2015.

The Box-Whisker chart gives monthly values and variations over a period of two years (2014–2015) in the cellular automata model for all simulations presented in this paper. The thick, red curve is the catchability function found for the trawl fishery on the NEA cod stock in Eide et al. (2003).

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Bioeconomic studies use different approaches for identifying the market price of NEA cod. While Eikeset et al. (2013) assumed a linear demand function, Diekert et al. (2010) allowed differences between size groups, with increasing price by increasing sizes of cod. Modelling the NEA cod price is also challenging because different cod products have different market dynamics. Furthermore, the ex-vessel prices in Norwegian fisheries are restricted by minimum prices set by the sales organisations. Heen and Flaaten (2007) concluded that the most robust approach to estimating the demand function of cod is to assume a constant price per unit of harvest. Also Hannesson (1975), Eide (2007) and Eide (2008) assumed that the cod fishers are price takers. Following this approach, this study assumes a fixed price per unit of harvest (p). Then the revenue (re) generated by the harvest of the given fleet in cell i is

$$re_i(e_i, x_i) = p h_i(e_i, x_i) \tag{2}$$

and the corresponding variable cost (vc) of the fishing operation is

$$vc_i(e_i, d_i) = (c_e + c_d d_i) e_i \tag{3}$$

where the variable d_i is the distance from homeport to cell i and the cost parameters c_e and c_d are the unit cost of effort and the per unit of effort unit cost of distance, respectively.

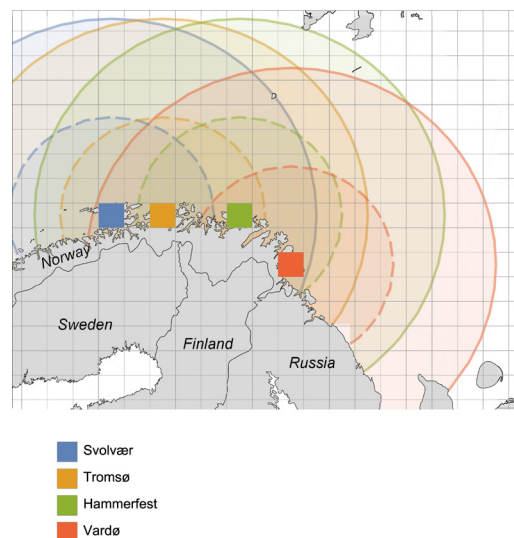


Figure 5
The Barents Sea area of the cellular automata model presented by an equal size projection.

The displayed grid is the 80 km \times 80 km grid resolution used in the model (Lambert Azimuthal, coordinates origin in 60°N 58°E). The cells of the four North-Norwegian fishing ports (Svolvær, Tromsø, Hammerfest and Vardø) are shown and the range of large and small fishing vessels operating from these ports is indicated by circles of radius 4 (dashed curves) and 8 (solid curves) cells for small and large vessels, respectively, as in Eide (2003).

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From equations (2) and (3) we find the contribution margin for a given fleet in cell i . If the contribution margin obtained in a cell is negative, the fleet will choose not to fish there since the revenue is not sufficient to cover the running cost. After this adjustment of effort, the total annual contribution margin (cm) in all cells is:

$$cm(\mathbf{e}, \mathbf{x}) = \sum_{m=1}^{12} \sum_{i=1}^n \{r e_{m,i}(e_{m,i}, x_{m,i}) - v c_{m,i}(e_{m,i}, d_i)\} \quad (4)$$

The matrices \mathbf{e} and \mathbf{x} give the fleet fishing effort and stock biomass for all cells and each month during a year, the index m indicates number of month and the integer n is the total number of cells available for the given fleet.

The number of available cells depends on both the physical range of the vessel (Figure 5) and the regulatory division of sea areas. In Norway the high sea vessels are not allowed to fish inside four nautical miles from the baseline.

Annual profit is found by withdrawing the fixed cost (fc) from the contribution margin described in equation (4):

$$\pi(\mathbf{e}, \mathbf{x}) = cm(\mathbf{e}, \mathbf{x}) - fc \quad (5)$$

The total fishing effort of a given vessel group at time t (time unit is one month) is the sum of the fishing effort placed in all available cells:

$$E_t = \sum_{i=1}^n e_{i,t} \quad (6)$$

Let V be the fleet capacity in terms of maximum fishing effort that may be produced per month, representing the fleet size in absolute terms. The relation between the fleet size (V) and the performed effort (E) is:

$$0 \leq E_t \leq V_t \quad (7)$$

Here, a pure or quota-regulated, open access fishery is assumed. While Vernon Smith in his seminal paper (Smith, 1968) assumed the flow of capital into the fishery to be proportional to profit, this study assumes fixed entry and exit rates of vessels. However, the degree of fleet utilisation (E/V) typically may be closer to the dynamics assumed by Smith, because the fleet utilisation also varies in space and time. The fleet dynamics in this study reflect the economic performance of the previous year, so that:

$$\begin{aligned} \text{If } \pi_t(\mathbf{e}, \mathbf{x}) < 0 \text{ then } V_{t+1} &= (1 - fd)V_t \\ \text{If } \pi_t(\mathbf{e}, \mathbf{x}) > 0 \text{ then } V_{t+1} &= (1 + fg)V_t \end{aligned} \quad (8)$$

The entry (fg) rate may differ from the exit rate (fd); normally, entry rates are expected to be higher than exit rates as in Eide (2007).

Distribution of fishing effort

Several studies have addressed effort distribution parameters (often referred to as density, dispersion or knowledge parameters). As in Eide (2014), this study merges fisher knowledge and economic rational behaviour, assuming the effort distribution to reflect the spatial distribution of revenue-cost-ratios. Fish-finding ability, here referred to by the smartness parameter s , depends on both technical equipment (as for example echo sounders), experience (local knowledge) and the skills of the crew (e.g. skipper effect). Hence, the smartness parameter value may increase over time and differ between fleet groups and homeports. Taking the revenue equation (2) and the variable cost equation (3), the effort of a specific fleet placed into cell j at time t is assumed to be

$$e_{j,t} = \frac{\left(\frac{r e_{j,t}}{v c_{j,t}}\right)^s}{\sum_{i=1}^n \left(\frac{r e_{i,t}}{v c_{i,t}}\right)^s} E_t \quad (9)$$

where $s = 0$ gives a uniform distribution of effort in all available cells (n), while $s = 1$ exactly reflects the revenue-cost-ratio distribution; $s > 1$, which may be referred to as smart fishing, reflects an increasing approach to the most profitable cells by increasing s value. Theoretically, $s = \infty$ places all effort of one fleet into the single cell having marginally the highest revenue to cost ratio.

Parameters and indicators

The fleet parameters have been set to roughly imitate historic economic performance and catch quantities in the Barents Sea fishery, based on recent observations (Anon, 2013). As the aim is not to explain previous fishing activities, the model is not a statistical representation of the past. As shown in Figures 3 and 4, however, the spatial and temporal performance of the model fit the observed variation, confirming that the spatial and temporal distributions in the model are realistic, representing situations to which the fishing fleet may be exposed.

Table 1. Values used for fleet parameters and variables between model simulations

Parameters and variables	Symbol	Small vessels	Large vessels
Unit price of harvest (NOK/kg)	p	13.00	13.00
Stock-output elasticity	β	0.70	0.50
Catchability coefficient	q	0.66	0.24
Unit cost of effort (mill. NOK/standardised effort)	c_e	0.00035	0.00055
Unit cost of distance (mill. NOK/80 km)	c_d	0.00025	0.00035
Fixed cost per year (mill. NOK/year)	$f\hat{c}$	30	60
Annual fleet entry rate (%)	$f\hat{g}$	10	7
Annual fleet exit rate (%)	$f\hat{d}$	8	5
Monthly fleet range (cells, 80 × 80 km)	–	4	8
Quota share (%)	–	60	40
Fishing effort ^a	E	≤ V	≤ V
Fleet capacity (in terms of possible fishing effort) ^a	V	≥ E	≥ E
Smartness coefficient ^b	s	1 – 10	1 – 10
Fishing mortality rate used in quota setting ^b	F	0.1 – 0.4	0.1 – 0.4

^aDynamic variable within simulations

^bVariable between simulations

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For the fleet performance a reasonable representation of previous fisheries is obtained by employing harvest functions based on Hannesson (1983) and Eide et al. (2003), assuming a stock-output elasticity of 0.7 for the coastal (small) vessels and 0.5 for the high sea (large) vessels. Rather high fleet turnover rates ($f\hat{g}$ and $f\hat{d}$) are assumed, also based on the existence of alternative fisheries. The turnover rate is assumed to be higher for the small-scale vessel than for the larger boats. Fleet parameter values are shown in Table 1, together with the range of variations between simulations, including fixed values of smartness (s) and the fishing mortality rates (F) used for quota setting.

The total Norwegian quota is shared between the coastal (small) vessels and the high sea (large) vessel in a fixed ratio (60/40), which is a slight simplification of the current regulation system. Since the NEA cod stock is equally shared between Norway and Russia, a Russian catch of the same quantity as the Norwegian catch is included. The spatial distribution of the Russian catch is assumed to mimic the distribution of cod biomasses in the area available for Russian vessels. No coastal Russian fishery is included in the model.

A high-resolution simulation model running over a period of 40 years, as in this study, produces large amounts of data, and it is challenging to organise and present the results clearly and in a useful manner. In order to provide a clearer presentation of the model outputs a fleet diversity index and centre of gravity calculations are introduced.

The Shannon Function H (Spellerberg and Fedor, 2003) is used as a fleet diversity index (The Shannon Index, SI):

$$SI = - \sum_{f=1}^{\varphi} \rho_f \ln(\rho_f) \quad (10)$$

where ρ_f is the measured effort in fleet f for all φ fleets. Effort may be measured in terms of fleet size (e.g. number of vessels registered in the fishery), corresponding to V in relation (7), or actual performed fishing activity (e.g. number of fishing days), corresponding to E in relation (7).

The centre of gravity of total fishing effort by all fleets is found by minimising the expression

$$\min_{1 \leq j \leq n} \sum_{i=1}^n d_{ij}^2 \sum_{f=1}^{\varphi} e_{i,f} \quad (11)$$

For cell j over n cells, $d_{i,j}$ is the distance between cells i and j and $e_{i,f}$ is the fishing effort of fleet f in cell i . Centre of gravity is found at the cell (or rather geographical coordinate), j , minimising Expression (11).

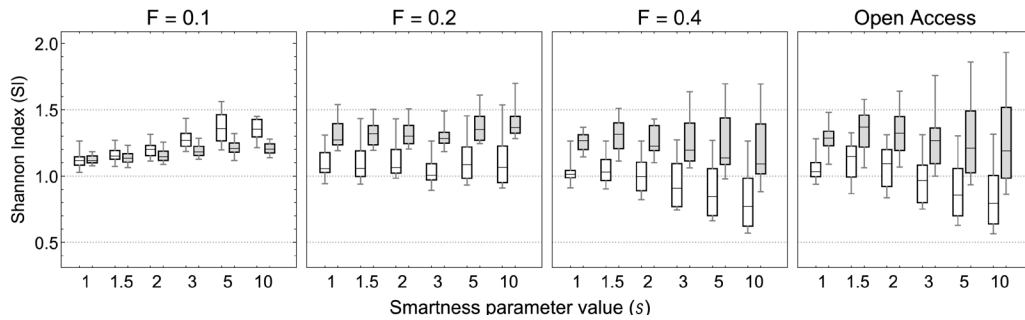


Figure 6

Annual fleet diversity for different values of the smartness parameter (s) and different management regimes.

Annual fleet diversity is expressed in terms of Shannon Index (SI, equation 10) over the simulation period of 2012–2052. Different management regimes are indicated by $F = 0.1$ (low exploitation rate) to $F = 0.4$ (high exploitation rate) and by open access (unregulated). The pairs of Box-and-Whisker plots represent the diversity of fleet size (V , relation 7) and produced standardised effort (E , relation 7) shown by white and grey boxes, respectively.

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Results and interpretations

The aim of this study is to focus on causes and consequences of fleet diversity. In real fisheries it is challenging to group vessels, but important grouping criteria are: targeted species (here: the NEA cod stock), geographical localisation (here represented by four different homeports) and type of gear (here represented by two different vessel types: small and large).

The results of this study indicate that technical development (here represented by the smartness parameter s) may expand or reduce fleet diversity, depending on the exploitation rate. Figure 6 displays a trend of increasing fleet diversity by increasing smartness (s) for a low exploitation rate ($F = 0.1$), while this trend is not visible for $F = 0.2$. At an exploitation rate of $F = 0.4$ and for an unregulated fishery (open access), the diversity in average is reduced by increasing values of the smartness parameter s . In these cases, also increasing temporal variability in fishing effort is found by increasing s -values.

Figure 7 shows the diversity of fleet size (V) as quantile plots of obtained profits by large and small vessels during the simulation period. With increasing smartness (s), high sea (large) vessels become more profitable than coastal (small) vessels at high exploitation rates. In all cases, increasing profitability seems to be related to increasing fleet diversity. In the case of large vessels the largest profits are found at higher smartness levels, while small vessels benefit at lower smartness levels. The difference between the two fleets indicates that a less efficient high-sea fishery (indicated by low s -values) benefits the stock and that the coastal fishery can take advantage of this benefit more easily than the high-sea fishery. At higher s -values a more successful high-sea fishery causes negative consequences for the coastal fishery.

An interesting shift between coastal and high sea vessels in terms of economic performance related to fleet diversity is seen at high exploitation levels ($F = 0.4$ and open access) when the smartness level passes a value close to 1.5. For smartness values below 2 the high sea fleet in general appears to perform better than the coastal fleet, and the positive impact of increased fleet diversity is higher than for the high sea fleet. It is reasonable to believe that the increasing difference in performance between small and large vessels at high smartness levels when the exploitation rate is high is related to the fact that the large vessels, due to their larger range, share a larger degree of their fishing grounds than do the small scale vessels. For example, a small scale vessel in Svolvær shares only 3.2% of its fishing area with small scale vessels in Vardø, while the corresponding value is 44.1% for large vessels (see Figure 5).

The effect of the increased environmental carrying capacity for NEA cod in the Barents Sea (as shown in Figures 1 and 2) is demonstrated in the distribution of cod biomass in Figure 8. The assumed management regime is close to the current regulation ($F = 0.4$), while two different smartness levels ($s = 2$ or 5) are assumed. In both cases the average stock biomass increases over the simulated period but the stock biomass profile over time differs between the two. When $s = 2$, the stock grows more or less steadily from start (2020) to end (2050). In the case of $s = 5$, the stock is reduced to a very low level in 2020 before exceeding the level of the $s = 2$ simulation in 2050. In both cases, however, the increase is particularly pronounced in the last two decades of the forty-year simulation period, in accordance with the expected environmental changes (Figures 1 and 2).

Figure 9 shows the effect of different exploitation patterns on the NEA cod stock. Clearly, the total exploitation rate determined by regulations (including the case of no regulations) has a greater impact on the stock development than different fleet distribution patterns determined by varying ability to target the most profitable areas (including the highest smartness value considered). The latter ability seems, however, to have an increasing impact on the stock distribution at increased exploitation rates.

The picture looks a bit different when the smartness parameter varies between fleets, as indicated in Figure 10. Differences in smartness between fleets follow two dimensions in Figure 10: Vessel type (SL: small and large vessels) or geography (SN: southern and northern homeports). If the smartness level is higher in north than in south or higher in the high sea fishery than in the coastal fleet, a regulated fishery of $F = 0.4$ is more similar to open access fisheries than to other regulated fisheries. At lower exploitation levels the clustering pattern is similar to the situation in Figure 9.

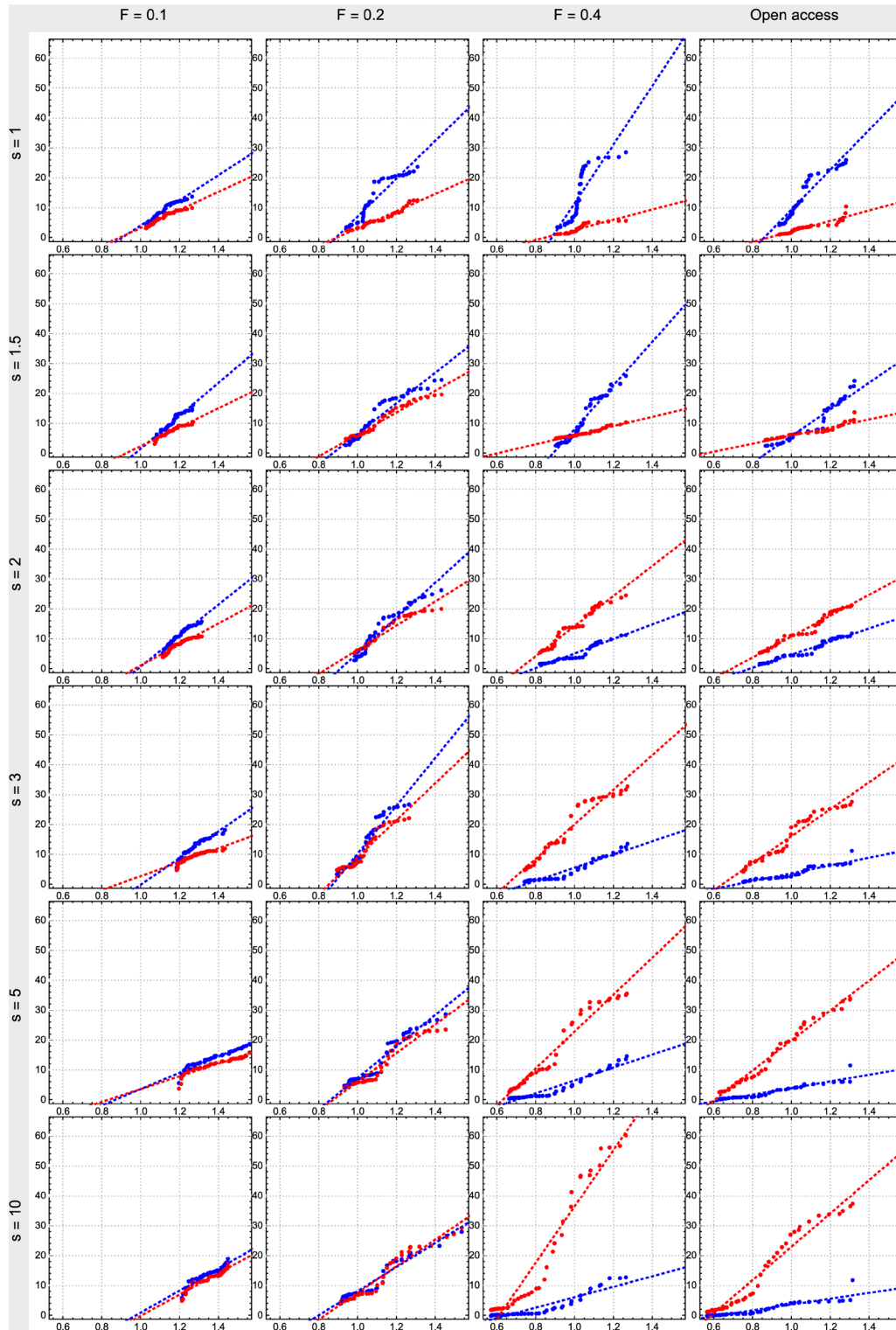


Figure 7

Diversity of fleet size as quantile plots of obtained profits by large and small vessels.

Quantile plots of total profits of small (blue) and large (red) vessels (measured by the vertical axes) and corresponding Shannon diversity index values (SI, equation 10) of the total fleet size (N) along the horizontal axes during the simulation period of 2012–2052. The dashed lines show linear fits of the displayed data points. Results for four different management regimes ($F = 0.1$ to $F = 0.4$ and open access, as in Figure 6) and six different smartness (s) values (between 1 and 10) are shown.

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Figure 11 shows how monthly centres of gravity for the total fishing effort (Expression 11) vary over the simulation period for the 24 different combinations of smartness parameter values and regulation regimes. Apart from the tendency of a concentration of centres of gravity in the cases of high smartness levels and low exploitation rate ($F = 0.1$), the distributions of centres of gravity do not seem to differ much between the different cases presented in Figure 11.

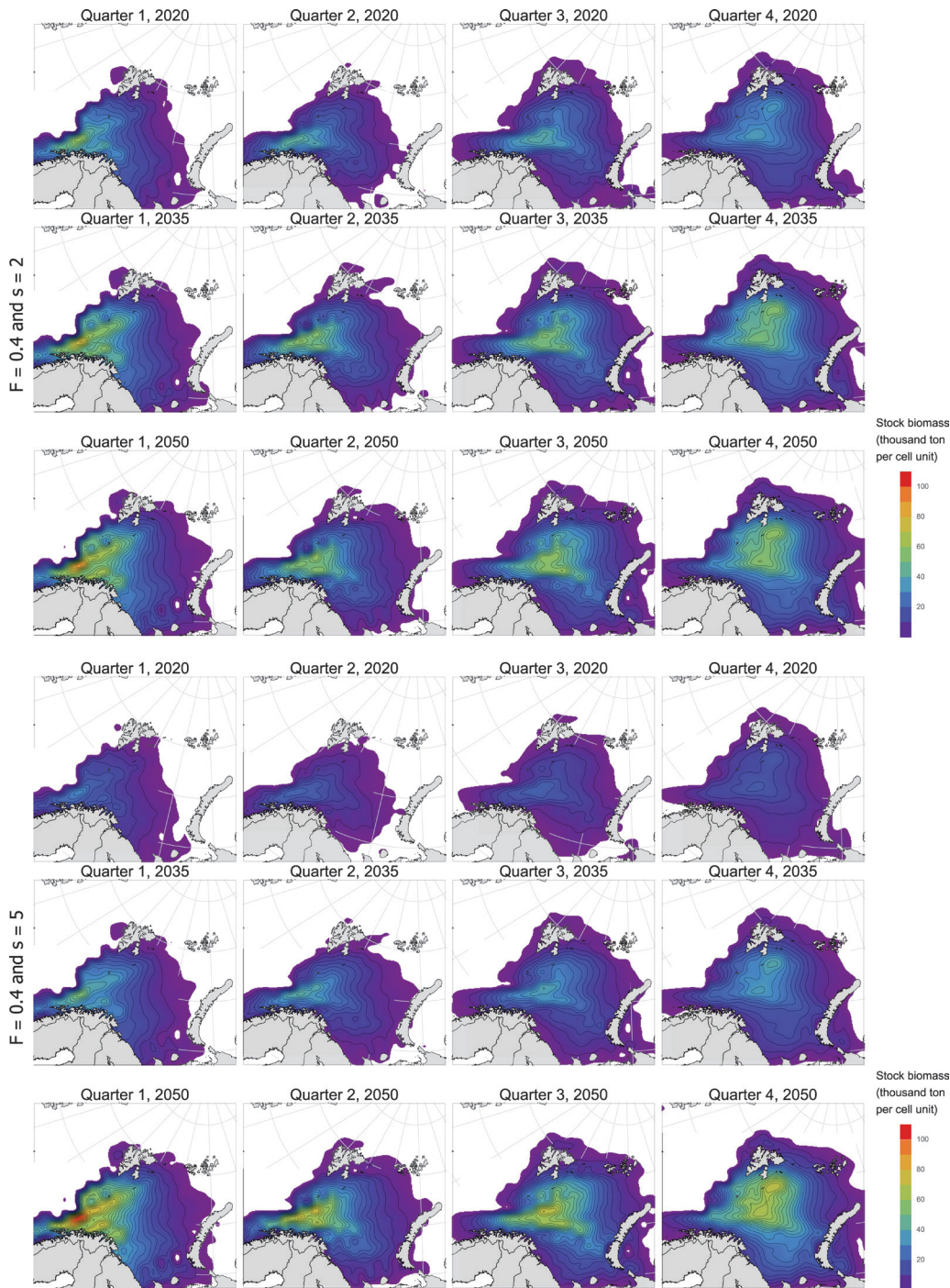


Figure 8

Spatial distribution of cod stock biomass for different levels of smartness under high fishing exploitation.

In the upper three rows of panels, fishing smartness (s) has been set at 5; for the lower panels, $s = 2$. In all cases, fishing exploitation has been set at $F = 0.4$, which is close to the current management regime.

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When examining how the different combinations cluster in a dendrogram (Figure 12), a similar pattern as in Figures 9 and 10 becomes visible, except for a potentially important difference: low s -values constitute a close cluster for all but the lowest exploitation level.

Finally, snap shots of fleet distributions of harvest in the last year of the simulation period (2052) are shown in Figures 13, 14 and 15. Figure 13 shows how the total fishing effort of all fleets is spatially distributed in year 2052, while Figure 14 shows aggregated catches over the year and Figure 15 displays the seasonal profiles of the different fleets under different management and smartness conditions.

Even though Figure 14 only displays the situation of year 2052, it reflects how increased smartness level benefits the high sea fisheries and disadvantages the coastal fleet at high exploitation levels. This model result is in line with the quantile plots shown in Figure 7. Figure 14 provides more refined information, however, as results differ between homeports. Even though Svolvær in catch terms is the largest port of

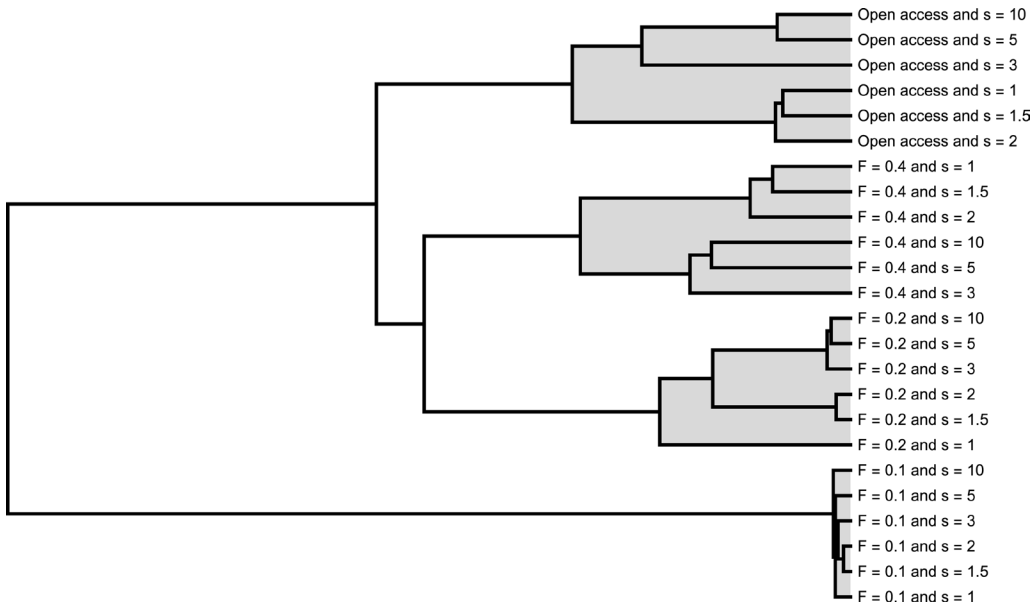


Figure 9
 Dendrogram of the effect on cod stock of different fishing exploitation and smartness patterns.

Different combinations of exploitation ($F = 0.1$ to $F = 0.4$ and open access) and smartness ($s = 1-10$) for the different temporal and spatial distributions of NEA cod biomass over the simulation period are shown. Agglomerative hierarchical clustering (Lukasová, 1979) level four is shaded and the horizontal axis measures the dissimilarities between clusters in terms of squared Euclidian differences.

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large scale vessels at high smartness levels in open access or when $F = 0.4$, this port experiences a decline in catches for s -values beyond 2 or 3, while the catches of other ports increase. This result probably reflects a more northerly distribution of the stock at high fishing pressure and increasing ability to target the most profitable fishing grounds.

The effect of a more northerly distribution may also explain the extended season lengths at high s -values and high levels of exploitation which are shown in Figure 15. At the highest level of smartness ($s = 10$) there is also a considerable fishing in the fall when no management is in effect (the case of pure open access).

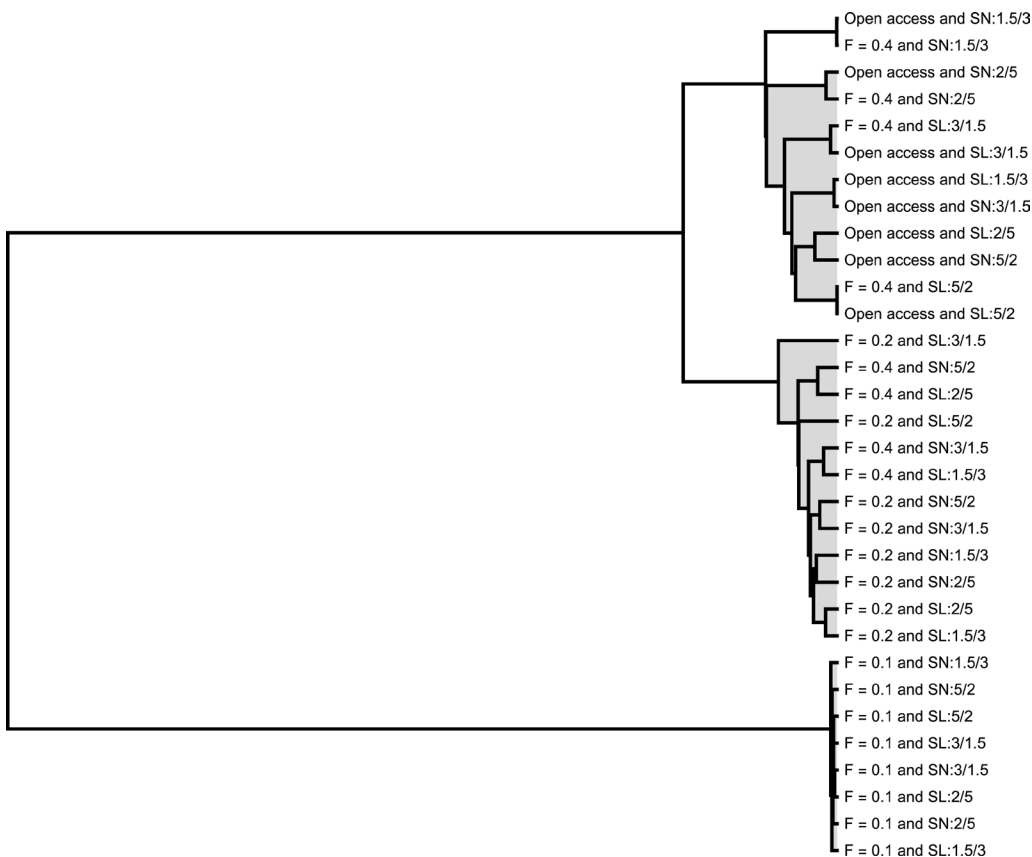


Figure 10
 Dendrogram of the effect on the cod stock of different combinations of fleet features.

The differences, which include the range of exploitation rates considered in previous figures and selected smartness values, follow two dimensions: small and large vessels (SL) and southern and northern fleets (SN). The latter dimension places Svolvær and Tromsø into the southern fleets, while Hammerfest and Vardø constitute the northern fleets (Figure 5). The numbers following the SL and SN labels give the two s -values related to the two letters, respectively; for example, SL:2/5 represents the combination of small vessels with smartness parameter value 2 and large vessels with smartness parameter value 5. Agglomerative hierarchical clustering (Lukasová, 1979) level four is shaded and the horizontal axis measures the dissimilarities between clusters in terms of squared Euclidian differences.

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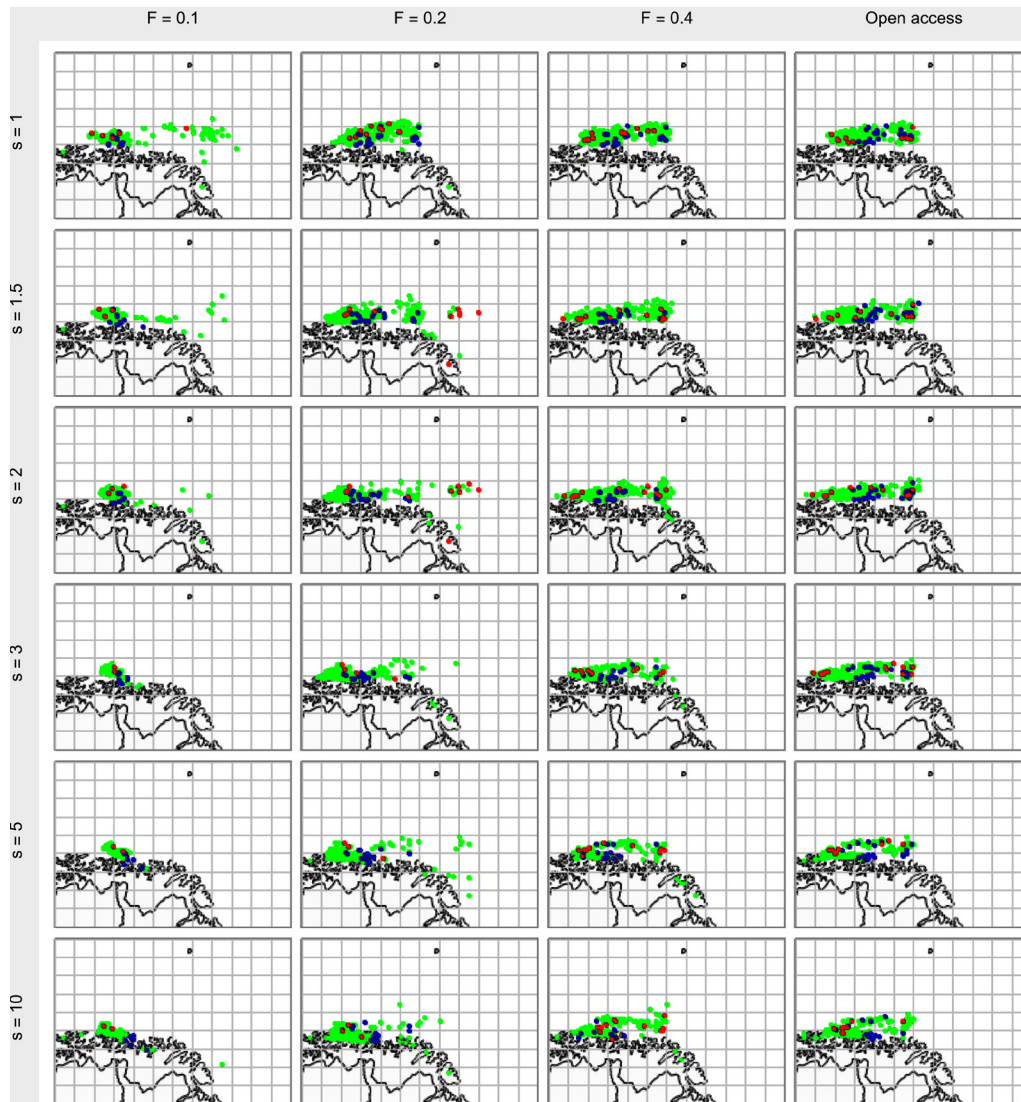


Figure 11
Monthly centres of gravity of total fishing effort for different management regimes and varying smartness.

Monthly centres of gravity (Expression 11) are shown over the simulation period 2012–2052, where data for the first year (2012) are shown by blue dots and, for the last year (2052), by red dots; green dots show the centres of gravity for the intervening years. Management regimes range from $F = 0.1$ to $F = 0.4$ and open access; smartness values (s) range from 1 to 10. Each square represents a cell in the model (80 km x 80 km; see Figure 5).

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Discussion

Assumptions in this study on cost patterns, production equations (including stock-output elasticities), entry-exit dynamics of the fishing fleet and the distribution of quota rights all clearly influenced the results of this modelling effort. The study shows, however, how one possible initial fleet composition and distribution in combination with realistic fleet parameters, leads to varying fleet patterns and profitabilities in the Norwegian NEA cod fishery, which also depend on temporal and spatial variations in the stock. Except for the case of an unregulated fishery (pure open access), the applied management regimes followed the principles of precautionary approach, assuming different precautionary fishing mortality rates ($F = 0.1, 0.2$ and 0.4).

Fleet diversity, profits and stock distributions

The results show that fluctuations in fleet diversity and profits increase when exploitation rates are increased at higher values of the smartness parameter (s) (Figures 6 and 7). Increased temporal fluctuations in fishing effort by increased fish-finding ability is a general finding, although it is not obvious that this phenomenon manifests itself in the seasonal pattern.

Figure 7 indicates that the fishery provides substantial profits on all investigated levels of utilisation. High fleet diversity linked to periods of high total profits may mask low and negative profits for specific fleet segments during the same periods. Variations in fleet activities are linked to stock fluctuations, providing large

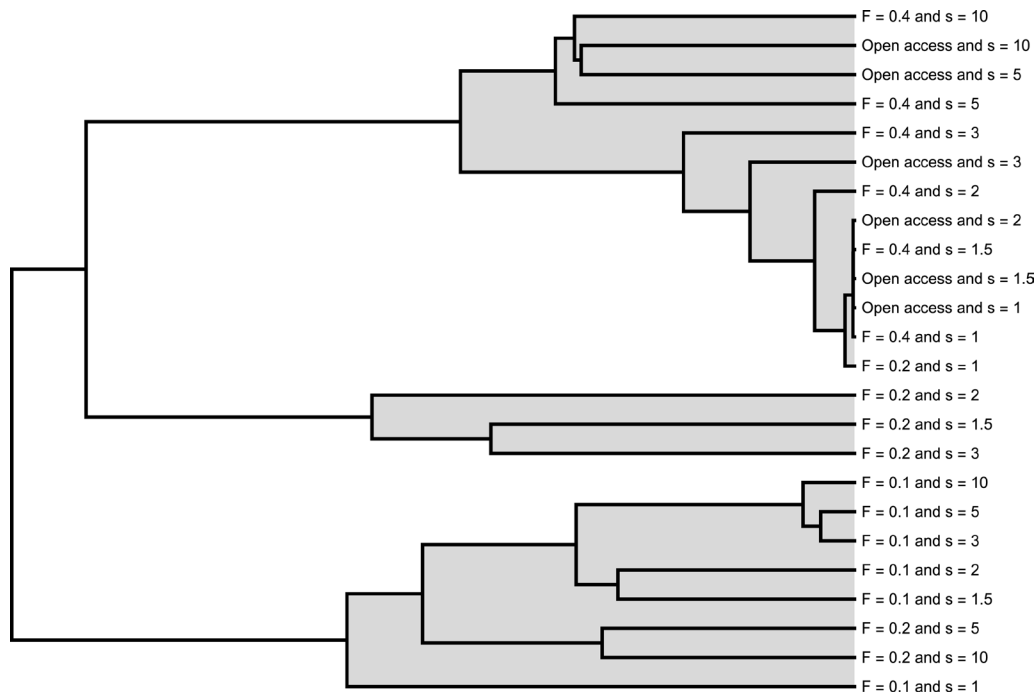


Figure 12
Dendrogram of the degree of similarity between different paths of centres of gravity.

The centres of gravity of the total fishing effort for the different management regimes ($F = 0.1$ to $F = 0.4$ and open access) and smartness values ($s = 1-10$) are shown in Figure 11. Agglomerative hierarchical clustering (Lukasová, 1979) level three is shaded and the horizontal axis measures the dissimilarities between clusters in terms of squared Euclidian differences.

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profits in some periods and low profits in others, depending on type of fleet and geographical placement. Quasi rent is typically generated during such periods, particularly when the marginal changes in stock size exceed the rate at which the fleet size and activities adjust to the stock situation (Eide, 2007, 2008).

The results support the contention that increased ability to track large fish concentrations leads to increased catches and may sustain a higher fishing effort in an open access fishery than what is the case when the common assumption of uniform distribution of effort is made. Cost of transport between fishing ground and homeport effectively leads to a higher exposure of local fishing grounds, even when fish densities are higher elsewhere. The biological effect of this higher exposure is not obvious for highly migratory species, as positive spillover effect from the less exposed areas may – or may not – compensate for heavy seasonal exploitation of local fishing grounds.

The cluster analyses of Figures 9 and 10, showing stock effects of different exploitation rates and smartness parameter values, both indicate that the development and distribution of the cod stock under a low exploitation rate ($F = 0.1$) differ the most from other stock patterns. In the case where all fleets enjoy the same smartness (Figure 9), the exploitation rate clearly is the main clustering dimension. When smartness varies between fleets along either of two dimensions – fleet size or homeport (Figure 10), for higher exploitation rates, differences in smartness tend to be the dominating clustering dimension in both cases.

As seen from Figure 2 the carrying capacity centres of gravity of 2012 and 2052 follow almost the same path. The stock distribution depends on a number of factors, however, in particular exploitation level and temporal and spatial distribution of fishing effort; the latter is displayed in Figure 11. When interpreting the maps in Figure 11 one needs to bear in mind a number of different factors. Low exploitation levels (e.g. $F = 0.1$) lead to short seasons (Figure 15), and the fishery takes place mainly in the spawning area. A higher exploitation level leads to longer seasons if the smartness level is not too high. In such cases, there is a tendency of northward moving centres of gravity of the fishing effort. Such tendencies are only found under these conditions, however, and not at higher exploitation levels and/or higher smartness values.

It may be difficult from Figure 11 to find similarities in the distribution of centres of gravity, and the sequences in time are not visible (only maps for the first and last year are shown). Figure 12 shows the clustering patterns of the 24 combinations of management regimes and smartness parameter values, identifying three major clusters. Low exploitation levels ($F = 0.1$) and medium exploitation levels ($F = 0.2$) at high smartness values make up the most distinct cluster. A minor cluster is found for the three medium smartness values ($s = 1.5, 2$ and 3) of medium exploitation level, while the third cluster includes the remaining combination of $F = 0.2$ and $s = 1$, together with all cases of $F = 0.4$ and open access fishery. The similarities in centres of gravity of effort distribution for different exploitation levels and smartness values do not give the full picture, however, as the distribution of effort obviously becomes more concentrated when the s -value increases for all cases.

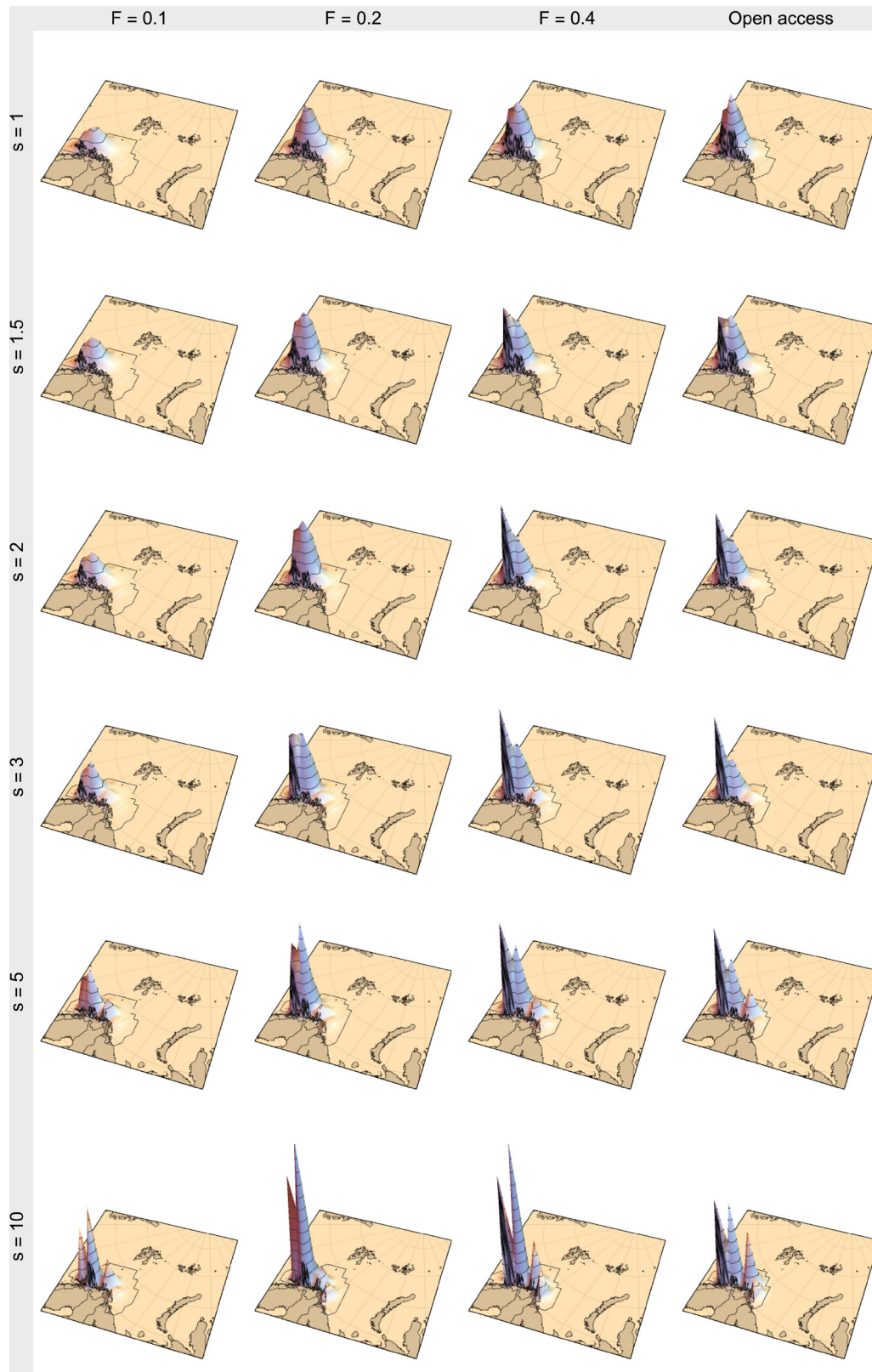


Figure 13
Spatial distribution of total standardised effort for the last year of the simulation period (2052).

Exploitation rates range from $F = 0.1$ to $F = 0.4$ and open access; smartness values (s) range from 1 to 10.

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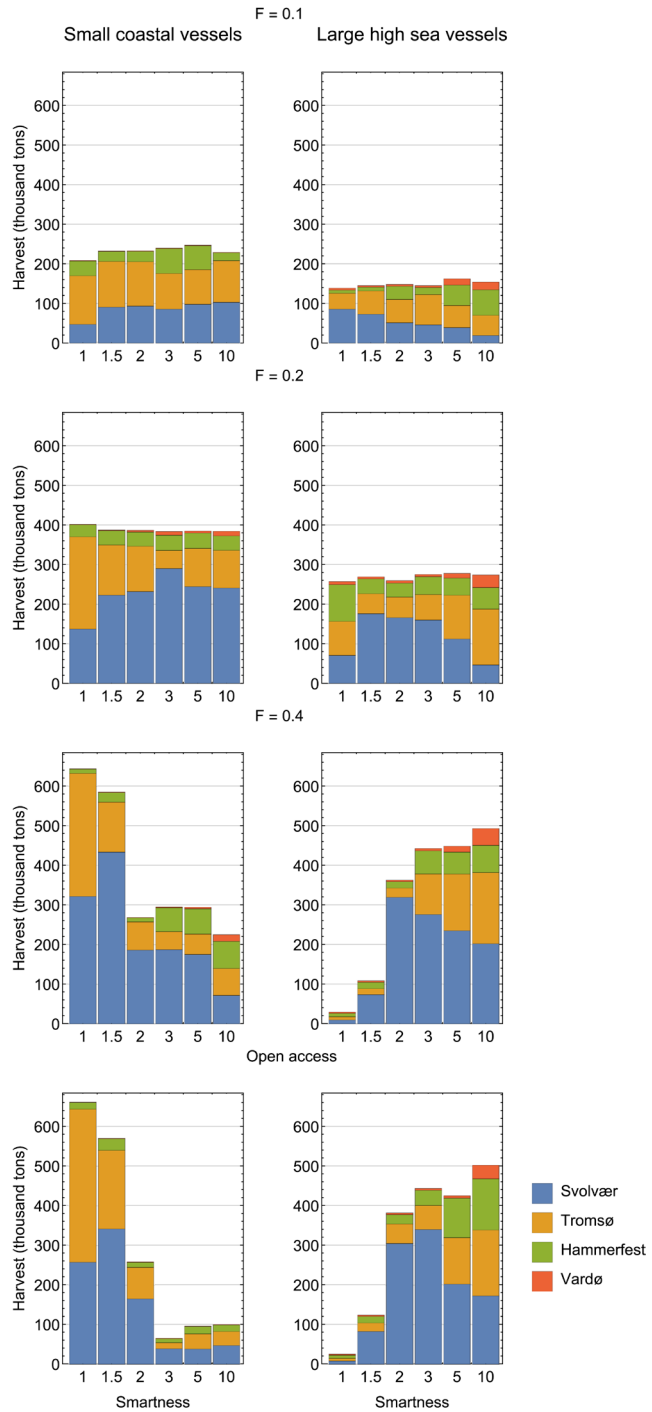


Figure 14
Harvest distribution between small and large vessels the last year of the simulation (2052).

Harvest is given in thousand tons and the distributions are formed under different management regimes (from $F = 0.1$ to $F = 0.4$ and open access) assuming different smartness parameter values ($s = 1-10$).

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The increased concentration by higher s -value is easily seen in Figure 13, which presents a snapshot of effort distribution for the last year of the simulation period. The figure also shows how higher exploitation levels at high smartness values allows a relatively higher fishing activity to take place in the northern ports (Hammerfest and Vardø), most prominently in the open access fishery at the highest investigated smartness value ($s = 10$). This result is also clearly visible from the fleet harvest data shown in Figure 14.

Catch, seasonal pattern and pulse fishing

The temporal distribution of harvest in the last year of the simulation period (2052; Figure 15) indicates shorter fishing seasons by increasing s -values in regulated fisheries, while the opposite is the case in the open access fishery where total quotas are not constraining the fishing activity. If the fleet has not fully utilised the quota during the first months of the year, when the availability of NEA cod is at its highest, a high degree

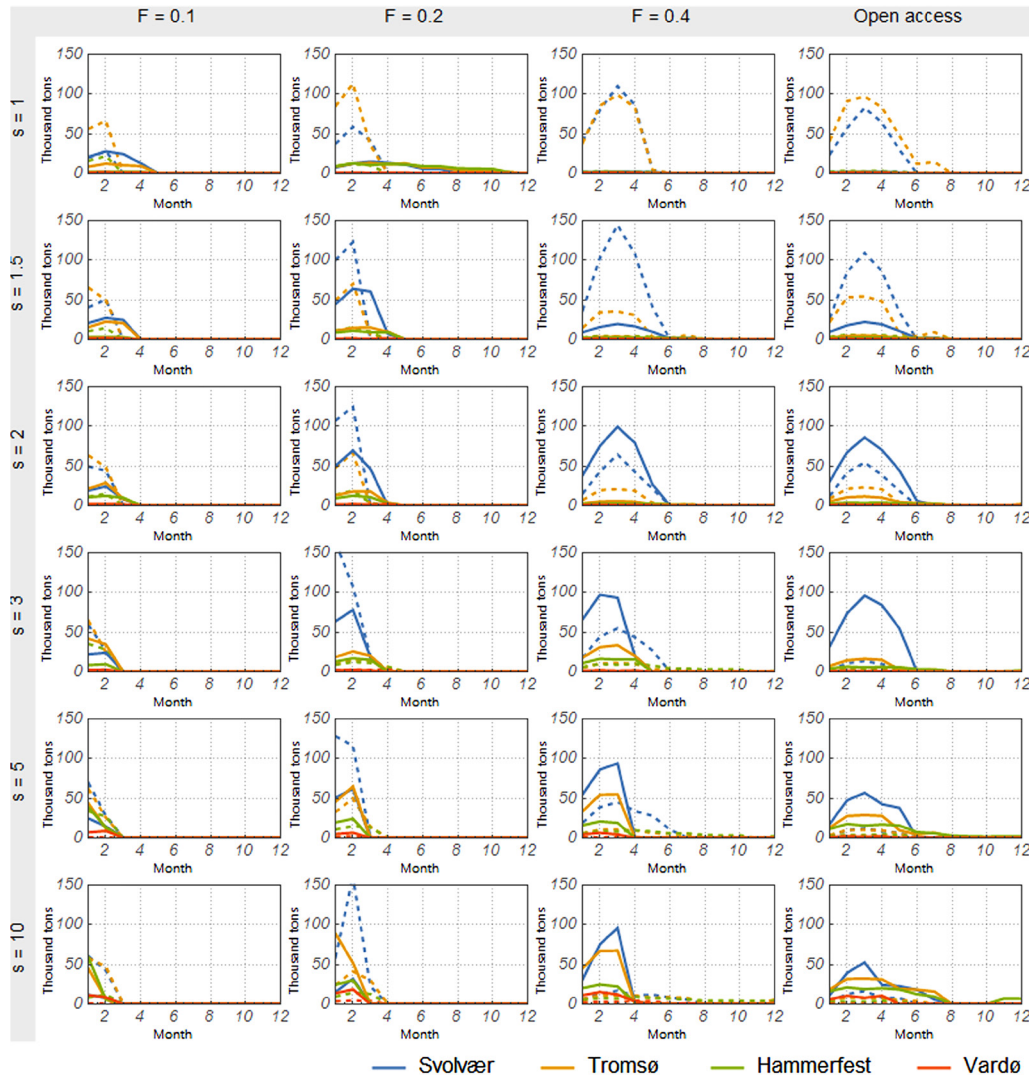


Figure 15
 Monthly distribution of harvest by fleet groups the last year of the simulation period (2052).

Distributions are shown for different management regimes (from $F = 0.1$ to $F = 0.4$ and open access) and smartness parameter values ($s = 1-10$). The horizontal axes show months by number and the vertical axes measure monthly fleet harvest in thousand tons. Dashed lines represent the small-scale coastal vessels, while solid lines represent the large high sea fishing vessels; different homeports are indicated by different colours.
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of smartness may contribute to making low season periods still profitable and, hence, prolong the fishing season. This profitability, however, depends on the stock situations, which also link to the utilisation of the stock in previous periods.

Figure 15 describes a pulse fishery with a significant peak in the first few months of every year. The seasonal pattern is solely driven by the stock dynamics and migration pattern. The profitability potential of pulse fishing (as described by Hannesson, 1975, and exemplified in Eide, 2007, for the NEA cod fishery) is utilised without including rational year planning based on knowledge about the seasonal structure of the fishery. The seasonal peak of this fishery occurs in the first part of the year for natural reasons. In the case of a seasonal peak during the last part of the year, the behavioural rules would probably need to include a year planning feature not to spoil the profitable high season fishery. Then a pulse fishery would follow from the annual profit maximisation, while a monthly time horizon in our case is sufficient for a pulse fishery.

Figure 15 reveals an interesting effect of increased fish-finding ability, namely that catch distribution between different homeports tends to be more equalised as the s -value increases. The distribution of small and large vessels shows another tendency, however, as the small vessels dominate the catches at high exploitation rates ($F = 0.4$ and open access fishery) when the s -values are low, while the large vessels dominate for higher s -values. The ability to take advantage of the available technology becomes less dependent on homeport, making the long-range vessels more competitive. Even in the case of the regulated fishery ($F = 0.4$), where the distribution of quotas on small and large vessels is fixed (60/40), this decreased dependency on homeport is the case, since negative contribution margins to a large degree put small-scale vessels in harbour at stock distribution situations obtained at high exploitation levels when the s -values are high (Figure 15).

Conclusion

This modelling study shows how fleet diversity is maintained in a fishery dominated by natural variations in the exploited biological resource. The impact fisheries have on the natural resource base also contributes to variations leading to fleet diversity and temporarily limited fleet capacity. Fleet changes, constrained by markets and possibly regulations, follow changes in the natural resource, most often at a lower marginal rate, which contributes to opportunities of substantial quasi rent, as also in the case of an unregulated fishery.

The idea of one homogeneous fleet, based on the most cost-efficient vessel, is contradicted by the findings presented in this paper. Hence, the optimal economic utilisation of the resource has to be found within a diverse fleet, presumably with a changing fleet diversity depending on the environmental changes. Maintaining a sufficient fleet diversity therefore becomes a management objective of its own, given the normal political objectives of today's fisheries. Since a diverse fleet seems to be a natural consequence of an unregulated fishery, the management goal in this respect is rather to avoid harming the natural diversification than to actively promote fleet diversity.

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Notes

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Competing interests

The author has no competing interests to declare.

Data accessibility statement

All generated research data will be available for any interested reader and will be provided upon request to the author.

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