

Environmental constraints, biological growth and fleet dynamics of a developing fishery: A model study of the Barents Sea snow crab (*Chionoecetes opilio*, Majidae) fishery

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Funding information

Norges Forskningsråd, Grant/Award Number: 267763

Abstract

The snow crab (*Chionoecetes opilio*, Majidae) has recently entered the Barents Sea, and a crab fishery is developing. Information on how the crab appeared and where it is moving is limited. We study how the characteristics of the fleet may affect the further development of the fishery. A spatial model is constructed as a grid of cells given a carrying capacity for crab determined by environmental data, assumed to reflect crabs' preferences. The biological dynamics are modelled using cellular automata, describing the growth and movements of the crabs. The fleet dynamics is represented by scenarios of fleet behaviour and aptitude, using standard theories of harvest production and economics. Pattern-oriented modelling is used to calibrate the model. The fishery started in the Loophole, but is anticipated to expand as the crabs populate adjacent areas. We use simulations to explore a potential geographical expansion of the fishery. The fleet is assumed to continually expand the current fishing area by initiating fishing in adjacent areas, relying only on their own judgement to locate promising fishing grounds. We find an inability to successfully quantify the amount of crabs in the areas subject to exploration and the willingness to take risks to be two forces contributing to a long-term utilization of the stock. Both forces appear to make the fishers explore non-lucrative grounds, potentially leading them to lucrative grounds. However, information from other sources indicating the presence of crabs at various locations appears to be necessary to ensure a more complete exploration of the fishery.

KEYWORDS

bioeconomics, cellular automata, fleet behaviour, new fisheries, pattern-oriented modelling, spatial bioeconomic dynamics

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1 | INTRODUCTION

Recently, the snow crab (*Chionoecetes opilio*, Majidae) has invaded the Barents Sea, and a fishery has developed. The first observation of snow crabs in this area was in 1996, in the Goose Bank. The existence of this snow crab population, in terms of where it came from and how it got here, remains uncertain (Anon., 2017). There is extensive uncertainty concerning the current and the potential size of the population (Anon., 2017), but the population is anticipated to spread throughout suitable parts of the Barents Sea area, depending on factors such as depth and temperature (Anon., 2019a).

In a well-established fishery, fishers tend to have extensive information, learned through fishing activities, about which fishing areas are the most valuable. However, in a new fishery, such information simply does not exist. This raises some interesting questions regarding how the behaviour of the fishers and their aptitudes shape the biological and economic dynamics of the fishery. Such information is needed in order to establish an adequate management plan for the fishery. To study these questions, a spatio-temporal model could be constructed, representing the biological, economic, and environmental components of the crab fishery.

Marine biological systems are based on physical laws (e.g. oceanography) and biological processes (e.g. growth, mortality, predation) that often lead to extensive models expressed by complicated systems of differential equations, where extrapolation may be difficult (Ermentrout & Edelstein-Keshet, 1993). A cellular automaton (CA) mimics a complex system by the use of simple rules. A CA may be used with a simple 1D model, where each cell could have one of two states (e.g. 0 or 1) (Wolfram, 1984). The state of each cell develops over time through discrete time steps by applying predefined rules.

Models using continuous cellular automata (CCA) have been developed. In these, the state of each cell is given by a continuous quantity, for example by introducing the fractional part of a real number as the state value of each period (Wolfram, 2002). A feature of CAs is their ability to incorporate cell-specific characteristics (Eide, 2012). For instance, this allows us to model how some fishing grounds are more successful than others at providing a habitat for the crab. Eide (2012) bioeconomic developed a 1D model where the population dynamics was expressed by CCA rules, combining this with a harvest function in order to estimate the possible effects of marine sanctuaries. Further use of CCA for fisheries includes a two-dimensional CCA model inspired by the Northeast Arctic cod fishery (Eide, 2011) and a simulation study of the same fishery (Eide, 2014).

There is a need for models addressing the rational development of a new fishery (Branch et al., 2006). This has led us to focus on the economic and biological dimensions in a spatially diversified environment, something common to all fisheries. This is a necessary focus in the management of fisheries. Therefore, in this study, a pure open access fishery of the snow crab is assumed, without any other constraints on the harvesting other than those imposed by Nature. This corresponds to the initial phase of the snow crab fishery. The fishery started out as an open access fishery located in the high sea

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areas of the Barents Sea, referred to as the *Loophole* (Henriksen, 2020). New fisheries generally have a development phase where regulations are minimized to motivate entrepreneurs to explore the fishery (Branch et al., 2006) or simply because the catch sizes are too low to have a significant effect on the sustainability of the fishery.

It is now well known from simple models following (Gordon, 1954) that in pure open access fisheries, rent is dissipated. However, such models only consider states of biological and economic equilibria in a self-sustaining, uniformly distributed, fishing ground and do not include the possible effects of spatial diversity. Some argue that models that take into account spatial heterogeneity will be more successful than more aggregated and simplified models in studying economic activities (such as economically motivated fleet behaviour) (Sanichirico & Wilen, 1999).

The development of fishing effort over time can be seen as a function of the economic performance of the fleet (Smith, 1969). However, within a shorter time frame, when the level of effort is fixed, the fleet needs to decide how to use the fishing capacity, as well as when and where to carry out fishing activities (Hilborn, 1985). A fleet does not deploy an uniform distribution of effort: in order to maximize its benefits (Caddy, 1975), a fleet efficiently targets areas believed to contain larger biomasses. In multi-patch frameworks, effort has been modelled heterogeneously over the fishing ground as proportional to local catch per unit of effort (CPUE) (Caddy, 1975), sequential allocation of effort to the unit with the highest catch rate (Hilborn & Walters, 1987), and using a concentration parameter linked to catch rates, fishers' objectives, economic factors, and available information (Walters et al., 1993).

When modelling the spatial distribution of effort, the process of discovering fishing grounds is sometimes explicitly included. Allen and McGlade (1986) identify two types of fishers, differing in their appetite for risk. A *Cartesian* will only consider fishing at fishing

grounds known to be the valuable, while a *stochast* will take the risk of exploring new fishing grounds (Allen & McGlade, 1986). In a scenario with only *Cartesians*, Allen and McGlade, (1986) find that the fleet will end up exploiting only a small fraction of the total area, resulting in a relatively small fleet and low catches, while the behaviour of a *stochast* in the long run will be beneficial for all. Hilborn and Walters (1987) allocate the lesser part of the fleet's annual fishing effort to the exploration of unknown areas, in order to uncover the potential of different fishing grounds, using the new information when allocating the remaining effort to the most promising fishing grounds.

This paper presents several simulations inspired by the developing snow crab fishery. In the simulations, we enter at an early stage of the crab invasion and thereby also the fishery. The aim of the simulations is to examine how the fleet dynamics affect the biological and economic dynamics of the fishery. The method applied is presented in the next section along with the model including environmental, biological and economic factors affecting the habitat of the snow crab, the development of its population and the dynamics of the fishing fleet.

2 | METHODS AND DATA

2.1 | Environmental carrying capacity for the snow crab

The environmental model employed in this study is constructed in order to map the suitable habitat for the snow crab population in the Barents Sea. A crucial element of the modelling process has been to take into account the fact that the Barents Sea seabed is not homogeneous, that is, recognizing that some areas are more suitable than others for the snow crab. The model is built upon an $i \times j$ lattice where each cell represents a specific geographic area within the Barents Sea. Each cell may sustain a snow crab biomass up to a cell-specific carrying capacity level.

The suitability of a habitat for the snow crab is a function of its preferred ocean depths and temperature range (Agnalt et al., 2011; Anon., 2017). We assume that the suitability of a habitat, that is an area providing a positive snow crab carrying capacity, is fully determined by these two variables. Thus, for a cell to provide a positive carrying capacity for the snow crab, it has to be within a certain range of both ocean depth and average temperature.

The bottom temperatures and ocean depths are provided by the SinMod model (Slagstad et al., 2015), which has a spatial resolution (grid) of 20 times 20 km in the Barents Sea. The average depth of the ocean in cell (i, j) will be denoted by $D_{i,j}$, and its average temperature by $T_{i,j}$. The depth function $\text{depth}_{i,j}(D_{i,j})$ represents a binary number assumed to be a habitat switch factor for the possible presence of crab (1) and its absence (0), depending on the average depth (in metres) of cell (i, j) , as illustrated in Figure 1. The annual average bottom temperature $T_{i,j}$ of cell (i, j) is calculated from the monthly averages of 2016 and measured in degrees Celsius. We consider a scale for the suitability of this habitat, from a minimum of 0 (not suitable) to a maximum of 3 (perfect), as illustrated in Figure 1.

The carrying capacity of cell (i, j) is defined as a function of the habitat factors depth and temperature. It is a normalized product of $\text{depth}_{i,j}$ and $\text{temp}_{i,j}$. With m and n representing the maximum number of cells in each direction, it can be expressed as follows:

$$\text{cap}_{i,j}(T_{i,j}, D_{i,j}) = \frac{\text{temp}_{i,j}(T_{i,j}) \cdot \text{depth}_{i,j}(D_{i,j})}{\sum_{i=1}^n \sum_{j=1}^m \text{temp}_{i,j}(T_{i,j}) \cdot \text{depth}_{i,j}(D_{i,j})} \quad (1)$$

The normalization arranges that the sum of the carrying capacities of all cells $\sum_{i=1}^n \sum_{j=1}^m \text{cap}_{i,j} = 1$. Cell (i, j) is defined as habitable when $\text{cap}_{i,j} > 0$, with a relative carrying capacity given by the value of $\text{cap}_{i,j}$. In Section 2.6, the normalized carrying capacities are scaled by a factor K (the environmental carrying capacity of the snow crab in the Barents Sea in terms of crab biomass) to reflect the carrying capacities in terms of the maximum crab biomass each cell can sustain. Figure 2 displays how the distribution of cell carrying capacities within the geographical area is based on bathymetrics and the average bottom temperatures in 2016. The figure illustrates how the local carrying capacities are heterogeneously distributed over the area.

2.2 | Biological growth and spatial distribution

We assume the biological dynamics of the Barents Sea snow crab population to be described by a surplus production model that includes biomass diffusion, providing the spatial distribution of biomasses in the $i \times j$ lattice. A constant per period growth rate g is assumed, while natural mortality triggers a local collapse when the specific maximum biomass level of each cell is exceeded. The discrete redistribution of biomasses assumes a Moore neighbourhood

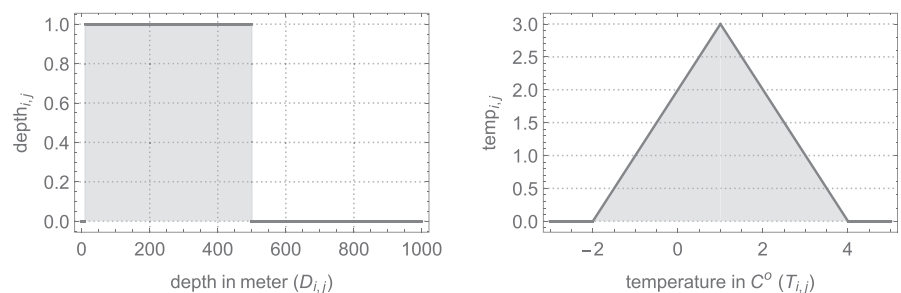


FIGURE 1 The values for depth (to the left) and temperature (to the right) that are assumed to be suitable to be a habitat for snow crab. For a cell to provide a positive carrying capacity for snow crab, it has to be within both ranges

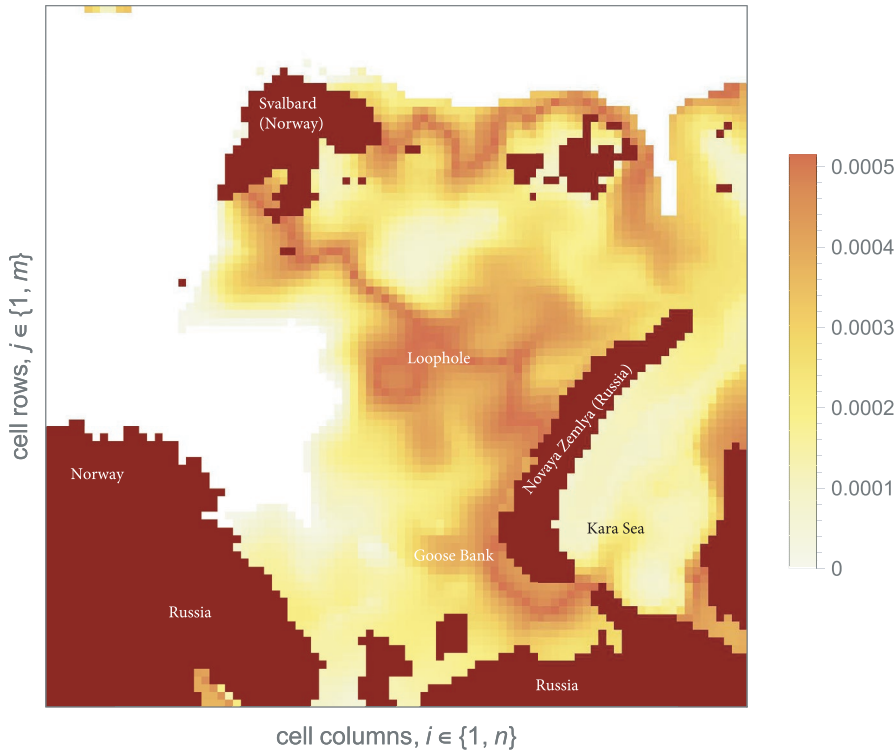


FIGURE 2 Distribution of normalized carrying capacities of snow crab in the Barents Sea, according to Equation (1) on the basis of SinMod data from 2016. Dark brown indicates land areas. The legend to the right refers to the value of the normalized carrying capacity of one cell. Also shown is how each cell's coordinate is defined by the value of (i, j) . Note that some areas outside the Barents Sea that belong to the Kara Sea are also included and have positive carrying capacities given the assumption of the model

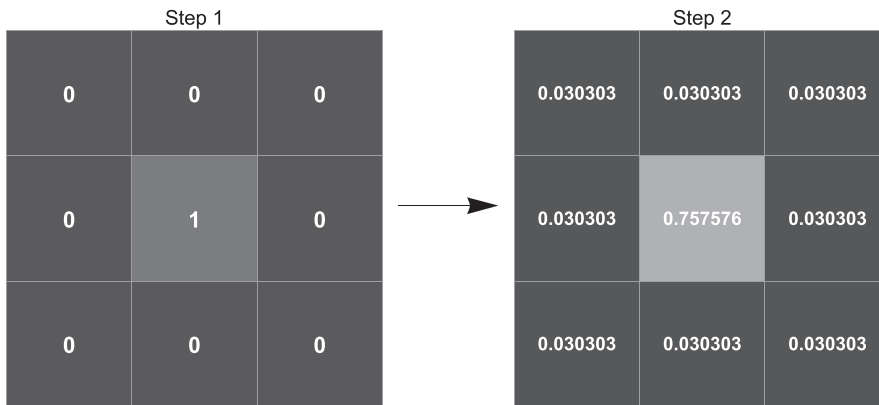


FIGURE 3 With one biomass unit in the middle cell to the left (step 1), the biomass distribution to the neighbouring cells in the next time step (assuming a Moore distribution of range 1) follows a diffusion matrix, M , calibrated by the POM approach, as shown by the value of each cell to the right (step 2)

of range 1, as indicated in Figure 3. The redistribution of the biomass $b_{ij,t}$ contained in cell (i, j) at time t is modelled by CCA rules. Each period includes a surplus growth of biomass before the new biomass is redistributed between the neighbouring cells and the cell itself, as indicated in the right-hand panel of Figure 3.

After the redistribution of cell biomass, the fractional part of the ratio $b_{ij,t}/cap_{ij}$ is retained in the cell. Hence, when $b_{ij,t}$ exceeds the capacity level cap_{ij} , the biomass is reduced accordingly, reflecting how natural mortality is implemented in the CCA model. The combined growth, recruitment, mortality and distribution determine the crab biomass of each cell at time $t + 1$. Hence, the biomass is given as a function of (1) the cell's biomass at time t , (2) the biomasses of the neighbouring cells, (3) the diffusion properties, (4) the growth rate and (5) the carrying capacities of each cell. This study assumes an absorbing boundary, meaning that the biomass dispersed from a

habitable area into a non-habitable area will disappear, that is it will experience 100% mortality.

During the early benthic stages, the snow crab is presumed to be stenothermic, where early juvenile instars are found to prefer temperatures in the range between 0°C and 1.5°C (Dionne et al., 2003). This sensitivity can affect the ability of the species to reproduce in an area. Therefore, growth is only implemented in cells with temperatures between 0°C and 1.5°C.

The total crab biomass within all cells in period t , B_t , is given by summing

$$B_t = \sum_{i=1}^n \sum_{j=1}^m b_{ij,t} \quad (2)$$

where b_{ij} is the biomass of cell (i, j) .

2.3 | Spatial distribution of fishing activity

Fishers must continually decide how the fishing effort is to be spatially distributed. In this developing crab fishery, we assume the fishing effort to be distributed both in areas where earlier fishing activities have taken place and in new fishing grounds. Hence, there are two distinctly different sets of lattice cells exposed to fishing effort: one where earlier fishing has occurred, and another set of previously unexplored cells.

Let H_t and U_t be two binary $i \times j$ matrices representing previous fishing activities in the $i \times j$ lattice at time t . If effort was distributed in cell (i, j) of matrix H_t earlier, the entry $h_{i,j,t}$ of H_t equals 1, but 0 if not. Similarly, with reference to U_t , $u_{i,j,t}$ equals 1 if this is the first time period, fishing takes place in the cell, but 0 if not.

The total number of cells where fishing takes place at time t is therefore given by the sum of the two matrices, $(\sum_{i=1}^n \sum_{j=1}^m (u_{i,j,t} + h_{i,j,t}))$.

We assume the fleet assigns a certain share, a_t , of its total fishing effort, E_t , at time t to exploratory fishing. The remaining share of effort, $(1-a_t)$, is allocated to already explored grounds. Fishing effort in previously explored cells is assumed to be distributed according to the first case of Equation (3):

$$e_{i,j,t}(h_{i,j,t}, u_{i,j,t}) = \begin{cases} \frac{b_{i,j,t}^d \cdot h_{i,j,t}}{\sum_{i=1}^n \sum_{j=1}^m b_{i,j,t}^d \cdot h_{i,j,t}} \cdot (1-a_t) \cdot E_t & \text{when } h_{i,j,t} = 1 \\ \frac{a_t \cdot E_t}{\sum_{i=1}^n \sum_{j=1}^m u_{i,j,t}} & \text{when } u_{i,j,t} = 1 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The fishing effort placed in previously explored cells (defined by H) depends on (1) the density of biomass in each cell, (2) the value of the concentration parameter d , (3) the share of fishing effort placed in previously unexplored cells a and (4) the total fishing effort allocated to the crab fishery E . If $d = 0$, the total fishing effort of these cells, $(1-a)E$, is uniformly distributed in the cells defined by H . If $d = 1$, the distribution of effort is proportional to the distribution of biomass in the cells; and if $d > 1$, the concentration in cells with the highest biomass density increases by the value of d , in agreement with Caddy (1975) and Walters et al. (1993).

The second rule provided in Equation (3) expresses how fishing effort is distributed in previously unexplored cells. We assume that the expectation of obtaining a harvest in an unexplored area, defined by U , is equal for all these cells. Hence, the total fishing effort allocated to exploratory fishing, $a \cdot E$, is assumed to be uniformly distributed over those cells where fishing is taking place for the first time.

2.4 | Dynamics of exploring new fishing grounds

We assume that the crab fleet has the necessary basic knowledge about the crab's habitat preferences to exclude all cells without living conditions for crabs. We further assume that as long as the fishery is still developing, there will always exist unexplored areas.

Hence, the fishers must choose which of these areas they want to explore at any time during the development.

Let R_t be a binary $i \times j$ matrix reflecting the remaining unexplored cells in the $i \times j$ lattice at time t . If the cell (i, j) remains unexplored at time t , $r_{i,j,t}$ equals 1, 0 if not. R_t therefore defines the cells remaining unexplored at time t . Initially, at time $t = 0$, all cells having positive crab carrying capacity remain unexplored, as expressed by Equation (4)

$$r_{i,j,t=0}(\text{cap}_{i,j}) = \begin{cases} 1, & \text{when } \text{cap}_{i,j} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The fishers are assumed to expand the fishing ground by expanding the already explored area at any time. Hence, we assume that only cells adjacent to already explored cells are considered for exploration. The rationale behind this is the assumption that fishers continually perceive the potential of unexplored fishing grounds next to the area they already are exploiting. These cells define the binary $i \times j$ matrix R'_t , where each cell with value 1 is a subject for exploration at time t . If the cell (i, j) at time t remains unexplored (defined by R_t) and is located next to an already explored area (defined by H_t), $r'_{i,j,t}$ takes the value 1 and 0 otherwise.

The number of cells subject to exploration selected by the fishers will depend on the anticipated potential of each cell relatively to the assumed potential in the already explored areas, in addition to the aptitude of the fleet and its willingness to take risks. In order to operationalize the exploration process, we introduce a measure of the assumed potential in the already explored area, referred to as the *Threshold Level of Biomass (TLOB)*, defined by

$$\begin{aligned} \text{TLOB}_t &= \sum_{i=1}^n \sum_{j=1}^m \left(b_{i,j,t} \cdot \frac{b_{i,j,t}^d \cdot h_{i,j,t}}{\sum_{i=1}^n \sum_{j=1}^m b_{i,j,t}^d \cdot h_{i,j,t}} \right) \\ &= \sum_{i=1}^n \sum_{j=1}^m \frac{b_{i,j,t}^{1+d} \cdot h_{i,j,t}}{\sum_{i=1}^n \sum_{j=1}^m b_{i,j,t}^d \cdot h_{i,j,t}} \end{aligned} \quad (5)$$

where n is the total number of rows and m is the total number of columns in the lattice. Equation (5) expresses TLOB as the sum of the biomass $b_{i,j,t}$ in every cell within set H at time t raised to the d th power, corresponding to Equation (3), where increasing values of d increase the fleet's ability to identify cells of high biomass density in the already explored areas. By including the term $h_{i,j,t}$, we specify that only explored cells are given positive weights, that is, have an effect on TLOB. Hence, TLOB represents the density of crabs the fleet expects to find when fishing in an explored area.

We define two types of exploration strategies, one rational and one irrational, reflecting different scenarios for the fleet's willingness to take risks. In the rational strategy, a cell subject to exploration will be explored if the anticipated size of the crab biomass in the cell exceeds TLOB. In the irrational strategy, the cell will be explored if the anticipated biomass level exceeds 50 per cent of TLOB. We also specify two branches of each strategy, assumed to reflect different scenarios of the fleet's aptitude.

In the *Rational FI* and *Irrational FI* strategies, the fleet receives full information of the state of the crab stock in the adjacent unexplored cells: they are able to successfully determine the biomass level in an adjacent unexplored cell. The strategies where the fleet only has limited information are denoted by *Rational LI* and *Irrational LI*, where the fishers are, with equal probability, able to anticipate the biomass level in an adjacent unexplored cell to be in the interval of ± 100 per cent of the actual biomass level.

These strategies enable us to specify under which circumstances exploration is allowed to take place, by linking the decision to the available biomass in the explored areas, taking into account the fact that it is not a forgone conclusion that the fleet will carry out any exploration. The aim is to add credibility to the fleet's reasoning in the exploration process by preventing clearly unrealistic behaviour.

Hence, for a given strategy, $u_{i,j,t}$ is given the value 0 or 1 in period t according to the following rules:

$$u_{i,j,t}(r'_{i,j,t}, b_{i,j,t}) = \begin{cases} \begin{cases} 1, & \text{when } r'_{i,j,t} \cdot b_{i,j,t} > \text{TLOB}_t \\ 0, & \text{otherwise} \end{cases} & \text{for RationalFI} \\ \begin{cases} 1, & \text{when } r'_{i,j,t} \cdot b_{i,j,t} > \frac{\text{TLOB}_t}{2} \\ 0, & \text{otherwise} \end{cases} & \text{for IrrationalFI} \\ \begin{cases} 1, & \text{when } r'_{i,j,t} \cdot X \cdot b_{i,j,t} > \text{TLOB}_t \\ 0, & \text{otherwise} \end{cases} & \text{for RationalLI} \\ \begin{cases} 1, & \text{when } r'_{i,j,t} \cdot X \cdot b_{i,j,t} > \frac{\text{TLOB}_t}{2} \\ 0, & \text{otherwise} \end{cases} & \text{for IrrationalLI} \end{cases} \quad (6)$$

where X is a random number between 0 and 2.

If $u_{i,j,t}$ equals 1, then cell (i, j) in the lattice is chosen by the fishers to be explored at time t . The term $r'_{i,j,t}$ specifies that only cells subject to exploration at time t may be chosen. When the fleet has decided which areas to explore, it also needs to set aside a share of effort for the exploratory fishing. We assume that the proportion of effort used for exploratory fishing at time t is given by the ratio between the number of cells where exploratory fishing will be performed and the total number of cells where all fishing activities will be performed. a_t is therefore defined by

$$a_t = \frac{\sum_{i=1}^n \sum_{j=1}^m u_{i,j,t}}{\sum_{i=1}^n \sum_{j=1}^m h_{i,j,t} + \sum_{i=1}^n \sum_{j=1}^m u_{i,j,t}} \quad (7)$$

where n is the total number of rows and m is the total number of columns in the lattice. If no cells subject to exploration are found to meet the criterion for being explored ($\sum_{i=1}^n \sum_{j=1}^m u_{i,j,t} = 0$), the total fishing effort will be distributed over the already explored cells. This criterion may cause some cells to remain unexplored at the end of the simulation period.

The number of remaining unexplored cells (defined by R) diminishes over time by cell exploration according to

$$R_t = R_{t-1} - U_{t-1} \quad (8)$$

The percentage of the carrying capacity the fleet has revealed at time t is expressed as

$$\text{rev_cap}_t = \left(\sum_{i=1}^n \sum_{j=1}^m \text{cap}_{i,j,t} \cdot (h_{i,j,t} + u_{i,j,t}) \right) \cdot 100 \quad (9)$$

where n is the total number of rows and m is the total number of columns in the lattice.

One last scenario is added for the sake of comparison: The *Fully Explored* scenario assumes the fleet to have explored all cells in advance and therefore do not need to start exploration.

2.5 | Harvesting economics

The harvest, $y_{i,j,t}$, captured in cell (i, j) at time t , when the density of biomass is $b_{i,j,t}$ and the fishing effort equals $e_{i,j,t}$, is given by the Cobb-Douglas equation

$$y_{i,j,t}(e_{i,j,t}, b_{i,j,t}) = \begin{cases} q \cdot e_{i,j,t} \cdot b_{i,j,t}^\beta & \text{when } b_{i,j,t} \geq q \cdot e_{i,j,t} \cdot b_{i,j,t}^\beta \\ b_{i,j,t} & \text{when } b_{i,j,t} < q \cdot e_{i,j,t} \cdot b_{i,j,t}^\beta \end{cases} \quad (10)$$

where q is the catchability coefficient while β is interpreted as the output elasticity of biomass. Thus, a change of one per cent in the biomass b results in a corresponding β per cent change in the harvest. Eide et al. (2003) argue that active gears or gears attracting fish by bait will have a value of β below one, and found that the β of the Barents Sea cod trawl fishery was just above 0.4. In the snow crab fishery, pots are applied, designed to lure crabs with bait into the pots, suggesting a β below one.

The total harvest at time t is given by

$$Y_t = \sum_{i=1}^n \sum_{j=1}^m y_{i,j,t} \quad (11)$$

where n is the total number of rows and m is the total number of columns in the lattice. The abnormal profit π_t in period t is given by

$$\pi_t = p \cdot Y_t - c \cdot E_t \quad (12)$$

where the price p is the unit price of harvest (Y_t), and the unit cost of effort E_t , including opportunity cost, is c . Economic performance is measured in terms of abnormal profit, π , which determines the evolution of effort. When $\pi > 0$, more participants are encouraged to join the fishery and when $\pi < 0$, fishers will start leaving the fishery. The evolution of effort over time (increasing, decreasing, or steady state) is modelled according to the principles used by Smith (1969), defined by

$$\Delta E_t = \gamma \cdot \pi_{t-1}, \quad (13)$$

γ being a constant stiffness parameter controlling the speed of changes in fishing effort due to changes in the abnormal profit.

Equation (13) shows that the change in effort in period t is proportional to the abnormal profit in period $(t - 1)$.

2.6 | Model validation and parameter settings

In order to make a representative model of the developing snow crab fishery, the model and the model parametrization have to be in line with the observed characteristics of the fishery. Therefore, the model has been calibrated using a pattern-oriented modelling (POM) approach. In general, the main object of POM is to use the observed patterns (in the actual fishery) to guide the design of the model describing the system (Grimm et al., 2005). A *pattern* is a characteristic of the system and can be interpreted as an indicator of the underlying structure and processes of the system (Grimm et al., 2005). In our study, two patterns have been used to calibrate the model.

The first pattern consists of the observed CPUEs revealed during the fishing activity in the Loophole from 2014 to 2016. The snow crab fishery started in the Loophole, and to a large extent, all fishing activities took place in this area during this period of time (Hogrenning & Henriksen, 2021). The observed CPUEs are calculated using the same data material and method as outlined in Hogrenning and Henriksen (2021). The data are based on the electronic reporting systems and are publicly available (Anon., 2019c), administrated by the Norwegian Directorate of Fisheries. In Hogrenning and Henriksen (2021), the CPUE is calculated as the ratio of the annual harvest with the number of pots used in the harvest operations. Hence, the number of applied pots is used as a measure of effort. The same method has been adopted here in calculating the CPUE, while the calculations are monthly instead of annual.

The data material only covers observations of harvest operations carried out by Norwegian vessels and therefore only represents a share of the total operations carried out by the vessels from all the nations involved. We therefore assume the calculated values of the CPUE for 2014–2016 to be valid for all vessels and the harvest and

effort levels of the Norwegian vessels to be proportional to the total harvest and effort levels of each month. In the following, the coefficient of proportionality is denoted by pp .

Table 1 (Table A1) in Anon. (2019a, p. 6) shows the total annual harvest, grouped by the different nations involved in the fishery. For the years 2014–2016, we calculate the annual pp as the ratio between the annual Norwegian harvest and the annual total harvest, using the values in the table. We calculate the annual pp s in the absence of monthly observations of the total harvest levels. The observed $CPUE_{y,mo}$ for month mo in year y is therefore given by

$$CPUE_{y,mo} = \frac{\widehat{harvest}_{y,mo}}{\widehat{effort}_{y,mo}} = \frac{pp_y \cdot harvest_{N,y,mo}}{pp_y \cdot effort_{N,y,mo}} \quad (14)$$

where the subscript N refers to the harvest and effort levels of Norwegian vessels only. The hat operator indicates that the value is an estimate of the actual value. The value of \widehat{effort} in month mo in year y is given by

$$\widehat{effort}_{y,mo} = effort_{N,y,mo} \cdot pp_y \quad (15)$$

In the simulation, we instruct the fleet to execute the observed effort levels in an area designed to be a discrete spatial representation of the Loophole area. The simulated CPUE subsequently were compared to the observed CPUE. The Euclidean distance between the two was calculated based on the periodic differences of the two time series. A relatively low absolute value of the Euclidean distance suggests a good fit. Note that there were some fishing activities within the Loophole area before 2014, and some fishing activities outside of the Loophole in 2016, but only to a modest extent. This implies that the simulated level of effort executed in the Loophole does not fully reflect the actual fishing activities within the area during the given period. This is also visible in Figure 4, which shows the fishing activities by the Norwegian vessels during 2014–2016 and the geographical range of the Loophole.

TABLE 1 Parameter values for the selected simulation providing the best fit

Parameter	Value	Description	Section	POM
g	0.05	Growth rate	2.2, 2.6	Yes
d	1	Concentration parameters	2.3	No
K	950,000	The total capacity (tonnes)	2.6	Yes
M	(Figure 3)	Diffusion matrix	2.2, 2.6	Yes
q	0.0001	Catchability coefficient	2.5, 2.6	Yes
β	0.9	Output elasticity of biomass	2.5	Yes
p	50	Unit price of harvest (NOK)	2.5	No
c	193	Unit cost of effort (NOK)	2.5	No
γ	0.00015	Stiffness parameter	2.5	No
pwh	758	Number of periods conducted before the harvest started	2.6	Yes
T	2,000	The total number of periods conducted	2.6	Yes

Note: The POM column specifies if the parameter value is an outcome from the POM procedure (Yes) or obtained from another source (No). The column section gives a reference to the section(s) in the paper where the parameter is described.



FIGURE 4 The observed distribution of fishing effort from the Norwegian vessels up to 2017. The Loophole is the area represented by light grey. Black colour indicates land areas. We observe that fishing is taking place both inside and outside of the Loophole. The Norwegian vessels only amount to a minority of the total fishing activities

The second pattern used in carrying out the POM is a map representing the spatial distribution of crabs at a specific point in time. The map is based on an ecosystem survey performed in 2013, illustrated in figure 3.4.2 (Figure A.1) in Anon. (2016, p. 74). This figure was visually compared with the simulated spatial distribution of crabs for the same time period. The simulated spatial distribution of crabs is depicted in the panel $t = 758$ in Figure 5. The visual evaluation was performed by searching for the simulation that had the best fit to the observed pattern.

The POM approach was operationalized to calibrate the model:

1. A random sample from a distribution of reasonable values was drawn for each of the following ranges of parameter values:
 - *Growth rate*: $0.01 < g < 0.2$. The net growth is determined by the spatial diversity in the growth, diffusion, local collapses, and an absorbing boundary. Hence, the lump-based growth rate represented by g is not easily identified, and therefore, a relatively wide range was used. The lower limit is the lowest growth rate found to facilitate a sustainable level of biomass in the absence of fishing mortality.
 - *Catchability coefficient*: $0.0001 < q < 0.01$. q can be interpreted as the probability of any crab in a given cell being caught by one pot during one time step. There are no good indications for the possible values of this parameter, and therefore, a relatively wide range has been investigated.

- *The total capacity of the system*: $700,000 \text{ tonnes} < K < 1,680,000 \text{ tonnes}$. Estimated probability densities for the snow crab capacity in tonnes/km² based on the Canadian snow crab stock are presented in Figure 5 (Figure A2) in Anon. (2019a). The figure depicts values in the interval of 0.5–1.2 tonnes/km² as the most likely values. The values within this range are scaled according to the size of the Barents Sea (about 1,400,000 km²) and used as the range of possible values of the total carrying capacity.
- *The diffusion matrix M* defines the redistribution of biomasses at the cell level. Observations of movements of the snow crabs are used as the basis for creating the diffusion matrix. Nichol et al. (2017) have estimated the rates of movement for a sample of snow crabs in the Bering Sea using data storage tags. The values in the column labelled 'Mean distance per day' (km) in Table 1 (Table A2) in the referred study is used. We further aggregate these values into monthly values. For each simulation, we randomly drew a subset of 50 per cent of these values. The sample was divided into two parts. The share of values below 20 km represents the share of crabs remaining in the cell, while the rest are equally divided between the neighbouring cells.
- *The output elasticity of biomass*: $0.1 \leq \beta \leq 1$. From the arguments given above, β is expected to be a positive value below one and all realistic values are covered by the assumed range.
- *Number of periods without a harvest*: $240 < \text{pwh} < 960$, from the start of the invasion until the observed effort levels were

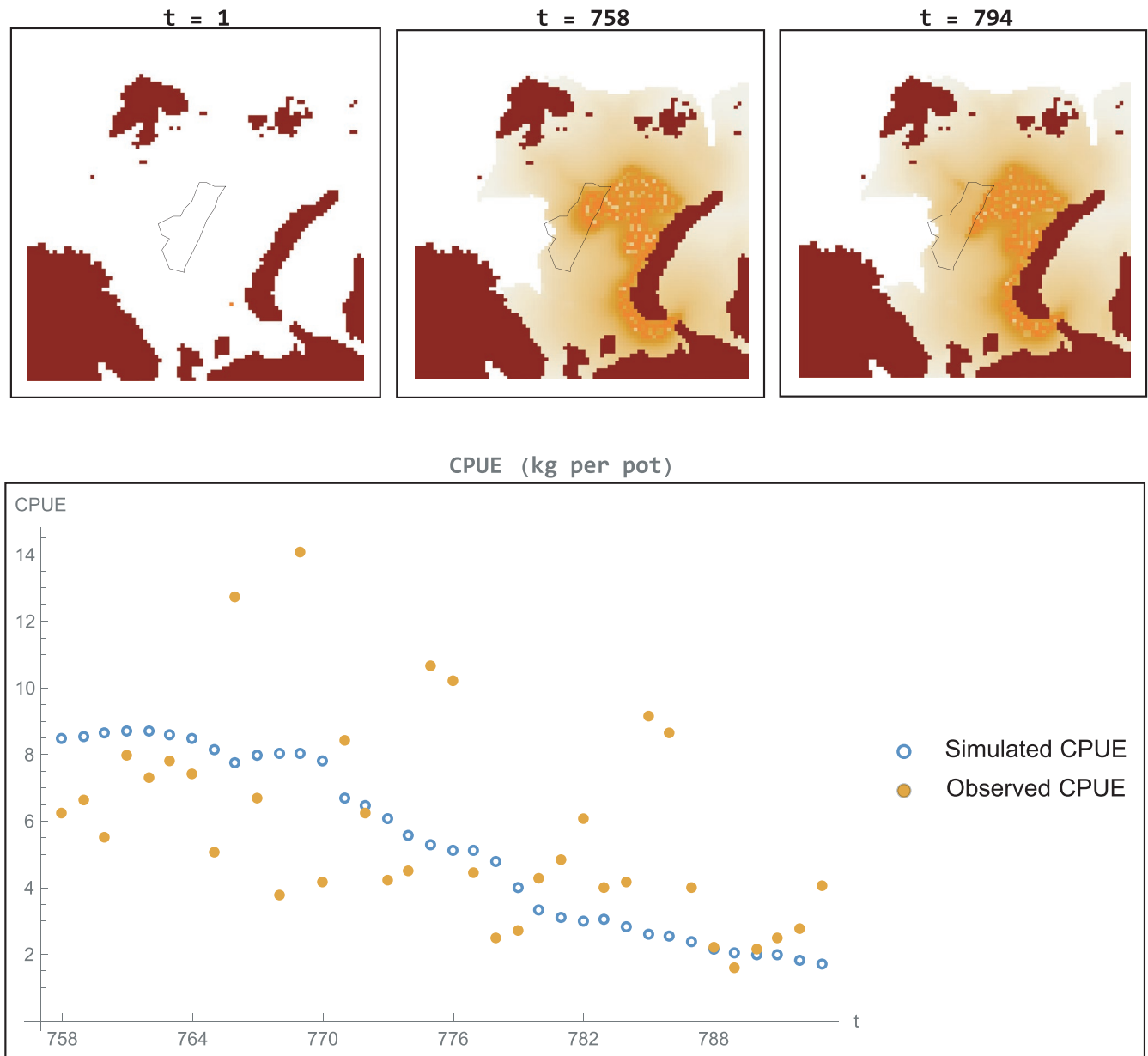


FIGURE 5 Snapshots of the distribution of snow crabs in the Barents Sea at different stages during the simulated invasion. Dark brown indicates land areas while white represents sea areas not occupied by the crabs. The remaining colours indicate the density of crab: more intense colours indicate higher densities. The representation of the Loophole is the polygon sketched by black lines. The lower panel shows the simulated and observed values of CPUE

- implemented. The unit of time is the month, which is the unit used for the variable t throughout the present paper.
- At time $t = 1$, one unit of biomass (1 kg) is released into the area of the Goose Bank, representing the start of the snow crab invasion, and a simulation is run based on a random sample of parameter values.
 - The number of simulated time periods without a harvest is defined by the value of pwh , after which the observed effort is implemented in the discrete spatial representation of the Loophole for the following 36 periods.
 - The Euclidean distance is calculated based on the periodic differences between the simulated and the observed CPUE.

- Steps 1-4 were repeated 10,000 times and the 10 simulations providing the shortest Euclidean distance were selected for further inspection.
- A subjective expert evaluation was conducted on the basis of the 10 selected simulations in order to identify the one with the best fit to the second pattern. The chosen simulation was selected as the base simulation for further studies of the development of the snow crab fishery.

The economic parameters are not included in the POM approach but obtained from other sources. The unit price of harvest and explicit unit cost of effort have been estimated to be 50 NOK/kg and 193 NOK

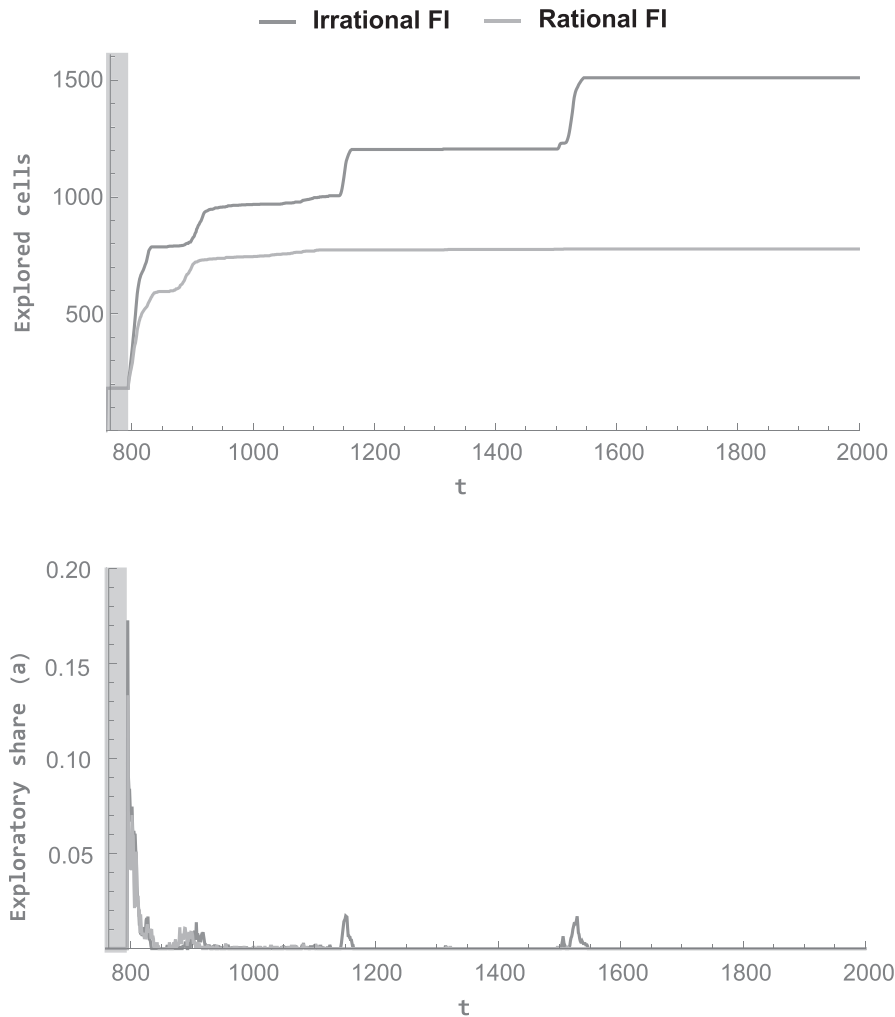


FIGURE 6 The top figure shows the cumulative number of explored cells $\sum_{i=1}^n \sum_{j=1}^m (u_{i,j,t} + h_{i,j,t})$ and the bottom figure shows the exploration rate (a_t) at time t . The figure shows the development from time period $t = 759$ and onwards. The grey background colour indicates the phase of the historic fishing activities taking place in the Loophole from 2014 until the end of 2016. The white background colour indicates the simulated further development of the fishery depending on the fleet's strategy. The dark colour indicates the *Irrational FI* scenario, and the grey colour represents the *Rational FI* scenario

per pot (Hogrenning & Henriksen, 2021), and we use these values for p and c . In the simulations, the stiffness parameter (see Equation 13) has been set to $\gamma = 0.00015$, determining the speed of fleet dynamics.

The parameter values of the selected simulation providing the best fit to the observed data are listed in Table 1. Figure 5 provides a visual representation of the chosen simulation in selected periods. We see that the fishing has affected the density of the crabs in the area where the fishing took place. The lower panel in Figure 5 shows the simulated and observed values of CPUE during the period of fishing.

3 | RESULTS

Figure 6 displays the simulated development of effort devoted to exploratory fishing (a) and the number of explored cells for a fleet conducting a *Rational FI* and *Irrational FI* exploration strategy. Starting at time $t = 759$ and continuing for 36 time periods, fishing is allowed to occur in the model's discrete representation of the Loophole. The number of

explored cells is shifted upwards by the number of habitable cells in this area. This event represents the historic fishing activities taking place in the Loophole from 2014 until the end of 2016. After this phase is finished, we allow the fleet to start exploring areas outside the Loophole. From time $t = 795$ and onward the different strategies are mapped by different scenarios, differing both in terms of the share of effort devoted to exploratory fishing and the development of explored cells.

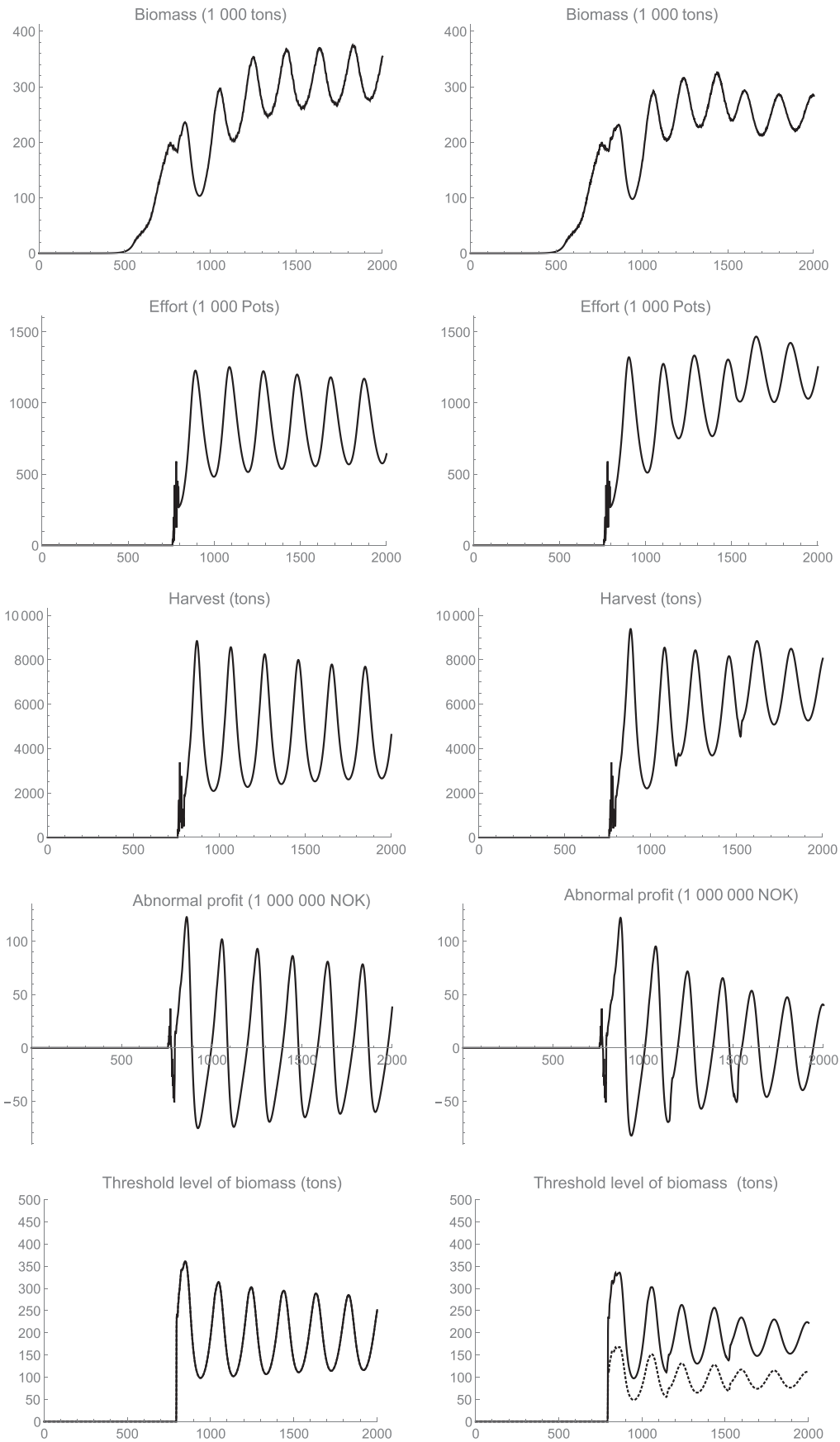
In the *Irrational FI* scenario, we observe that a relatively large share of the fishing effort is placed into exploratory fishing during some stages of the development. Hence, a large number of new cells are being explored. The development in the number of explored cells is characterized by periods of intensive exploration, interrupted by periods of almost no exploration. The first occurs as exploration is allowed to be carried out; additionally, there are three phases of exploration occurring around times 900, 1,150 and 1,500, before exploration of new areas comes to an end.

In the *Rational FI* scenario, a relatively low number of cells are explored compared to the *Irrational FI* strategy. However, in the *Rational FI* scenario there are no further phases of exploration after

FIGURE 7 The solid lines represent the levels of biomass, fishing effort, harvest, abnormal profit and threshold level of biomass (TLOB) in the two scenarios. In the *Irrational FI* scenario, the figure representing TLOB also includes a dotted line. This line represents the biomass level required in an unexplored cell in order for it to be explored. In the *Rational FI* scenario, this level coincides with the level of TLOB and the line is therefore not visible

Rational FI

Irrational FI



the second phase. In order to verify that exploration did not restart after 2,000 time periods, we ran both simulations for another 3,000 time periods without obtaining any new areas being explored.

Figure 7 shows that both systems appear to approach a bioeconomic equilibrium as the simulations move towards the final period. The *Irrational FI* strategy appears to be stabilizing at a higher level of harvest and effort and at a lower level of snow crab biomass than the *Rational FI* strategy does. It also shows what appears to be a correlation between the aggregate levels of biomass and the TLOB, which is determined by the biomasses of the explored cells and consequently is a function of the combined biological and economic dynamics reflected in fluctuations over time. A correlation is therefore to be expected. A reduction in TLOB may change the status of an unexplored cell from not being qualified for exploration to being qualified, and vice versa, according to (6). The figure shows that the biomass level required in an unexplored cell in order for it to be explored is on average substantially lower in the *Irrational FI* scenario than in the *Rational FI* scenario.

The plots of *harvest*, *abnormal profit* and TLOB in Figure 7, show what appear to be irregular positive shifts in the *Irrational FI* scenario. These shifts coincide with periods of large scale exploratory fishing and are visible around times 1,150 and 1,500 and occur at low levels of TLOB. This indicates that exploratory fishing starts when the harvest potential in the explored areas is relatively low, and that newly explored areas contribute to increased harvest and profit.

We now include the *Fully Explored* scenario, where we assume the fleet to have explored all cells in advance and there is nothing more to explore. This unlikely scenario is added for the sake of comparison. Table 2 includes figures displaying the spatial distribution of the snow crab fishery in the Barents Sea area in the cases of the three scenarios. A much higher share of the habitat is explored by conducting an *Irrational FI* strategy (56.7%) than by a *Rational FI* strategy (31.2%) (Table 2). However, the *Irrational FI* strategy also leaves a large share of the cells unexplored. It should be noted that the *Fully Explored* strategy also leaves

some habitable cells unexplored (0.8%). This is due to the fact that some habitable cells are disconnected from the main area and consequently could not be occupied by snow crab, given the assumptions in our model.




These differences in the explored shares of the habitat have consequences for the levels of the harvest and effort. The values do not differ substantially between the *Irrational FI* and the *Fully Explored* scenarios. The *Fully Explored* scenario achieves an annual harvest around 89,000 tonnes of biomass by employing around 16,500 thousand pots, while the *Irrational FI* scenario achieves an annual harvest around 79,000 tonnes of biomass by employing around 14,300 thousand pots. In the *Rational FI* scenario, the levels of effort and harvest are substantially lower. The annual harvest is around 51,500 tonnes obtained by applying around 9,700 thousand pots. The results from the simulations show that a fleet employing an *Irrational FI* strategy will explore a larger number of cells and exploit a higher share of the habitat than a fleet employing a *Rational FI* strategy. Hence, the results suggest that a larger share of the habitat will be explored when the fleet is willing to take risks.

Table 3 presents the descriptive statistics for both branches (*FI* and *LI*) of the *Rational* and the *Irrational* strategies. The table shows that the *LI* scenario covers a higher percentage of snow crab populated cells than the corresponding coverage of the *FI* scenario. The maximum values in Table 3 reveal that the *Rational LI* scenario is capable of obtaining a distribution corresponding to the values obtained in the *Irrational LI* scenarios. The results suggest that when the fleet is not able to fully determine the biomass level in adjacent unexplored cells, a larger share of the habitat will be explored.

4 | DISCUSSION

The model has been calibrated to represent the Barents Sea snow crab fishery by the use of a pattern-oriented approach. Although the model does not necessarily reflect all factors involved in the growth

TABLE 2 Final states of explored cells for the Rational FI, Irrational FI and Fully Explored scenarios

Rational FI	Irrational FI	Fully explored
		
Exploration rate: 31.2%	Exploration rate: 56.7%	Exploration rate: 99.2%
Effort = 9,703.6	Effort = 14,308.7	Effort = 16,422.1
Harvest = 51,524.1	Harvest = 79,128.6	Harvest = 89,414.2

Note: White indicates non-habitable cells. Light grey indicates habitable cells left unexplored in the scenario. Dark grey indicates explored habitable cells in the scenario. Black indicates land areas. The exploration rate refers to explored habitable cells as a percentage of all habitable cells in each scenario, calculated according to Equation 9. Effort (measured in thousands of pots per year) and harvest (measured in tonnes per year) are approximations of the equilibrium annual fishing effort and harvest. The two latter are averages over the last 500 time periods—in situations close to equilibrium.

TABLE 3 Descriptive statistics showing the exploration rates (percentage of the snow crab habitat explored by the fleet) in different scenarios

Scenario	Mean	SD	Min	Max	N
Rational FI	31.2		31.2	31.2	1
Irrational FI	56.7		56.7	56.7	1
Rational LI	49.1	5.05	45.2	63.1	20
Irrational LI	63.0	0.20	62.6	63.3	20

Note: The statistics are obtained by running each scenario the number of times specified in column N. The exploration rates are presented in terms of average values of the runs (Mean), standard deviation (SD), and minimum (Min) and maximum (Max) values of all runs.

and distribution of the snow crab, it seems to reproduce the observed patterns quite well. However, this is not a guarantee that the model will reflect future distribution patterns.

Our results confirm that different fleet strategies affect the fishery both in short- and long-term perspectives. In both the *Rational FI* and the *Irrational FI* scenarios, the fleet explores areas east of the Loophole towards Novaya Zemlya and some areas northwest, towards Svalbard, motivated by the potential harvest in these areas. The attractiveness of these areas is also apparent in Figure 2, reflecting the basic assumptions of habitat preferences. The majority of the cells with the largest capacities are located in an area of several interconnected cells. This area includes the Loophole, where the fishery was located when the process of exploration started.

In the *Rational FI* scenario, the fleet does not discover clusters of high capacity areas located further away from the initial area. It appears that the unfavourable areas separating the areas of high biomass carrying capacity might serve as barricades to exploration. This indicates that if the crabs are clustered together in areas separated by patches with lower amounts of crabs, the fleet might not identify these areas as long as the fleet behaves rationally. This will potentially leave profitable areas unexplored and thereby leave dense areas of crab biomass unexploited.

When introducing a riskier exploration behaviour, the fleet also explores other areas of high capacity located further away from the initial area. The *Irrational FI* strategy is consistent with the definition Allen and McGlade (1986) give of a *stochast*, because the fleet risks deploying effort into unexplored cells with significantly lower biomasses than in the already explored area. This may lead the fleet to explore cells acting as gateways to more valuable fishing grounds, which would not be explored by a fleet employing a *Rational FI* strategy. We also find that harvest and effort levels are closer to the levels found in the *Fully Explored* scenario. This supports the findings of Allen and McGlade (1986), suggesting that a fishery will benefit in the long run from the behaviour of a *stochast*. Additionally, our results indicate that the long-run gains from the *stochast's* behaviour depend on the spatial heterogeneity in the distribution of the species of target.

In the *FI* strategies, we give the fleet the ability to know whether or not an adjacent unexplored cell has a crab density surpassing what

the fleet on average would locate by fishing in the explored area. This is a very strict and unrealistic assumption. However, the fleet is likely to formulate hypotheses about crab densities both in the areas where they are currently fishing and in unexplored neighbouring areas, and explore accordingly. With the *LI* strategies, we allow the fleet to miscalculate the biomass level of unexplored adjacent cells by ± 100 per cent. The *LI* scenarios, reflecting that these hypothesis are correct to a varying degree, find a larger percentage of the habitat than their counterparts, the *FI* scenarios. Because of the limited information about the density of crabs in the unexplored area next to the known fishing grounds, the fleet unintentionally explores areas of lower density than anticipated, leading as pathways to more prosperous fishing grounds.

Limited information of the density of crabs in the unexplored grounds next to the explored grounds and an irrational behaviour contribute to identifying new fishing grounds to be exploited. Because both forces appear to contribute to exploration, it is difficult to attribute causation to a specific force when exploration is observed. This is in line with Branch et al. (2006), stating that it is difficult to identify risk-taking behaviour in a fishery. They claim that fishers may also have made a bad decision, had insufficient information, or simply been unlucky. Of course, the two forces do not guarantee that all valuable fishing grounds will be explored, but our study suggests that both contribute to revealing larger parts of the dense area of snow crab. Different rules of irrational behaviour and fish-finding capabilities may change the magnitude of the effect of the particular force, without changing the implication of a combination of spatial heterogeneity and the two forces.

Our results emphasize the serious consequences of ignoring spatial diversity when modelling fisheries. The distribution of carrying capacities is defined by the average depth and annual temperature within an area of 20 by 20 km. There may be a significant heterogeneity within each area. Models based on different spatial resolutions may therefore find different distributions of the environmental carrying capacities for the snow crab. Modifications of the rules (Figure 1) defining the environmental carrying capacity will alter the distribution. The simulated development of the fishery could then change, but we still expect the interaction between the fleet dynamics and the spatial distribution of crabs to be important for its development.

In our model, we assume that once a fishing ground is explored the information describing the particular ground is common knowledge for the entire fleet the next period. Hence, we do assume that there are no competitive advantages for a particular vessel from discovering a fishing ground beyond the single period of the exploration. This is in conflict with Barney (1991), who argues that a firm can experience a sustainable competitive advantage by implementing a strategy that no other competitor is able to duplicate. However, the Norwegian statistics covering harvest operations (such as harvest rates and fishing locations) are with only few exceptions considered public information (Anon., 2019b). Therefore, it is reasonable to assume that a strategy of fishing on a newly explored, particularly lucrative fishing ground,

can be followed by other vessels, and so it might be tempting for a vessel to refrain from exploratory activities and wait for others to explore an area. This observation may question to what extent we would expect to find vessels following the *Irrational* strategy. Therefore, we suggest that exploratory fishing is most prominent in times when the harvest rates in the explored areas are inadequate to facilitate profitability, leaving the vessels with no other options than exploring new areas if they want to earn profits (assuming the vessels to be reluctant to leave the fishery). If this is the case, the exploration of new areas will be a function of the profitability of the vessel. We have ignored differences in the cost of transportation to different fishing grounds, but we expect the fishers to explore fishing grounds minimizing the cost of transportation all else equal. The model can be adjusted to incorporate the effect of transportation costs given the existence of such cost estimates. Another, potentially important, factor in the snow crab fishery is that we do not consider the potential unavailability of some fishing grounds due to environmental conditions, for example, the presence of sea ice.

In this study, we focus on a fleet targeting a species expanding its presence in a new area. The habitat distribution is assumed fixed and therefore only needing to be explored once. However, habitats are likely to change over time, making the process of discovering lucrative fishing grounds a continuous effort for the fishers. Annual bottom trawl surveys on the eastern Bering Sea (EBS) shelf indicate that this may be the case in the Bering Sea snow crab fishery. In the EBS, a cold pool of bottom water is formed by the seasonal melting of ice (Stabeno et al., 2001). Recently, a reduction in the range of the distribution of the snow crab has been associated with a reduction of this pool (Fedewa et al., 2020). In the northern Bering Sea (NBS), observations of snow crabs have historically been of sizes outside the scope of commercial value; however, a substantial increase in large size crabs has recently been observed, indicating the potential for a future commercial fishery in the NBS (Fedewa et al., 2020). In general, any species having a shifting habitat distribution over time is likely to continually generate the exploration and exploitation dynamics we have examined in this study.

Decisions about the management of fisheries are often based on historical data and catch records (Hilborn, 2012). Our results suggest that fishery managers should be aware that the distribution of fishing effort only represents the discovered resource distribution. One implication of this is that any unexplored area could act as a unintended no-take zone and in this way decrease the risk of biological overexploitation. It also signifies the role surveys may play for fishers as a source of information. In the model specifications, we have considered areas available for exploration to be limited to neighbouring areas to those already explored. In practice, a non-adjacent unexplored area may be pinpointed for exploration due to by-catch observations or information from research activities, as was the case with the first observation of the snow crab in the Barents Sea in 1996 (Anon., 1997). Our model does not take into account the contribution of such events in identifying attractive fishing grounds.

Hence, surveys can provide fishers with information that leads to a more complete exploration of a new fishery. However, observations from the Bering Sea snow crab fishery indicate that this role is not limited to new fisheries (Fedewa et al., 2020).

Management constraints could have influenced the development of the crab fishery in a number of ways. A regulation may limit both the exploitation area and the Total Allowable Catch (TAC). However, independently of the management regime, a spatial exploration of potential fishing grounds needs to take place. Our results suggest that exploration is often initiated when the biomass level is reduced in the explored areas. The TAC may serve to prevent biological over-exploitation and hinder the exploration process at the same time as preventing biomass suppression in the explored areas. This shows how fishery management could alter the dynamics of exploration. Further studies should investigate the effect of different management regimes on spatial exploration and the long-term exploitation in the crab fishery.

The *Fully Explored* scenario provides the open access levels for the simulated crab fishery given that the whole area is explored. It suggests that the open access harvest level of the fishery is around 89,000 tonnes per year. This result depends heavily on the assumptions of the model. However, the estimated open access harvest level is within the range of future harvest rates estimated by the Norwegian Institute of Marine Research. Their estimate is within the range of 50,000 to 170,000 tonnes, acknowledging that this estimate is associated with a high degree of uncertainty (Anon., 2015). While this is a study of the Barents Sea snow crab fishery, our model also includes parts of the Kara Sea as a suitable habitat for the snow crab. This is consistent with recent findings of snow crabs in the Kara Sea (Anon., 2019a).

There are uncertainties related to the structure of the biological, environmental, and economic model, as well as its parameter values and initial conditions. Snow crabs have a life cycle involving a pelagic larval phase and may therefore also spread by larval drift due to ocean currents (Siikavuopio et al., 2019). If this kind of dispersion is an important factor in creating the patterns we observe, we might have omitted an important element describing the spread. Even if we had included important elements describing the system, a larger number of simulations would be necessary to explore the entire parameter space of the model. The pattern-oriented modelling approach seems to be promising, as it produces comparable estimates and allows the inclusion of more patterns in the calibration process as more knowledge is gained and more observations are obtained.

5 | CONCLUSION

By using a cellular automata approach, it has been possible to model spatial diversity on a rather detailed scale. The interaction between the fleet dynamics and spatial distribution of the snow crab appears to be of great importance. Our study suggests that the most lucrative fishing grounds for snow crab are heterogeneously distributed over the Barents Sea, separated by patches of lower densities. The fleet dynamics affects which fishing grounds are explored and exploited.

We consider the findings to also have implications for how to model other fisheries where the species are heterogeneously distributed. Further studies should aim at validating this finding by incorporating different scenarios of fleet dynamics. For instance, we suggest having the exploration dynamics depend on the profitability of the fishery, influenced by information from other sources and a spatially distributed cost structure. Further research should also look more closely at the development of a new fishery under various regulatory measures.

Although our model represents a new fishery, we anticipate the exploration and exploitation dynamics also to be present in mature fisheries where the species of interest reallocates itself over time. However, the fishers are likely to be in need of external information to ensure a more complete exploration of new fisheries and in order to stay updated on lucrative fishing grounds in existing fisheries. Information from surveys appears to be important.

ACKNOWLEDGEMENT

This work was supported by the Research Council of Norway (project: 267763). We are grateful to the participants in the interdisciplinary research project SnowMAP and two anonymous referees for their constructive inputs.

DATA AVAILABILITY STATEMENT

The data used in this study are openly available, and the sources are clarified within the article.

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How to cite this article: Hogrenning, E., & Eide, A. (2021). Environmental constraints, biological growth and fleet dynamics of a developing fishery: A model study of the Barents Sea snow crab (*Chionoecetes opilio*, Majidae) fishery. *Fish and Fisheries*, 00, 1–18. <https://doi.org/10.1111/faf.12618>

APPENDIX 1

TABLE A1 Norwegian quota recommendation, established quotas, and landings of snow crab (in tonnes) in the Barents Sea in the period 2012 to 2020 divided by each nation. This table is the authors' own translation of table 1 originally published in Norwegian in Anon. (2019a, p. 6)

Year	Recommended Norwegian Quotas (tons)	Quotas (tons)		Landings (tons)			Total landings (tons)
		Norway	Russia	Norway	Russia	EU countries	
2012		-	-	2	0	0	2
2013		-	-	189	62	0	251
2014		-	-	1800	4104	2300	8204
2015		-	1100	3482	8895	5763	18140
2016		-	1600	5290	7520	3690	16500
2017	3600–4500	4000	7840	3153	7780	2	10847
2018	4000–5500	4000	9840	2804	9728	-	12532
2019	3500–5000	4000	9840	3775 [*]	9840	-	13615 [*]
2020	<5500						

^{*}Data as of 19 November 2019.

FIGURE A1 Map of snow crab distribution from the ecosystem survey reports for 2013 (Anon., 2016, p. 74).

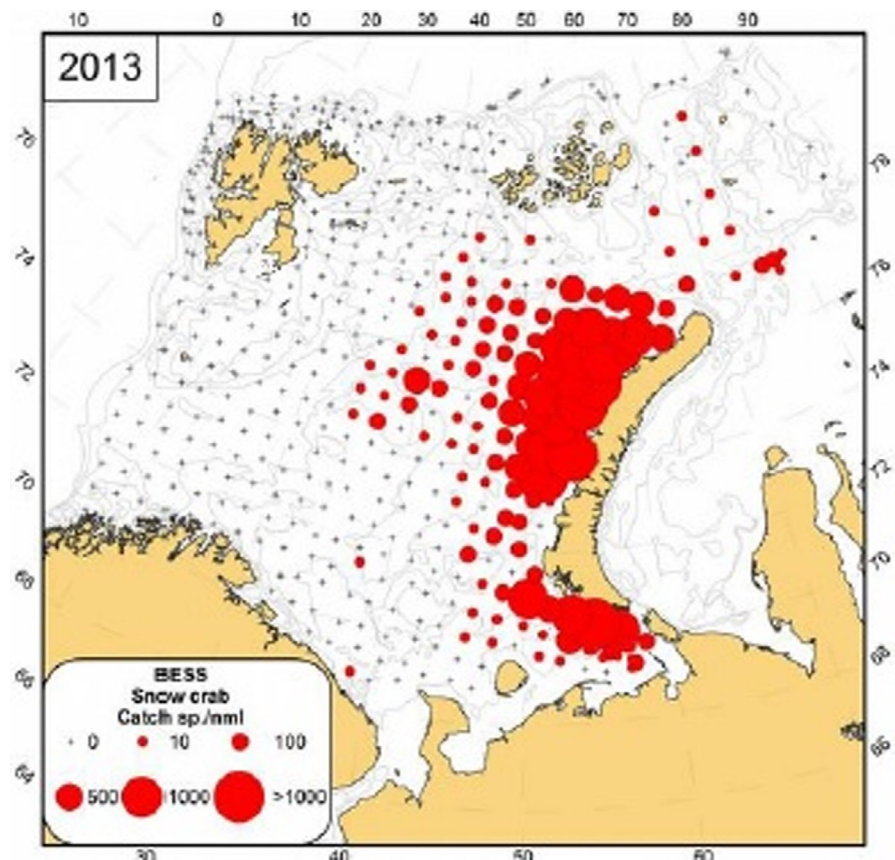


TABLE A2 Summary of the distances moved by morphometrically mature (Large-clawed) male snowcrab (*Chionoecetes opilio*) released with data storage tags in the eastern bering sea. Distances reflect across-shelf movements only, estimated for each crab as the daily change in bottom depth divided by the bottom slope (Nichol et al., 2017).

Table 1.
Summary of the estimated distances moved by morphometrically mature (large-clawed) male snow crab (*Chionoecetes opilio*) released with data storage tags in the eastern Bering Sea. Distances reflect across-shelf movements only, estimated for each crab as the daily change in bottom depth divided by the bottom slope.

Crab identification number	Release date	Days recorded ¹	Carapace width (mm)	Mean overall temperature (°C)	Cumulative distance moved (km)	Mean distance per day (km)	Maximum distance per day (km)	Maximum distance per month (km)	Month/year of maximum distance ²
5655	4/19/2010	309	119	3.6	63.2	0.2	3.5	19.2	5/2010
5660	4/19/2010	312	122	3.6	53.8	0.2	1.3	6.5	5/2010
5665	4/19/2010	255	126	3.2	107.9	0.4	1.9	26.7	11/2010
5749	4/19/2010	282	121	3.4	61.2	0.2	2.5	16.6	5/2010
5756	4/19/2010	296	116	3.1	267.2	0.9	5.1	36.0	5/2010
5770	4/20/2010	320	109	3.5	96.6	0.3	2.1	28.7	9/2010
5771	4/20/2010	286	115	3.6	28.8	0.1	1.1	6.5	5/2010
5776	4/20/2010	303	114	3.6	56.3	0.2	1.6	15.9	5/2010
5782	4/20/2010	286	125	3.5	101.0	0.4	2.8	21.3	7/2010
5786	4/20/2010	317	119	3.1	219.6	0.7	3.4	52.2	5/2010
5791	4/20/2010	93	111	2.5	71.9	0.8	5.6	28.6	4/2010 (8)
5792	4/20/2010	276	110	3.3	104.6	0.4	3.6	29.9	5/2010
5798	4/20/2010	293	100	2.6	260.7	0.9	6.4	47.3	9/2010
5809	4/20/2010	138	121	3.3	35.3	0.3	2.4	20.8	5/2010
5816	4/20/2010	316	123	3.6	47.9	0.2	1.4	9.7	5/2010
5819	4/20/2010	279	117	3.6	35.9	0.1	2.2	17.3	5/2010
5820	4/20/2010	279	119	3.6	48.0	0.2	1.4	6.9	5/2010
5845	4/21/2010	467	100 ³	3.2	416.8	0.9	6.5	97.6	4/2011
5846	4/21/2010	287	110	3.4	170.7	0.6	5.9	50.9	5/2010
5851	4/22/2010	318	102	2.9	255.4	0.8	6.0	57.6	5/2010
5854	4/22/2010	278	117	3.5	147.3	0.5	7.0	24.3	11/2010
5855	4/22/2010	296	112	3.1	338.3	1.1	6.3	83.8	12/2010
5859	4/22/2010	317	125	3.4	99.2	0.3	3.0	19.5	1/2011
5880	4/22/2010	277	115	3.2	126.7	0.5	6.5	32.7	9/2010
7340	3/08/2011	440	112	2.2	242.3	0.6	5.6	38.5	11/2011
7352	3/08/2011	299	120	2.6	89.4	0.3	1.4	14.3	5/2011
7368	3/08/2011	454	123	2.3	110.6	0.2	1.4	12.2	3/2012
7371	3/08/2011	426	100	2.2	210.8	0.5	3.3	26.7	4/2011
7387	3/08/2011	45	115	2.4	16.8	0.4	1.9	6.7	3/2011 (21)
7424	3/08/2011	441	119	2.4	118.9	0.3	1.9	14.7	3/2012
7425	3/08/2011	435	117	2.3	149.1	0.3	3.1	23.6	6/2011
7448	3/08/2011	34	123	2.4	15.5	0.5	2.2	11.6	3/2011 (21)
7456	3/08/2011	69	106	2.3	77.8	1.1	3.7	44.7	4/2011

¹ For crab identification numbers 5865, 5791, 5509, 5845, 7387, 7448, 7456, the tag depth sensors failed after the indicated days recorded, and thus days recorded do not equal days at liberty.
² Number in parentheses indicates the total days of the month in which data was collected, for months that were not complete (i.e., the month of tag release).

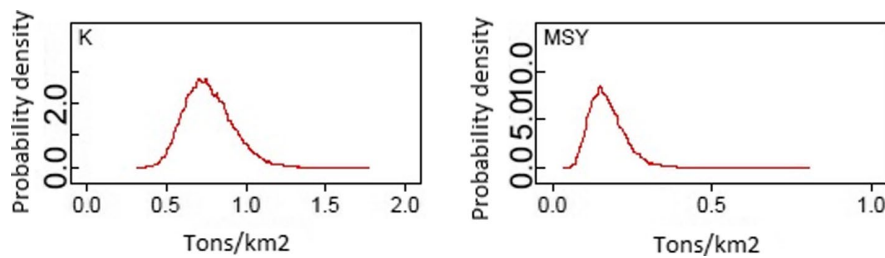


FIGURE A2 Probability densities for carrying capacity (*K*) and maximum sustainable yield (*MSY*) in tons/km² based on estimates for the snow crab population in Canada. This figure is the authors' own translation of figure 5 originally published in Norwegian in Anon. (2019a, p. 8).