Title: Simulating the effects of environmental and market variability on fishing industry structure

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Abstract:

An Agent-Based Model comprising a fish stock, a fishing fleet and a fish market is used to investigate the combined effects of environmental and market variability on the structure of a fishery. Over 15-year simulations, agents make daily fishing decisions and annual entry, exit, and investment decisions based on the fishery's past economic outcomes and their individual risk preferences and opportunity costs (*e.g.*, an alternative source of income). Environmental variability is simulated through fishing success variability while market variability is simulated through changes in the elasticity of the demand curve (*i.e.*, the responsiveness of market prices to changes in daily landings). Our findings indicate that changes in variability lead to changes in economic and biological conditions of the fishery by influencing the composition of risk preferences within the fleet. Counter to expectations, market stability did not dampen the negative impacts of environmental variability but rather stimulated over-investment and increased harvesting by a small number of risk-seeking fishers. Results from this research suggest that climate-driven increases in fisheries variability, coupled with increases in market integration that act to reduce local price signals, may lead to inefficient investments and reduced fishery resources.

Keywords: Agent-Based Model; fisheries; decision-making; environmental variability; fishing industry organization

Introduction

Variability in the abundance of fish stocks and fisheries production results from shifting environmental conditions (Jacobson et al., 2001; Lehodey et al., 2006) and may be amplified by exploitation (Anderson et al., 2008; Hsieh et al., 2006) and changes in age and spatial structure of the spawning stock (Berkeley et al., 2004; Ottersen et al., 2006). Large inter-annual changes in production can reduce access to fishery resources and have detrimental impacts on fishers and their communities (Badjeck et al., 2010; Caviedes and Fik, 1992; Sumaila et al., 2011). Diversification of catch and production across stocks, species, or fishing grounds has been shown to stabilize incomes and reduce exposure to natural variability and risk (Anderson et al., 2017; Cline et al., 2017; Kasperski and Holland, 2013; Schindler et al., 2010). Still, climate change and continued fishing pressure are expected to increase fisheries' variability globally

(Brander, 2010, 2007; Perry et al., 2010) and many communities may have limited alternatives for diversification as over 90% of assessed stocks are currently considered fully- or overfished (Food and Agriculture Organization, 2018).

The Food and Agriculture Organization estimates that over 40 million people rely on wild capture fisheries as sources of income and employment (Food and Agriculture Organization, 2018). If considering ancillary industries and indirect employment, the livelihoods of hundreds of millions depend on this sector (Teh and Sumaila, 2013). In addition to income, jobs in capture fisheries have also been argued to serve important sociocultural (Weeratunge et al., 2014), gender (Weeratunge et al., 2010; Williams, 2008), and development (Béné et al., 2010) functions. While it is obvious that human communities who depend on fishery resources for income and employment are affected by variability in species' temporal and spatial abundances, mechanistic pathways and magnitudes of response are less obvious. Additionally, the economic effects of fisheries' variability are modulated through prices, suggesting market structure may be consequential when considering the relationship between natural variability, income, and employment.

Bioeconomic analyses have considered fisheries variability in examining optimal investment, harvest, and management strategies, finding increased variability generally reduces optimal investment and harvest levels (Charles, 1983; Hannesson, 1993; Poudel et al., 2013), though optimal policies may depend critically on costs associated with changes in fleet size or capacity (Singh et al., 2006). There are few studies considering the effect of resource variability on individual investment decisions and fleet development in commercial fisheries (Nøstbakken et al., 2011). The impacts of uncertainty on investment and firm behavior have been studied in more general settings (*e.g.*, Dixit and Pindyck, 1994) and can inform expectations in commercial fisheries (*e.g.*, hysteresis, or the failure of an effect to reverse when its underlying cause reverses, commonly observed in firm entry and exit behavior, Dixit, 1989; Dixit and Pindyck, 1994). However, the influence of variability on individual behavior and industry development in commercial fisheries may be unique as fluctuations in fish abundance and availability are often large, short-lived, and heterogeneously distributed across fishery participants.

Agent-Based Models (ABMs), also referred to as Individual-Based Models (IBMs), enable researchers to simulate complex systems and evaluate emergent phenomena resulting from the aggregate behavior of individual agents (Bonabeau, 2002; Holland and Miller, 1991). Agents may follow decision-making rules, interact with one another, and exhibit heterogeneity in individual traits, hence enabling ABMs to explicitly simulate population-level variability as a consequence of inter-individual variability. ABMs are particularly useful when individual behavior is non-linear or exhibits thresholds, is characterized by temporal correlation, or is subject to stochastic processes (Bonabeau, 2002). This modeling approach has been applied in fisheries to understand fleet dynamics and fishing behavior (Cabral et al., 2010; Millischer and Gascuel, 2006; Soulié and Thébaud, 2006; van Putten et al., 2012), explore decision-making in response to regulations or management alternatives (Bailey et al., 2019; Bellanger et al., 2018; Gao and Hailu, 2011; Little et al., 2009; Soulié and Thébaud, 2006), and analyze emergent economic and ecological outcomes under a variety of agent decision rules (BenDor et al., 2009; Wilson et al., 2007).

We utilize an ABM framework to better understand the effects of environmental and market variability on fisher entry, exit, and investment behavior. In the model, individual agents make daily fishing decisions and annual entry, exit, and investment decisions by comparing expectations regarding fishing profits against individual opportunity costs and risk preferences. Simulations using combinations of fishing success variability (proxy for environmental variability) and fish price elasticity (proxy for market variability) were run, and, the state of the fishery after fifteen years of operation was quantified through a range of metrics (*e.g.*, number of active fishers, investment levels, fish biomass, fishing profits).

Methods

General approach

An Agent-Based Model (ABM) designed to capture the salient characteristics of a system comprising a fish stock, a fishing fleet and a fish market is described. The overarching goal of this study is to investigate the combined impact of environmental and market variability on fishers' decision-making and its consequences. Due to the paucity of information available for the calibration of the model, each of its elements is represented in its simplest form. The fish stock is represented by a biomass which can be removed through harvesting and is regenerated each year to simulate annual recruitment events. One hundred fishers are simulated and have the opportunity, once a year, to enter or exit the fishery and to invest into a larger vessel. The decision-making process is based upon the economic outcomes of fishing operations (past profits and their variance) while accounting for individual behavioral traits (risk preferences and alternative income sources). Profits depend upon fishing success (which variability is modulated to simulate different levels of environmental variability), vessel capacity (on which depend catch and operational costs), and, fish price (which elasticity is modulated to simulate different levels of market variability).

Dynamics are simulated for 15 years with a daily time-step; for simplicity, twelve 30-days months are simulated for each year. A set of key metrics (*e.g.*, fish biomass, number of fishers, investments, profits) computed at the end of simulations are stored for subsequent analysis. All computations were done in the R statistical computing environment, version 3.5.0 (R Core Team, 2019).

Model description

The structure of the model is described in the following sections. The sequence of daily computations is further summarized in Figure 1 and model parameters are given in Table 1.

Fish stock

The fish stock is represented by a fish biomass (*B*, t) which may be harvested every day by each fisher. On January 1st, fish biomass is reset to an initial value (*Bi*, table 1) to simulate annual recruitment. Fish biomass is set as to be non-limiting (*i.e.*, fishers never deplete the stock).

Individuals

Each individual is characterized by 8 variables and 3 constants (η, ρ and ω, which are set prior to running a simulation), as described below.

- *Fisher* (status, binary): initially set to 0, becomes 1 if the individual enters the fishery, reverts to 0 if the individual exits the fishery.
- *Invs* (accumulated investments, \$): initially set to 0. Every time a fisher decides to invest, accumulated investments are incremented by a constant investment cost (*Inv*, \$):

$$Invs = Invs + Inv \qquad (1)$$

  Accumulated investments are nullified if the individual decides to leave the fishery.
- *InvTime* (time of last investment, days): If a fisher invests, it is updated as being equal to the number of days elapsed since the beginning of the simulation, otherwise it remains unchanged.
- *DInvs* (depreciated investments, \$): Takes part in the decision to leave the fishery. When a fisher decides to invest, depreciated investments are updated while accounting for the depreciation of past investments:

$$DInvs = \frac{DInvs}{(1+0.05)^{\frac{t-InvTime}{Ddep}}} + Inv \qquad (2)$$

  , where *t* is the number of days elapsed since the beginning of the simulation, *Ddep* is the duration (one year) over which a 5% (0.05) rate of depreciation is assumed. Depreciated investments are nullified if the individual decides to leave the fishery.
- *VC* (vessel capacity, kg): Controls both landings achievable in a day and operational costs. Vessel capacity is a linear function of accumulated investments:

$$VC = Invs \times VCsl + VCint \qquad (3)$$

  , where *VCsl* and *VCint* are slope and intercept parameters respectively.
- *Π* (accumulated profits, \$): sum of past profits and new profits (π, \$), updated daily.

- *Catch* (kg): amount of fish caught on a given fishing day.
- *Trip* (status, binary): initially set to 0, set to 1 if fisher decides to go fishing on a given day.
- η (response to variance in profits, unit-less): randomly generated from a normal distribution with a mean of $\bar{\eta} = 0$ and a standard deviation of σ_η. Negative values correspond to risk-seeking individuals and positive values correspond to risk-averse individuals.
- ρ (opportunity costs/preference toward fishing, \$): randomly generated from a normal distribution with a mean of $\bar{\rho}$ and a standard deviation of σ_ρ. High values correspond to individuals with better alternative sources of income (*e.g.*, a more lucrative job opportunity) and/or a dislike of fishing while low values correspond to individuals without better alternative and/or a fondness of fishing.
- ω (belief/knowledge of other's economic outputs, unit-less): randomly generated from a uniform distribution bound between 0 and ω_{max}. Each individual is assigned as many values as there are other individuals in the model and self-belief/knowledge is set to 1. Takes part in decision-making computations and is used to weight the economic outputs (average and variance of profits) from other individuals, hence controlling the relative importance of fleet-wide profits and individual profits.

Fishing operations

In order to account for the seasonality of fishing operations, a time-varying probability of leaving port (*Plp*) is used. This probability is computed as a double logistic function of time (*t*, days), resulting in the fishery being opened only for a part of the year:

$$Plp = \frac{1}{1+e^{-a(t-b)}} \times \left(1 - \frac{1}{1+e^{-c(t-d)}}\right) \qquad (4)$$

Parameters *a*, *b*, *c* and *d* control the shape of the double logistic function, where *a* and *c* control the speed of the opening and closing of the fishing season respectively, and, *b* and *d* control the timing of the opening and closing of the fishing season respectively. Every day, for each fisher that decides to go fishing (i.e. with a '*Trip*' status of 1), if a random number generated from a uniform distribution bound between 0 and 1 is inferior to *Plp*, that fisher goes fishing.

Daily catch *(Catch, kg)* is computed as a stochastic process depending on fishing success (*success*) and vessel capacity (*VC*).

$$Catch = success \times VC \qquad (5)$$

Fishing success is randomly generated daily for each fisher from a uniform distribution bound between (0.5-0.5×*Svar*) and (0.5+0.5×*Svar*), with success variability (*Svar*) ranging from 0 to 1 and set constant during a simulation. An averagely successful day (i.e., *success*=0.5) therefore enables a fisher to reach half of the vessel's capacity with fish catch. Under maximum success variability (*Svar*=1), catch ranges between 0 and *VC*. Through this formulation, the effect of variability in fishing success may be investigated without affecting average catch (and therefore average profits).

Market

Fish price (*Price*, $\$.kg^{-1}$) is computed at the end of the day, after the conclusion of fishing operations, based on total daily landings (*TL*, kg; i.e., the sum of individual *Catch*) and potential total landings (*PTL*, kg), following an isoelastic formulation:

$$Price = \min(Pmax, Pmid \times \left(\frac{TL}{PTL}\right)^{(1/-PED)}) \qquad (6)$$

Fish price is therefore limited to a maximum price (*Pmax*, $\$.kg^{-1}$), reduces with increasing landings according to the Price Elasticity of Demand (*PED*) and reaches an average price (*Pmid*, $\$.kg^{-1}$) when total daily landings equal potential total landings. Potential total landings are the total landings expected from an average fisher population at the mid-point of the simulation (see Supplementary Information 1). This formulation enables testing a range of *PED* values – which control the slope of price as a function of landings and represent market variability – while maintaining the average price constant (i.e., at *Pmid*). In doing so, changes in decision-making caused by changes in *PED* are not biased by changes in average price.

Profits

Daily profits (π, $) are computed as the balance between gains from selling fish and losses from costs, which are proportional to the vessel's capacity (*VC*) and revenue:

$$\pi = Catch \times Price \times (1 - Cf) - (Cb + Cm) \times VC \qquad (7)$$

Where *Cb* ($\$.kg^{-1}$) is the base cost rate for all vessel owners (e.g., docking fees, taxes, fishing license…), *Cf* (unit-less) is the fishing cost rate (*e.g.*, crew salary, gas…), and, *Cm* ($\$.kg^{-1}$) is the maintenance cost rate (*e.g.*, fishing gear repairs, engine maintenance…). *Cf* and *Cm* are only accounted for individuals that decided to go fishing on a given day (*i.e.*, individuals with a '*Trip*' status of 1). As fishing revenues and costs are proportional to vessel capacity, this form of the profit function implies constant marginal returns of individual investments (*i.e.*, profits scale proportionately with vessel capacity under constant prices).

Decision-making

Four decision-making computations are executed in the model (Fig. 1). The decision to go fishing is taken daily by fishers (individuals that have entered the fishery, with a '*Fisher*' status of 1) and is based on yesterday's economic outcomes, while the three remaining decisions are taken on January 1st (fishery entry, fishery exit, investment) and are based on historic economic outcomes. Economic outcomes are cross-fleet weighted means of past profits and their variance,

using ω (individual belief/knowledge of other's profits) as weights. Only the economic outcomes of fishers are considered.
On a given day (t), yesterday's average profits, as perceived by individual i (characterized by its individual belief/knowledge of other's profits, ω_i) are:

$$\widehat{\pi_{\iota t}} = \frac{\sum(\pi_{t-1} \times \omega_i)}{\sum \omega_i} \quad (8)$$

, and the unbiased estimate of weighted variance in profits is:

$$Var(\widehat{\pi_{\iota t}}) = \frac{\sum \omega_i (\pi_{t-1} - \widehat{\pi_{\iota t}})^2}{\sum \omega_i - \sum \omega_i{}^2 / \sum \omega_i} \quad (9)$$

The decision to go fishing is taken daily by fishers. A fishing trip is made on day t by fisher i when:

$$\widehat{\pi_{\iota t}} - \eta_i \times \ Var(\widehat{\pi_{\iota t}}) > \rho_i \quad (10)$$

Yesterday's perceived profits, their variance and the individual's response to variance are compared to the individual's opportunity costs/preference toward fishing. A risk-averse individual would therefore decide not to go fishing if he had sufficiently lucrative alternative opportunities on that day.

The remaining three decision-making computations occur on January 1st and are based on past profits and their variance. In order to put more weight on recent economic outcomes relative to former ones (e.g., last year's economic outcomes are more relevant today than those from ten years ago), a logistic function of time is used as a weight in a weighted mean of past economic outcomes. In addition, the seasonality of fishing operations (*Plp*, eq. 4) must be accounted for so that individuals consider profits generated while the fishery is open (otherwise decisions would be biased by negative profits while the fishery is closed). On day t, a time-dependent formulation of historic weights (w_h) is computed as:

$$w_h = \frac{1}{1+e^{-TDr[\tau_1^t - (t-360)]}} \times Plp_1^t \quad (11)$$

, where τ is a sequence of integers from 1 to the current count of days (t), *TDr* is a rate of decay and *Plp* is evaluated for all days up to t. This formulation results in historic weights reaching maximum on day t, decreasing for preceding times, and reaching close to zero on day t – 5 years. Historic economic outcomes are computed as weighted means of past economic outcomes using w_h as weight. On day t, historic profits, as perceived by individual i, are:

$$\widehat{H\pi_{\iota t}} = \frac{\sum(\widehat{\pi_{\iota t}}_1^t \times w_h)}{\sum w_h} \tag{12}$$

, where $\widehat{\pi_{\iota t}}_1^t$ are past perceived profits (eq. 8), from the first day of simulation to the current day *t*.

Similarly, historic variance in profits is:

$$HVar(\widehat{\pi_{\iota t}}) = \frac{\sum(Var(\widehat{\pi_{\iota t}})_1^t \times w_h)}{\sum w_h} \tag{13}$$

Combining historic economic outcomes, with the individual's response to variance (η) and opportunity costs/preference toward fishing (ρ), a decision-making variable is computed for each individual *i* on each day *t*:

$$\Delta_{it} = \frac{\widehat{H\pi_{\iota t}} - \eta_i \times HVar(\widehat{\pi_{\iota t}}) - \rho_i}{0.05} \tag{14}$$

Δ_{it} corresponds to the discounted stream of expected future net benefits associated with fishing. The numerator of this term is equal to the individual's historic daily profit expectation minus their response to historic profit variance and individual opportunity costs/fishing preferences. This term, which represents a daily expectation of individual net benefits associated with fishing, is divided by a discount rate of 5% such that (14) is equal to the discounted infinite sum of these benefits. This value captures the individual's perceived net benefits from the ability to fish daily indefinitely into the future, adjusted for an assumed average time preference (*i.e.*, fishing profits today are seen as more valuable when compared to fishing profits tomorrow).

The decisions to enter the fishery and to invest are separately assessed on January 1st of each year as:

$$\Delta_{it} > Inv \tag{15}$$

When this inequality is true, the perceived benefits of entering the fishery or investing in additional fishing capital outweigh the associated costs and individual *i* enters the fishery and may, later on, invest.

The decisions to enter the fishery and to invest are separated by the decision to exit the fishery (Fig. 1), computed as:

$$\Delta_{it} < DInvs \tag{16}$$

Therefore, exit occurs when the discounted stream of future net benefits derived from fishing is less than the scrap value of fishing capital investments. When this inequality is true, the individual can gain more financially by scrapping their investment and leaving the fishery.

Hence, on January 1st, the following sequence of decisions are taken (Fig. 1):

- Fishery entry (eq. 15): Assessed only for individuals that have not yet entered the fishery (*i.e.*, individuals with a '*Fisher*' status of 0). For those deciding to enter the fishery, *Fisher* becomes 1.
- Fishery exit (eq. 16): Assessed only for individuals that have entered the fishery (*i.e.*, with a *Fisher* status of 1). For those deciding to leave the fishery, *Fisher* becomes 0, and, accumulated investments (*Invs*, eq. 1), depreciated investments (*DInvs*, eq. 2) and vessel capacity (*VC*, eq. 3) are nullified.
- Investment (eq. 15): Assessed only for individuals that have entered the fishery (*i.e.*, with a *Fisher* status of 1). For those deciding to invest, accumulated investments (*Invs*, eq. 1), depreciated investments (*DInvs*, eq. 2) and vessel capacity (*VC*, eq. 3) are updated to account for the additional level of investment (*Inv* in eqs. 1 and 2), and the time of investment (*InvTime*) is updated.

Simulations and metrics of interest

The objective of this study is to investigate the combined effects of environmental variability (represented by fishing success variability; *Svar*, used to control '*success*' in eq. 5) and market variability (represented by the Price Elasticity of Demand; *PED*, which controls the slope of price as a function of total daily landings in eq. 6) on the dynamics of the simulated fishing fleet. These dynamics are captured at the end of a 15-year simulation by computing a set of metrics of interest (hereby referred to as 'key metrics') which combinedly depict a snapshot of the final state of the system. The key metrics are:

- Fish biomass (tons): remaining fish biomass after the last year of fishing operations (fish biomass is re-initialized to 100,000 t. every year). Decreases if the fleet is larger and/or composed of larger vessels.
- Number of fishers (count of individuals with a '*Fisher*' status of 1): Indicative of the willingness/need of individuals to be fishers. All following key metrics are computed only for those individuals as to depict a snapshot of the active fleet (without being biased by those individuals that decided not to join the fishery and those that decided to leave it).
- Median of η (response to variance in profits, unit-less) of fishers: lower values correspond to a fleet composed of more risk-seeking individuals.
- Median of ρ (opportunity costs/preference toward fishing, \$) of fishers: lower values correspond to a fleet composed of individuals that need/like to go fishing.

- Interquartile range, median and sum of investments ($) of fishers: stems from the attractiveness of the fishery to investments, depends on the number of fishers and their individual investments, and, is indicative of the fleet's size and composition (since Vessel Capacity is proportional to investments).
- Interquartile range, median and sum of accumulated profits ($) of fishers: depends on the balance between gains and costs and is also indicative to the fleet's size and composition.

Due to the stochastic nature of the model (the series of decision-making computations may be viewed as a sequence of Bernoulli trials) a single model run may not provide a representative picture of the system's average response. The model was therefore run 1,000 times and the average of key metrics was computed, for each set of parameter values.

Prior to the analysis of the model's response to environmental and market variability, the model was calibrated based on reasonable assumptions (see Supplementary Information 1), a sensitivity analysis through parameter perturbation was undertaken (see Supplementary Information 2), and the model response to the modulation of three key parameters was analyzed (see Supplementary Information 3).

Investigating the combined effects of changes in *Svar* and *PED*

The response of key metrics to concurrent changes in fishing success variability (*Svar*) and Price Elasticity of Demand (*PED*) was investigated. To do so, both *PED* and *Svar* were incrementally changed within a range of values ($0.0 \leq Svar \leq 1.0$ and $0.5 \leq PED \leq 1.5$) each by 11 increments, and, each of the 121 resulting combinations of values was used in 1,000 simulations. The mean of key metrics was then computed for fishers at the end of the simulations.

Results

Combined effects of changes in *Svar* and *PED*

The results of this analysis are displayed in the form of colored grids, where each grid cell corresponds to a combination of *PED* and *Svar* values and colors correspond to the value reached by the key metric of interest. Overall, the response of key metrics to changes in *PED* and *Svar* can be classified in three broad visual classes: (i) unidirectional gradients, where a key metric's values appear to be only affected by one variable, (ii) bidirectional gradients, where a key metric responds monotonically to changes in both *Svar* and *PED*, and (iii) complex gradients, where for example, key metrics display a localized maximum (*i.e.*, a dome) within the *PED*-*Svar* domain.

Unidirectional gradients

Unidirectional gradients were only seen under particular circumstances; both the number of fishers and the median of η decreased when *Svar* increased over 0.5, and appeared insensitive to changes in *PED*.

Bidirectional gradients

At maximum *Svar* and *PED* (*i.e.*, top-left corner), Fish biomass was minimal, the median of ρ was maximal, and, the variability (IQR), median and sum of investments were maximal. The median and sum of accumulated profits were minimal.

At minimum *Svar* and maximum *PED* (*i.e.*, bottom-left corner), the number of fishers and the median of η were maximal.

At minimum *Svar* and *PED* (*i.e.*, bottom-right corner), the sum of accumulated profits was maximal.

Complex gradients

The variability (IQR) and median of accumulated profits displayed dome-shaped responses. These key metrics reached their maxima at minimum *PED* and for a *Svar* value at *ca.* 0.6. Albeit noisy, the response of the median ρ appeared mostly concave and reached a minimum at *Svar*=0.4.

In addition to the three broad classes of key metrics responses, it is worth noting that in some cases, there appeared to be a threshold – at *Svar*≈0.5 – across which responses changed. For instance, for values of *Svar*<0.5, *PED* had a limited impact on investments, and consequently on the fish biomass. Conversely, for values of *Svar*>0.5, *PED* had a limited effect on the number of fishers and their η.

Four quadrants of market and environmental variability

Although not all key metrics' responses could be divided in four quadrants in the *Svar-PED* space, this subdivision is helpful to interpret the results of this analysis, while considering *Svar* and *PED* as proxies of environmental and market variability, respectively.

From a resource and employment perspective, the ideal fishery would be characterized by long term stability in both fishing success and markets (*i.e.*, bottom-left quadrant, low *Svar* and high *PED*). Under such conditions, both the fish biomass and the number of fishers are the highest, while intermediate levels of fleet-wide profits (sum of accumulated profits) are generated. Weakly risk-seeking fishers (η is negative, but close to zero) enjoy stable revenues within a homogeneous fleet of small vessels with intermediate and negative opportunity costs (*i.e.*, individuals that like and/or need to go fishing) applying a low fishing pressure. Low investment levels are a response to low prices brought by the large number of fishermen who enter the fishery simultaneously, hence resulting in lower individual profits.

Departing from the stable environment, stable market scenario, an alternative, slightly more profitable state can be found at low *Svar* and low *PED* (*i.e.*, bottom-right quadrant). Fish biomass remains relatively high while a few risk-averse individuals with intermediate levels of opportunity cost leave the fishery due to the higher variability in profits (caused by the more variable prices). The fleet remains homogeneous and composed of small vessels but is more profitable thanks to the higher prices reached at low landings.

Surprisingly, the highest levels of resource depletion were found in the quadrant with high fishing success variability and high market stability (top-left quadrant). Under such conditions fish biomass reached its minimum, and, the number of fishers was low at high *Svar* irrespective of *PED*. The latter indicated the dominating effect of *Svar* over *PED* in entry/exit decisions under high *Svar* conditions, as confirmed by the concurrent low η values (*i.e.*, fishers become so risk-seeking that changes in *PED* do not affect their exit decisions). Median opportunity costs are higher for fishers in this quadrant because fishers are highly risk-seeking, making fishing in a variable environment more appealing and thus reducing the tradeoff between fishing and alternative income sources. The high prices reached at high landings under high *PED* (see also Fig. S1c) combined with the risk-seeking behavior stimulated the largest investments from fishers. The resulting small and heterogeneous fleet of larger vessels applied a high fishing pressure but did not generate higher profits due to the higher operational costs incurred by larger vessels. The highest landings, reached at maximum *Svar*, stabilized profits (lower IQR of profits) due to the flattening of the price curve (see also supplement S3). This compensation of environmental variability by market stability was diminished as *PED* decreased due to the resulting increased slope of the price curve (see also Fig. S1c).

High environmental and market variability (top-right quadrant) did not result in the lowest fish biomass, nor the lowest profits. When compared to the previous quadrant, investments were lower due to the steeper decrease of prices with increased landings. The fleet was as small and as risk-seeking but more homogenous, with intermediate sized vessels and intermediate levels of opportunity cost. Again, the effect of large investments at maximum *Svar* (causing a stabilization and lowering of prices) resulted in lower and less variable profits than at lower *Svar*. Because of the variability in prices brought by a lower *PED*, this quadrant hosted the maximum variability in profits. The maximum median profit was also found in this quadrant thanks to the intermediate level of investments (*i.e.*, moderate costs) and the lower competition due to the departure of more risk-averse individuals (enabling high prices due to relatively lower total landings).

The impact of variability on decision-making

Because our model incorporated measures of profit variability in the decision-making criteria of individuals, as well as the impact of the overall fleet's characteristics (through the effect of total daily landings on price), predicted responses to changes in environmental (*Svar*) and market variability (*PED*) were found to be complex and interactive. Overall, the results suggested that increasing environmental variability resulted in more investments from fewer but more risk-seeking individuals, which had detrimental effects on both the fish biomass and the overall wealth of the fishing community. At maximum environmental variability, the fleet was dominated by a few risk-seeking individuals investing at unreasonably high levels, resulting in high fishing mortality while diminishing profits. Somewhat unexpectedly, market stability amplified those negative impacts by enabling high prices at high levels of landing, leading to increased investment and fishing pressure. On the other hand, increasing market variability dissuaded large investments by reducing prices at large landings, which had a beneficial effect on both the fish biomass and fishing community.

In addition, our results suggest the existence of a dichotomy in the decision-making process between systems of high environmental variability (*Svar*>0.5) and those of low environmental variability (*Svar*<0.5). Under low environmental variability, changes in *PED* influenced entry and exit behavior (but not investment), while under high environmental variability, changes in *PED* influenced investment behavior (but not entry/exit). That is, in stable environments the responsiveness of market price primarily influenced decisions at the extensive margin (*i.e.*, whether to participate in the fishery or not), affecting fleet size but not its composition. Conversely, in variable environments, the responsiveness of market price largely influenced decisions at the intensive margin (*i.e.*, how much to invest), affecting fleet composition but not size. This differential response was due to the exiting of risk-averse individuals from fisheries characterized by high environmental variability, leaving fewer but more risk-seeking individuals whose decision-making was predominantly driven by the variability in profits rather than their level. Though risk-preferences were found to be the dominant force differentiating fishery outcomes across considered scenarios, it is worth noting that the model was calibrated such that approximately 95% of agents would view the level of profits as more important than their variance in individual decision-making (see Supplementary Information 1).

Discussion

The agent-based model explored here was developed to investigate fisher entry, exit, and investment behavior under varying levels of resource and market variability. Our fishery was open access and all agents were free to enter, invest and fish. Agents who entered and remained in the fishery tended to have low opportunity costs and/or strong preferences for fishing and risk. Changes in resource variability and demand elasticity influenced fleet composition as well as resource use and economic outcomes. These effects were found to be inter-dependent and suggest that market structure can alter the effects of changes in resource variability.

Increases in resource variability were found to produce smaller fleets composed of risk-seeking fishers who over-invested, harvested greater amounts of the resource but produced lower profits due to increased fishing costs and reduced prices from market flooding. It is important to note that this result runs counter to investment strategies typically found to be socially optimal under increased variability in fisheries (Charles, 1983; Hannesson, 1993; Poudel et al., 2013; Singh et al., 2006). Here, increases in resource variability acted as a selective pressure on agents, limiting the participation of those with risk averse preferences and promoting socially sub-optimal investments by those with risk seeking preferences. Risk seeking fishing preferences have been found for both large-scale commercial (Holland and Sutinen, 2000) and artisanal fishers (Eggert and Lokina, 2007); however, risk averse fishing behavior appears to be more common (*e.g.*, Bockstael and Opaluch, 1983; Smith and Wilen, 2005). There has been limited investigation of the relationship between risk preferences, participation in commercial fisheries, and investment in fishing capital (Branch et al., 2006). Eggert and Lokina (2007) did find that risk seeking artisanal fishers in Tanzania tended to have more capital-intensive fishing operations, however. Recognizing that changes in resource variability may cause changes in the risk preference composition of the fleet—as well as subsequent fleet decision making—is an important finding of this work. Anticipated increases in fisheries' variability (Brander, 2010, 2007; Perry et al., 2010) might therefore be expected to lead to increases in participation by risk-seeking individuals or entities and investment decisions motivated, perhaps inefficiently, by profit variance.

Decreases in the price elasticity of demand, which increases the responsiveness of market prices to changes in the daily supply of fish, were found to dampen the effects of resource variability. That is, greater variability in daily prices resulting from an inelastic demand curve tended to dissuade over-investment and increase fleet profits while reducing removals. This response arose because an inelastic demand curve sends strong market signals to fishers as large landings can flood the market, reducing prices and revenues. Thus, there is a disincentive to invest in increased fishing capacity, which is not present in a market with an elastic demand curve. While estimates of price elasticity of demand for fish products vary considerably across species and regions, demand in many markets has been found to be price elastic (Asche et al., 2005). Further, a meta-analysis of demand elasticity estimates for various meat products found fish to be more elastic when compared to demand for poultry, pork, and meat composites (Gallet, 2010). Continued increases in global seafood trade and market integration may further limit the responsiveness of market prices to changes in local supply. Our model suggests such a decoupling combined with increased environmental variability could adversely impact both fishing communities and fish stocks.

This analysis employed a number of simplifications to reduce model complicatedness (*sensu* Sun et al., 2016; *i.e.*, structural level of detail) and facilitate the interpretation of responses to changes in variability. The effects of environmental variability on fishery development were explored by changing the range of a random and uniformly distributed fishing success parameter. It was assumed that fish biomass was never limiting, and across simulations, exploitation rates ranged from 16% (under *PED*=1.0 and *Svar*=0.0; Fig. 2) to 34% (under *PED*=1.5 and *Svar*=1.0; Fig. 2). In most fisheries, fishing success is a function of stock abundance and catchability. Incorporating such variables into the simulation of fishing success would be a reasonable extension of the model presented here and is left for future research. Market variability, meanwhile, was investigated by modifying the responsiveness of market price to changes in daily landings, assuming exogenous factors did not influence price formation. The potential effects of stochastic price shocks (*e.g.*, due to changes in external markets) were therefore not investigated. It might, however, be expected that such price stochasticity would reduce the responsiveness of investment in a similar manner as would an increase in price elasticity. Finally, while other ABMs have incorporated dynamic and adaptive decision-making rules (*e.g.*, to better understand the emergence of norms and cooperative behavior; Wilson et al., 2007), our model assumed agents held constant opportunity costs and preferences for fishing and risk during simulations. Allowing for the evolution of decision-making criteria in response to shifts in environmental or market variability is an interesting area for future research and could inform our understanding of adaptive capacity within commercial fisheries.

In our simulations, the influence of management or regulatory controls on fisher behavior was not considered. Other studies have explicitly incorporated regulatory processes into fisher ABMs to investigate the impacts of management on fleet behavior and fishery outcomes (*e.g.*, Soulié and Thébaud, 2006; Little et al., 2009; Bellanger et al., 2018). While that was not the focus of this analysis, fisheries management could be introduced into our model by placing constraints on catch, investment, fleet size, or through modifications to individual decision-making rules (*e.g.*, agents might consider quota price and catch limits in assessing the profitability of fishing under an individual transferable quota program). The increasing use of simulation approaches to assess fishery management alternatives (*e.g.*, management strategy evaluation, Punt et al., 2016), coupled with the recognition that human behavior is a key source of uncertainty in fisheries (Fulton et al., 2011), suggests a growing need for ABMs in fisheries management. Parameterizing and initializing empirical ABMs can be challenging and data-intensive however (Smajgl et al., 2011), and thus improved data collection is necessary prior to operationalizing ABMs in many fishery management settings.

Conclusion

Fisheries are complex socio-ecological systems with many feedbacks, linkages, and couplings between biophysical, ecological, and human components (Garcia and Charles, 2008). By exploring the combined effects of environmental and market variability on the development of a simulated fishery, this analysis found that responses to changes in environmental variability were dependent upon the sensitivity of market prices to changes in daily landings. Model development and parameterization employed several simplifying assumptions, though key system dynamics were arguably accounted for. While the prospect of increasing variability in commercial fisheries is now well known and generally accepted (Brander 2007, 2010; Perry et al. 2010), the possible effects of such changes have not, to our knowledge, been viewed in the context of market structure. Our findings indicate market structure is critical in modulating the response of human communities to these changes and suggest the need for its inclusion when assessing the impacts of, and potential responses to, variability in fisheries.

Tables

Table 1. Parameters used in each model component (Fish stock, Individuals and Market). Equation numbers refer to those given in the main text. Values are given for the base simulation, as determined during calibration (see Supplementary Information 1).

Figures

Figure 1. Schematic of the daily computations occurring in each model component (Fish stock, Individuals and Market). Equation numbers refer to those given in the main text and scale symbols correspond to decision-making events.

Figure 2. Response of key metrics to concurrent changes in environmental (*Svar*) and market (*PED*) variability.

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Supplementary information 1 – Model calibration

Fig. S1: Individual profits, profits margins and price curves as computed in the average simulation (see text for details) under three different values of Price Elasticity of Demand (colors). Vertical lines indicate the midpoint of the average simulation.

Due to the paucity of available information for the calibration of the model, a set of reasonable assumptions were made to determine realistic values for its parameters. A theoretical average simulation was considered, to constrain calibrated values within reasonable bounds, in which 50% of individuals (n=50), all indifferent to risk (η=0) and to outside opportunities (ρ=0), and with a fishing *success* of 0.5 (eq. 5), would join the fishery and invest every other year. A set of values at the start (denoted X_{start}) and at the midpoint (denoted X_{mid}, the end of the 8th year of a 15-year period) were calibrated.

Assuming the smallest vessel a first-time fisher may invest in has a capacity of 1 ton (VC_{start}=1,000 kg) and the largest vessel has a capacity of 20 tons (VC_{max}=20,000 kg), the capacity of a vessel at the midpoint (after investing every other year, up to the 8th year) would be:

$$VC_{mid} = VC_{start} + \frac{VC_{max} - VC_{start}}{4} = 5{,}750\ kg \qquad \text{(S1-1)}$$

Following these assumptions, total daily landings for this average fleet (50 individuals with a 0.5 fishing *success*) would be, at the start of the simulation:

$$TL_{start} = 50 \times 0.5 \times VC_{start} = 25{,}000\ kg \qquad \text{(S1-2)}$$

And at the midpoint of the simulation (*PTL*, Potential Total Landings; eq. 6):

$$PTL = 50 \times 0.5 \times VC_{mid} = 143{,}750\ kg \qquad \text{(S1-3)}$$

Fish price is assumed to be at maximum 10$/kg ($P_{max}$=10) and to reach 5$/kg at the midpoint of the simulation (P_{mid}=5; eq.6).

The cost rate of fishing is assumed as 50% of gains (eq. 7):

$$Cf = 0.5 \qquad \text{(S1-4)}$$

And the basic cost rate is determined as to reach 30% profit margins at the mid-point of the simulation while assuming the maintenance cost as being the triple of the basic cost (Cm=3Cb; eq. 7), where:

$$\frac{Catch_{mid} \times P_{mid}}{Cf \times Catch_{mid} \times P_{mid} + (Cb+Cm) \times VC_{mid}} = 1.3 \qquad \text{(S1-5)}$$

,which simplifies to (see eq.5):

$$Cb = \frac{success \times P_{mid}}{4} \times \left(\frac{1}{1.3} - Cf\right) = 0.168 \qquad \text{(S1-6)}$$

, and,

$$Cm = 3 \times Cb = 0.504 \qquad \text{(S1-7)}$$

Given the equation of price (eq. 6) and assuming a *PED* of 1, the starting fish price is:

$$P_{start} = \min(P_{max}, P_{mid} \times \left(\frac{TL_{start}}{PTL}\right)^{\left(\frac{1}{-PED}\right)}) = 10\ \$/\text{kg} \qquad \text{(S1-8)}$$

According to the decision rules set for investment (Eqs. 14-15), investment costs (*Inv*, eq. 1) may be computed as a function of discounted expected first-time average profits (π_{start}) such that the average fisher (*i.e.*, η=0, ρ=0) is indifferent in their decision to enter the fishery as:

$$\frac{\pi_{start}}{0.05} = Inv \qquad \text{(S1-9)}$$

Or, when combined with equation 7:

$$Inv = \frac{Catch_{start} \times P_{start} \times (1-Cf) - (Cb+Cm) \times VC_{start}}{0.05} = 36{,}560\$ \qquad \text{(S1-10)}$$

Given the assumed maximum vessel carrying capacity (VC_{max}) the slope parameter in the formulation of vessel carrying capacity (*VCsl*, Eq. 3) is (where *Ny*=15 is the number of years simulated):

$$VCsl = \frac{VC_{max} - VC_{start}}{Inv * (Ny-1)} = 0.037 \qquad \text{(S1-11)}$$

, and the intercept is:

$$VCint = VC_{start} - VCsl \times Inv = -352.72\ kg \qquad \text{(S1-12)}$$

In order to calibrate η, minimum, average and maximum profits are computed (at the midpoint of the simulation) as a function of fishing success (0, 0.5 and 1 respectively). Minimum profits are:

$$\pi_{min} = -(Cb + Cm) \times VC_{mid} = -3{,}864\$ \qquad \text{(S1-13)}$$

, maximum total daily landings are (for 50 fishers):

$$TL_{max} = 50 \times 1 \times VC_{mid} = 287{,}500kg \qquad \text{(S1-14)}$$

, resulting in a price of (as *PED*=1):

$$P_{TLmax} = P_{mid} \times (\frac{TL_{max}}{PTL})^{(1/-PED)} = 2.5\$/kg \qquad \text{(S1-15)}$$

, and profits of:

$$\pi_{TLmax} = 1 \times VC_{mid} \times P_{TLmax} \times (1 - Cf) - (Cb + Cm) \times VC_{mid} = 3{,}323.5\$ \qquad \text{(S1-16)}$$

Similarly, average profits are:

$$\pi_{avg} = 0.5 \times VC_{mid} \times P_{mid} \times (1 - Cf) - (Cb + Cm) \times VC_{mid} = 3{,}323.5\$ \qquad \text{(S1-17)}$$

In the model, η values are randomly generated from a normal distribution with zero mean and a standard deviation of:

$$\sigma_{eta} = 0.5 \times \frac{\pi_{avg}}{var(U(\pi_{min}, \pi_{TLmax}))} = 3.86 \cdot 10^{-4} \qquad \text{(S1-18)}$$

Where the denominator denotes the variance of numbers randomly generated from a uniform distribution bound between π_{min} and π_{TLmax}. The formulation for the standard deviation of η was used to allow a range of responses to profit variability (positive and negative) while also ensuring that the majority of agents (~95%) weighed profits more heavily than profit variance in their decision making. Approximately 95% of the density of a normal distribution is contained within a range of plus or minus two standard deviations from the mean. Thus, the standard deviation of η was scaled to one half times the ratio of average profits to the maximum anticipated profit variance.

Finally, ρ was calibrated such that, with an expectation of zero profits, the average risk neutral individual would be indifferent to entering the fishery (i.e., both sides of inequality 15 are equal), therefore the mean ρ is:

$$\bar{\rho} = -0.05 \times Inv = -1{,}828\$ \qquad \text{(S1-19)}$$

, and its standard deviation is:

$$\sigma_\rho = |\bar{\rho}| = 1{,}828\$ \qquad \text{(S1-20)}$$

Supplementary information 2 – Sensitivity analysis

Fig. S2.1: Model response to a sensitivity analysis through parameter perturbation. Each parameter (x axis) was changed by +20% (grey bars) and -20% (black bars) and the response of each key metric (y axis), relative (given in percentages) to the base simulation is shown as bar heights. Responses falling within the dotted lines (derived from 'No_Change' simulations, where parameters have not been changed) may be considered as noise and ignored.

Fig. S2.2: Effects of the change in selected parameters on profits over time in the theoretical average simulation (see Supplement 1 for description).

The value of each parameter was changed by +20% and -20% sequentially while keeping other parameter values unchanged, each in 1,000 model runs. The mean response of key metrics (*e.g.*, sum of investments) was computed and their change, relative to the mean base response (from 1,000 model runs with the parameter values given in Table 1 in the main text), was investigated. Key metrics were computed for individuals that were fishers at the end of simulations. Two additional sets of 1,000 simulation runs were executed with unchanged parameter values (denoted as 'No_Change' in Fig. S2.1), to establish a baseline response to all the sources of stochasticity in the model. With an infinite number of simulation runs, 'No_Change' values would be null, however due to time restrictions 1,000 runs were executed and any change in key metrics with an amplitude similar to that of 'No_Change' (shown as doted lines in Fig. S2.1) should be considered as noise.

Initial fish biomass (Fbiomi)
During simulations, fish biomass was reset every January 1st to a value (*Bi*, Table 1) enabling unlimited harvesting. As such, *Bi* had a significant effect (*i.e.*, resulting in more than 5% change in a key metric) only on fish biomass itself, as expected.

Costs parameters (Cf, Cb, Cm)
Among costs parameters, fishing costs (*Cf*) had the greatest effect on key metrics. Increasing *Cf* resulted in a decrease in all key metrics except for the fish biomass, the number of fishers and their η. Where significant, the responses of key metrics to changes in basic (*Cb*) and maintenance (*Cm*) costs were similar but of lesser amplitude.
Increasing costs resulted in less variable and lower investments and profits. In a hypothetical population where half of individuals would invest every other year, increasing *Cf* by 20% resulted in economic losses after the twelfth year, compared to the fifteenth year in the base simulation (Fig. S2.2a). Such response was due to the link between costs and vessel size (Eq. 7), which in turn inhibited investment towards larger vessels. Since daily catch is bound between 0

and Vessel Capacity (Eq. 5), the fleet of smaller vessels had less variable catch and profits, which encouraged more individuals to become fishers. Those individuals were more risk-averse (higher η) and had fewer outside opportunities (lower ρ) when compared to the base simulation.

Price parameters (Pmid, PTL, Pmax, PED)

Given the parameterization of price (Eq. 6), the similar response of key metrics to changes in the average price (*Pmid*) and the potential total landings (*PTL*) was expected. The response was of similar amplitude but in reversed direction when compared to that of changing fishing costs. Increasing price, by increasing *Pmid* or *PTL*, resulted in a more heterogeneous fleet with fewer, more risk-seeking, fishers having larger vessels and accumulated profit.

Changing the maximum fish price (*Pmax*) had an effect on the number of fishers and their profits. Given the fast decrease of price with increasing landings, changing *Pmax* impacts profits only in situations of low landings. Decreasing *Pmax* resulted in lower profits but also decreased their variance by broadening the range of (low) landings at which price remains constant (and maximum). Interestingly, both increasing and lowering *Pmax* tended to slightly stimulate the decision to become fisher but did so through two different mechanisms. Increasing *Pmax* stimulated entry by increasing profits while decreasing *Pmax* did so by stabilizing profits at low landings.

Decreasing the Price Elasticity of Demand (*PED*) broadened the range of potential profit by increasing price at low landings and decreasing price at high landings. As such, decreasing *PED* increases the variance in accumulated profit by increasing profits for small vessels relative to larger ones (see Fig. S2.2b), consequently favoring lower investments and dissuading individuals from entering the fishery.

Fishing season parameters (a, b, c, d)

Larger profits may be made during a longer fishing season, which can occur if the start of the season is earlier (lower b), the end of the season is later (higher d) or if the opening and/or closing of the season is faster (higher a and/or c). Key metrics were overall relatively insensitive to the speed of opening/closing of the season. Increasing the fishing season duration by lowering b or increasing d increased accumulated profit and lowered fish biomass but with differing amplitudes. This asymmetry is due to the time-decaying weight put on past profits (and their variance) within the decision-making computations (Eq. 11), whereby older profits are less important than recent ones. As a result, a fishing season ending later had more of an effect than one starting sooner, since it was occurring closer to the time of decision-making (January 1st).

Vessel Carrying capacity parameters (VCint, VCsl)

The vessel carrying capacity parameters control the linear relationship between investments and daily landings (Eqs. 3 and 5). An increase in the intercept (*VCint*) or the slope (*VCsl*) of this relationship results in greater landings but does so differently across levels of investment; increasing the *VCint* increases landings proportionally at any investment level, while increasing *VCsl* increases landings more at high investment levels than at low investment levels. Since costs are proportional to vessel carrying capacity, changing *VCint* only moderately impacts average profits while changing *VCsl* modifies the relationship between profits and investments (see Fig. S2.2c and d). Increasing *VCint* or *VCsl* both favored smaller vessels by increasing profits at low investment levels (Fig. S2.2), which tended to lower median and total investment levels and profits and attract more individuals to invest small amounts and become fishers; a response similar to that observed when fishing costs were increased.

Fishing success variability (Svar)
Success variability (*Svar*) adds stochasticity to daily individual landings. It must be noted that the responses shown in this section are for a small range of *Svar* values (0.4 to 0.6) and a *PED* of one. An analysis of the effect of a broader range of *Svar* value under different *PED* values is given in the main text (and in Fig. 2). Increasing *Svar* logically increased the variance in investments and accumulated profit (higher IQRs) which stimulated fewer, but more risk-seeking individuals (lower η) to invest and become fishers. The resulting smaller fleet of larger vessels (*i.e.*, with higher costs) had lower and more variable profits.

Decision-making parameters (σ_η, $\bar{\rho}$, σ_ρ, ω_{max}, Ddep, TDr, Inv)
An individual with a higher η is more risk-averse and negatively reacts to variability in profits. An individual with high ρ has other potential sources of income and negatively reacts to low profits. Given that ρ and η values are assigned randomly to individuals at the start of a simulation, an individual may be characterized by a high η and a low ρ (risk-averse and indifferent to low profits), a low η and a high ρ (risk-seeking and high opportunity costs), or any other combination. η and ρ values are randomly generated from normal distributions with means of 0 and $\bar{\rho}$ and standard deviations of σ_η and σ_ρ respectively.

Increasing σ_η increased heterogeneity in risk preferences within the population and led to fewer, but more risk-seeking fishers (lower median η) with more variable investments and accumulated profit (higher IQRs). Increasing σ_η had a similar effect on key metrics as increasing *Svar*, by directly generating more risk-seeking individuals (while risk-seeking individuals are stimulated by higher *Svar*).

Increasing $\bar{\rho}$ or σ_ρ resulted in more high opportunity cost individuals, leading to fewer individuals that were more risk-seeking (lower median η) to invest and become fishers. Fishers had more variable investment levels and accumulated profits.

ω, the weight that an individual puts on other's profits is randomly generated for each individual from a uniform distribution bound between 0 and ω_{max}. As such, decreasing ω_{max} resulted in individuals being less affected by other's economic outputs when making decisions. Changing ω_{max} significantly impacted only a few metrics. In particular, decreasing ω_{max} resulted in fewer individuals becoming fishers and overall more risk-seeking individuals. By decreasing ω_{max}, each individual focused more on their own profits, which were more variable than the fleet's profits (variability is dampened by a larger sample size) hence resulting in fewer but more risk-seeking individuals becoming fishers.

Ddep controls the rate at which investments depreciate and is involved in the decision to exit the fishery (Eqs. 2 and 16). Decreasing *Ddep* increased the rate of depreciation rendering the decision to exit more likely. As a result, fewer individuals were fishers at the end of 15-year simulations, they were slightly more risk-seeking, and they had more variable investments and profits.

As part of the decision-making process, individuals put less weight on older profits than recent ones (Eq. 11). *TDr* controls the rate at which past profits are discounted, and, increasing *TDr* resulted in recent profits being more impactful than past ones in the decision-making process. Increasing *TDr* resulted in more individuals becoming fishers due to the resulting perception of more stable historical profits (by putting less weight on past year's entries/exits/investments).

Inv, the cost of investment (eq. 1), corresponds to the increment by which an individual's investments are increased each time that individual decides to invest. Given the relationship between investments and vessel carrying capacity, changing *Inv* or *VCsl* by the same proportion had the same effect on average profits (see Fig. S2.2d and e). The effect of changing *Inv* on key metrics was however different than the effect of changing *VCsl* because *Inv* is directly involved in the decisions to enter the fishery and to invest (see Eq. 15), as particularly seen in the differing response of the number of individuals becoming fishers.

Increasing *Inv* dissuaded some risk-averse individuals from becoming fishers. The resulting smaller and more homogeneous fleet had slightly more variable profits due to the risk-seeking behavior of its participants.

Decreasing *Inv* stimulated individuals to become fishers. The resulting larger and more heterogeneous fleet had more variable profits and investments and was consequently slightly more risk-seeking.

Supplementary information 3 – Effects of changes in *Svar*, *PED*, ω_{max}.

See FigS3_PSO-Analysis.tiff
Fig. S3: Mean (black line) and standard deviation (grey area) response of key metrics to changes in *Svar* (left column), *PED* (middle column) and ω_{max} (right column).

The response of key metrics (*e.g.,* median of investments) to changes in fishing success variability (*Svar*), price elasticity of demand (*PED*) and omega variability (ω_{max}) was investigated. To do so, two parameters were held constant (*e.g.*, *PED*=1.0 and ω_{max}=0.5) while the remaining parameter was incrementally changed within a range of values (*e.g.*, 0.0≤*Svar*≤1.0), and each combination of values was used in 1,000 simulations. The mean (and standard deviation) of key metrics was then computed for individuals that were fishers at the end of simulations.

Fishing success variability

Fishing success variability (*Svar*) values ranging from 0.0 to 1.0 were tested for *PED*=1.0 and ω_{max}=0.5 (Fig. S3, left column). Increasing *Svar* results in an increased variability in daily individual catch (Eq. 5) and therefore profits (Eq. 7).

At low levels of success variability (0.0≤*Svar*≤0.2), all key metrics were relatively insensitive to changes in *Svar*. At higher levels, increasing *Svar* caused a reduction in the number of fishers and their η, hence indicating the exiting of risk-averse individuals from the fishery. At maximum *Svar* fishers were also characterized by higher outside opportunities (higher ρ) indicating a weaker preference for fishing. Although counter-intuitive, this slight increase in ρ suggests that at very high *Svar*, the strong increase in η offsets the increase in ρ (*i.e.*, fishers who might have exited at lower *Svar* levels were now characterized by stronger preferences for risk and were thus less likely to exit the fishery). With increasing *Svar*, fishers tended to invest more, and their investments tended to be more variable. The increase in the variability of investments stems from the increasing importance of risk preference in investment decisions: risk-seeking individuals were increasingly likely to invest and remain in the fishery while risk-averse individuals were increasingly likely to forgo investment and exit the fishery. Median profits appeared to reach an optimum at a *Svar* of around 0.5. This optimum resulted from the combined optimum number of fishers and their investment levels; at lower *Svar*, the greater number of fishers resulted in larger landings and therefore lowered price, while at higher *Svar*, the larger investment levels resulted in higher costs.

Overall, increasing *Svar* led to a shrinking pool of ever-investing risk-seeking fishers. The resulting small and heterogeneous fleet of large vessels did not generate more profits on average due to the higher costs incurred by larger vessels, while causing a large reduction in fish biomass.

The response of the variability in accumulated profits pointed to a compensating mechanism: larger investments at higher *Svar* (>0.6) resulted in larger landings for which prices were more stable due to the flattening of the price curve at high landings. The effect of success variability on profit variability was therefore compensated by price stability at high landings levels.

Price elasticity of demand

Price elasticity of demand (*PED*) values ranging from 1.5 to 0.5 (elastic to inelastic) were tested for *Svar*=0.5 and ω_{max}=0.5 (Fig. S3, middle column). Decreasing *PED* results in a wider range of fish price across daily landings (Eq. 6, Fig. S1c).

The average response of key metrics to changes in *PED* were subtler than in the case of *Svar*. The number of fishers and their η slightly decreased with decreasing *PED*. Median investments slowly decreased while their variability slightly increased with decreasing *PED*. The most noticeable response was from profits, where all metrics (median, sum and IQR) increased with decreasing *PED*.

By increasing the range of prices across levels of landings, decreasing *PED* results in more variable profits. In addition, decreasing *PED* penalizes large investments (by reducing prices and thus revenues while costs remain proportional to investments; see Fig. S1a). Decreasing *PED* hence resulted in a slightly smaller (though more heterogeneous) fleet of slightly smaller vessels with slightly more risk-seeking captains catching slightly less fish. The higher prices reached at lower landings promoted higher – albeit more variable – levels of profits.

Both increases in success variability and decreases in price elasticity led to a smaller fleet whose captains were more risk-seeking. Interestingly, increases in success variability increased investments – and therefore costs – rendering the fleet less profitable. Conversely, decreases in price elasticity did not lead to increased investment, and fleet profitability increased. These opposing findings suggest that variability operating at the individual level (success variability) may lead to different industry outcomes when compared to that operating at more aggregate levels (price elasticity). Specifically, increases in success variability led to increases in revenue variability across the fleet on a given day, while decreases in price elasticity led to increases in revenue variability for a given vessel across days. In our model, risk-seeking individuals are incentivized to invest when profits across the fleet become more variable, thus increases in success variability led to a direct response in investment by risk-seeking individuals, as well as exit from the fishery by risk-averse individuals. Decreasing price elasticity did not increase intra-day profit variability directly as all vessels received the same daily market price. The resulting limited exit of risk-averse individuals from the fishery under decreasing price elasticity was therefore a response to the slight increase in the variability of investments, which produced a slightly more heterogenous fleet having slightly more variable intra-day profits.

Omega variability

Changes in ω (randomly generated from a uniform distribution bound between 0 and ω_{max}) variability, with ω_{max} values ranging from 0.0 to 1.0 were tested for *Svar*=0.5 and *PED*=1.0 (Fig. S3, right column). Increasing ω_{max} results in individuals putting more weight on other individual's economic outputs (the average and variance of profits) during decision-making (Eqs. 8 and 9).
The response of key metrics to changes in ω_{max} highlighted a dichotomy in the decision-making process between situations where ω_{max} is null (*i.e.*, no knowledge of other's economic output) and situations where ω_{max} is not (*i.e.*, any level of knowledge of other's economic output).

When ω_{max} is null, ω is null and an individual's decisions are based on his/her own average profits with a null daily variance. The absence of variance in profits was attractive to a small pool of 'risk-indifferent' (median η=0) individuals whose decisions were driven by the need for a source of income (low ρ; low outside opportunities and/or strong preference for fishing). This particular subset of individuals behaved relatively consistently (low variability in investments) and generated high profits thanks to the higher prices obtained from lower landings by a smaller fleet. The variability in price stemming from low landings resulted in highly variable profits.

The response of key metrics to an increase in ω_{max} was more pronounced at low values ($0.0<\omega_{max}\leq 0.2$). At the lowest non-null ω_{max}, fishers were particularly risk-seeking due to the spurious perception of profit variability caused by the large difference between the weight put on personal economic output (always set to one) and the weight put on other's economic outputs (close to zero). In other words, having a very limited knowledge of everyone else's economic output – a somewhat unrealistic position to be in – gives the false impression of a highly variable income source whenever that output differs from your own. Low ω_{max} values therefore favored fewer but more risk-seeking individuals who had more variable investment levels and profits. Risk-seeking individuals tend to invest more, resulting in lower profits due to the higher costs incurred by larger vessels. With ω_{max} increasing at higher values ($\omega_{max} > 0.2$) the better knowledge of other's economic outputs dampened the perception of income variance and stimulated more risk-averse individuals to join the fishery. Under such conditions, more individuals became fishers, who had less variable levels of investments and profits, as well as slightly lower investments and higher profits.

Figure 1

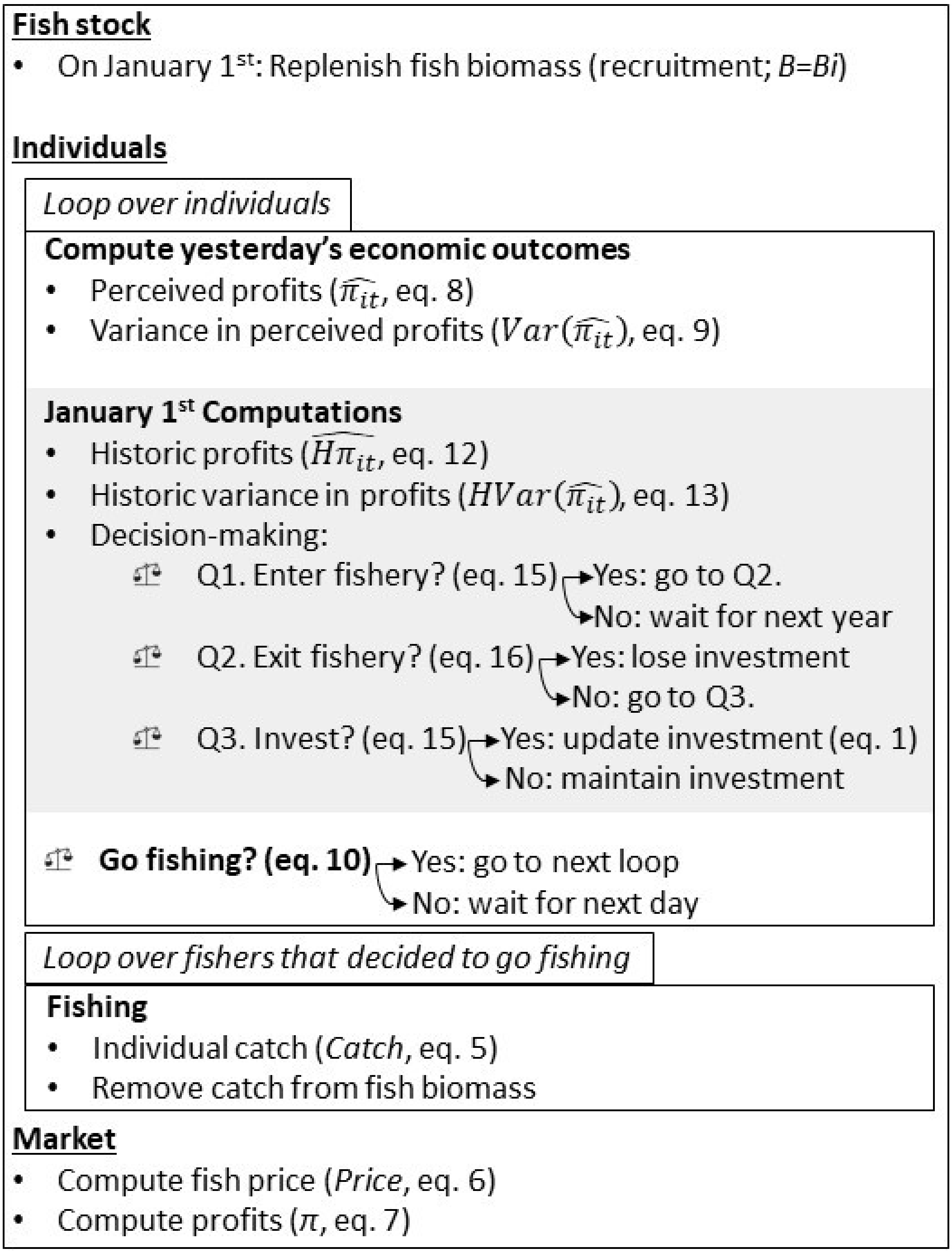

Fish stock
On January 1st: Replenish fish biomass (recruitment; *B*=*Bi*)
Individuals
Loop over individuals
Compute yesterday's economic outcomes
Perceived profits ($\widehat{\pi_{it}}$, eq. 8)
Variance in perceived profits ($Var(\widehat{\pi_{it}})$, eq. 9)
January 1st Computations
Historic profits ($\widehat{H\pi_{it}}$, eq. 12)
Historic variance in profits ($HVar(\widehat{\pi_{it}})$, eq. 13)
Decision-making:
Q1. Enter fishery? (eq. 15)
Yes: go to Q2.
No: wait for next year
Q2. Exit fishery? (eq. 16)
Yes: lose investment
No: go to Q3.
Q3. Invest? (eq. 15)
Yes: update investment (eq. 1)
No: maintain investment
Go fishing? (eq. 10)
Yes: go to next loop
No: wait for next day
Loop over fishers that decided to go fishing
Fishing
Individual catch (*Catch*, eq. 5)
Remove catch from fish biomass
Market
Compute fish price (*Price*, eq. 6)
Compute profits (π, eq. 7)

Figure 2

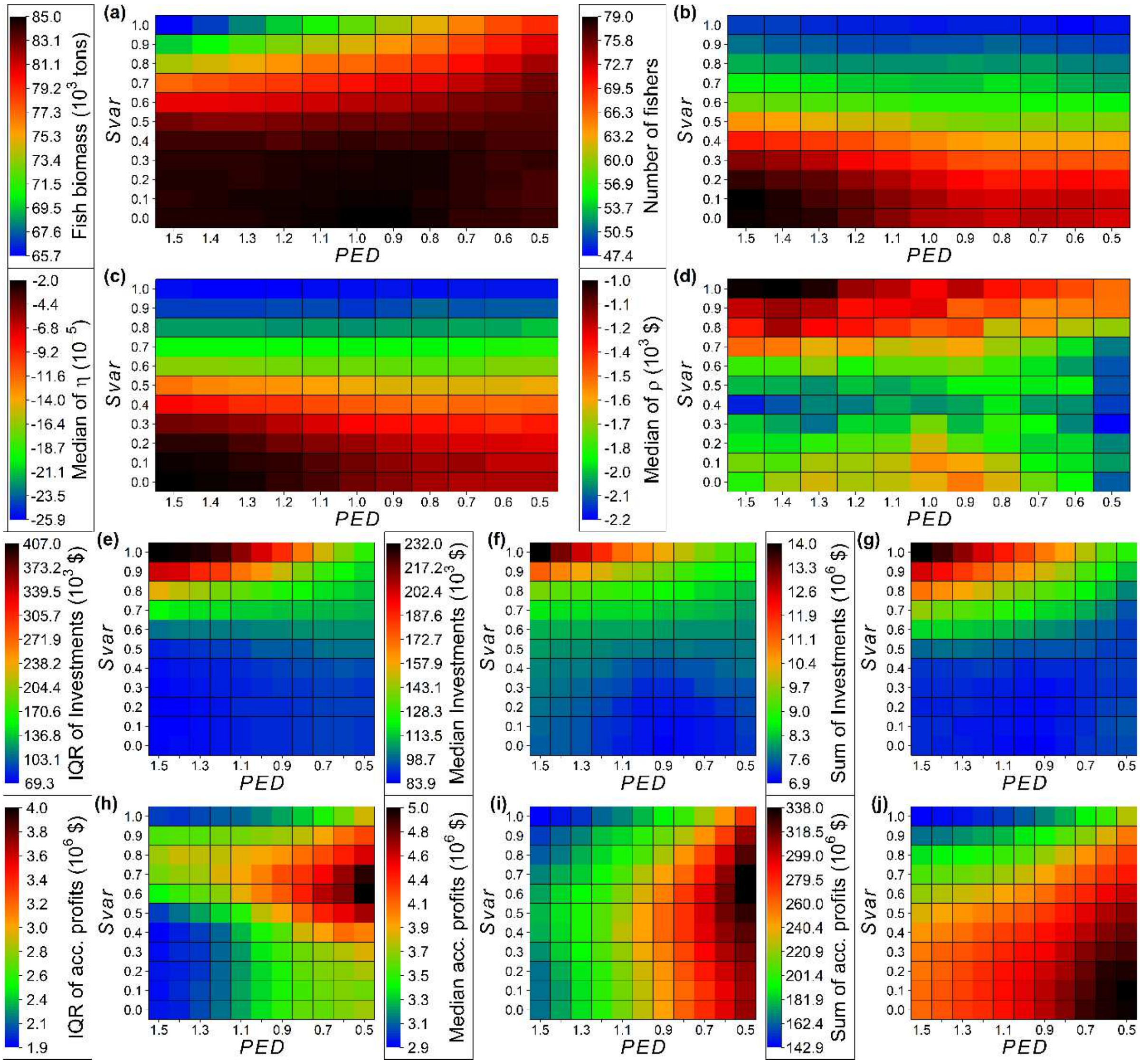
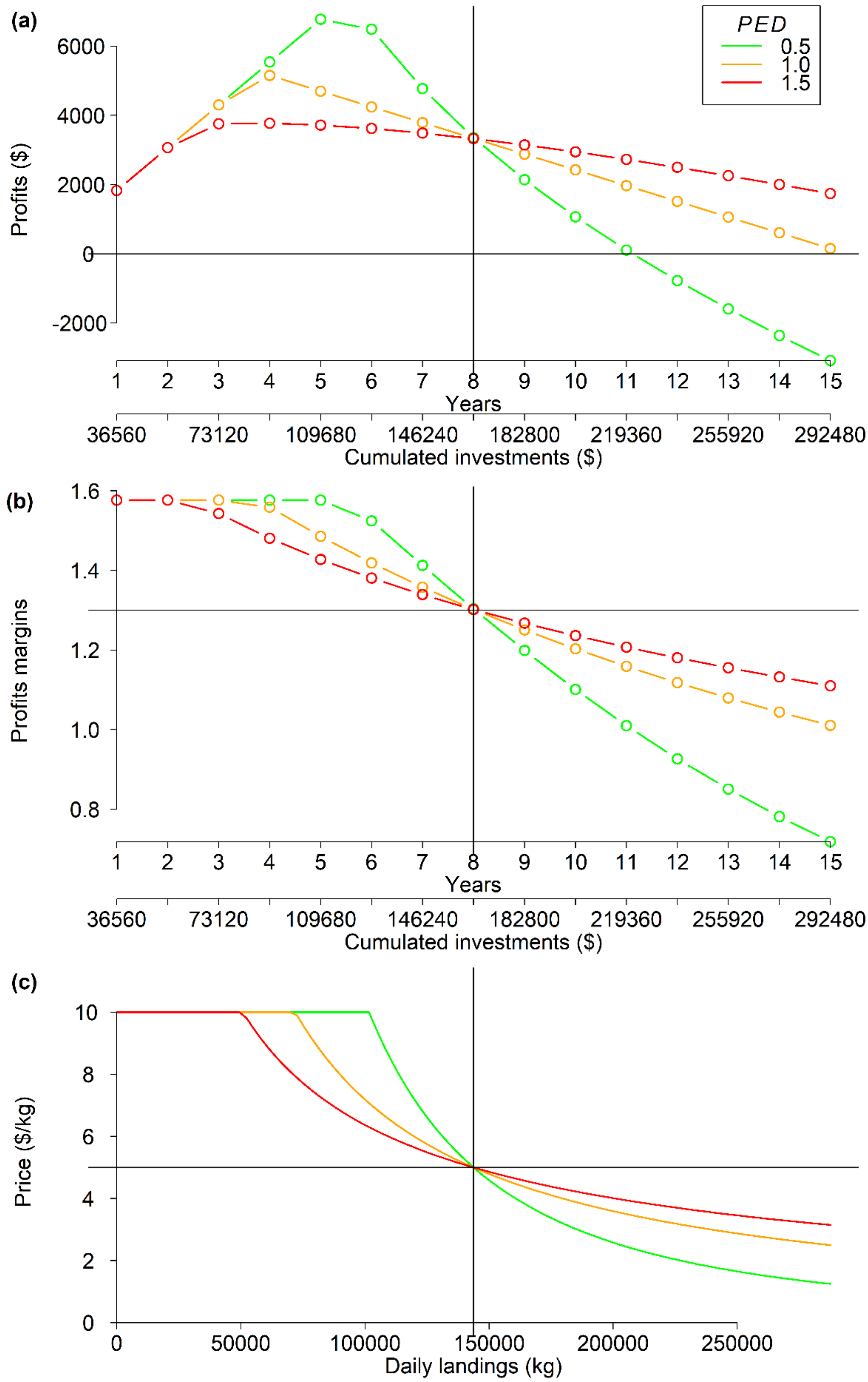

(a)
Fish biomass (10^3 tons)
Svar
PED
(b)
Number of fishers
(c)
Median of η (10^{-5})
(d)
Median of ρ (10^3 $)
(e)
IQR of Investments (10^3 $)
(f)
Median Investments (10^3 $)
(g)
Sum of Investments (10^6 $)
(h)
IQR of acc. profits (10^6 $)
(i)
Median acc. profits (10^6 $)
(j)
Sum of acc. profits (10^6 $)

Figure S1

(a)



(a)
6000
4000
2000
0
-2000
Profits ($)
PED
0.5
1.0
1.5
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Years
36560 73120 109680 146240 182800 219360 255920 292480
Cumulated investments ($)
(b)
1.6
1.4
1.2
1.0
0.8
Profits margins
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Years
36560 73120 109680 146240 182800 219360 255920 292480
Cumulated investments ($)
(c)
10
8
6
4
2
0
Price ($/kg)
0 50000 100000 150000 200000 250000
Daily landings (kg)

Figure S2.1

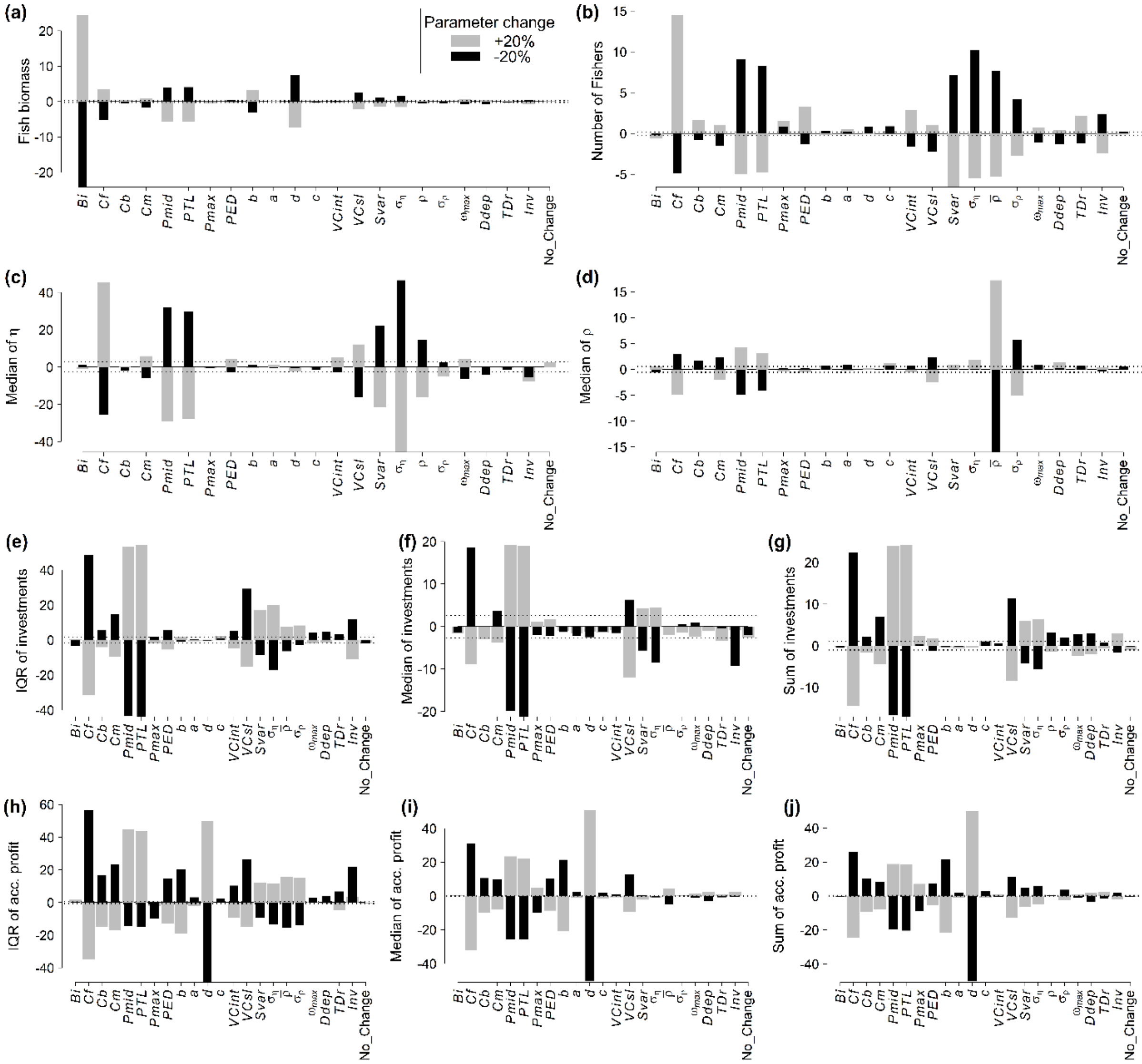
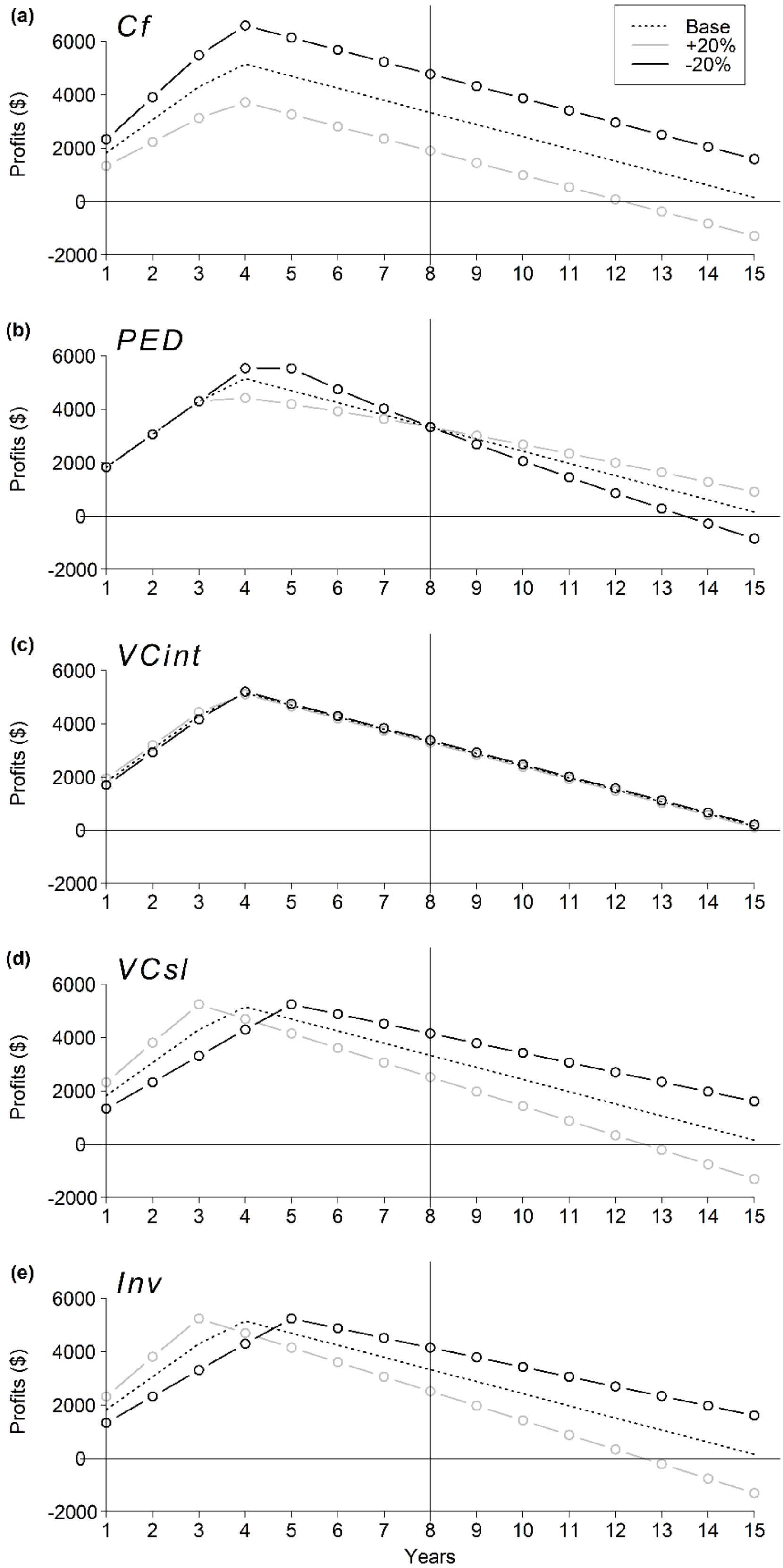
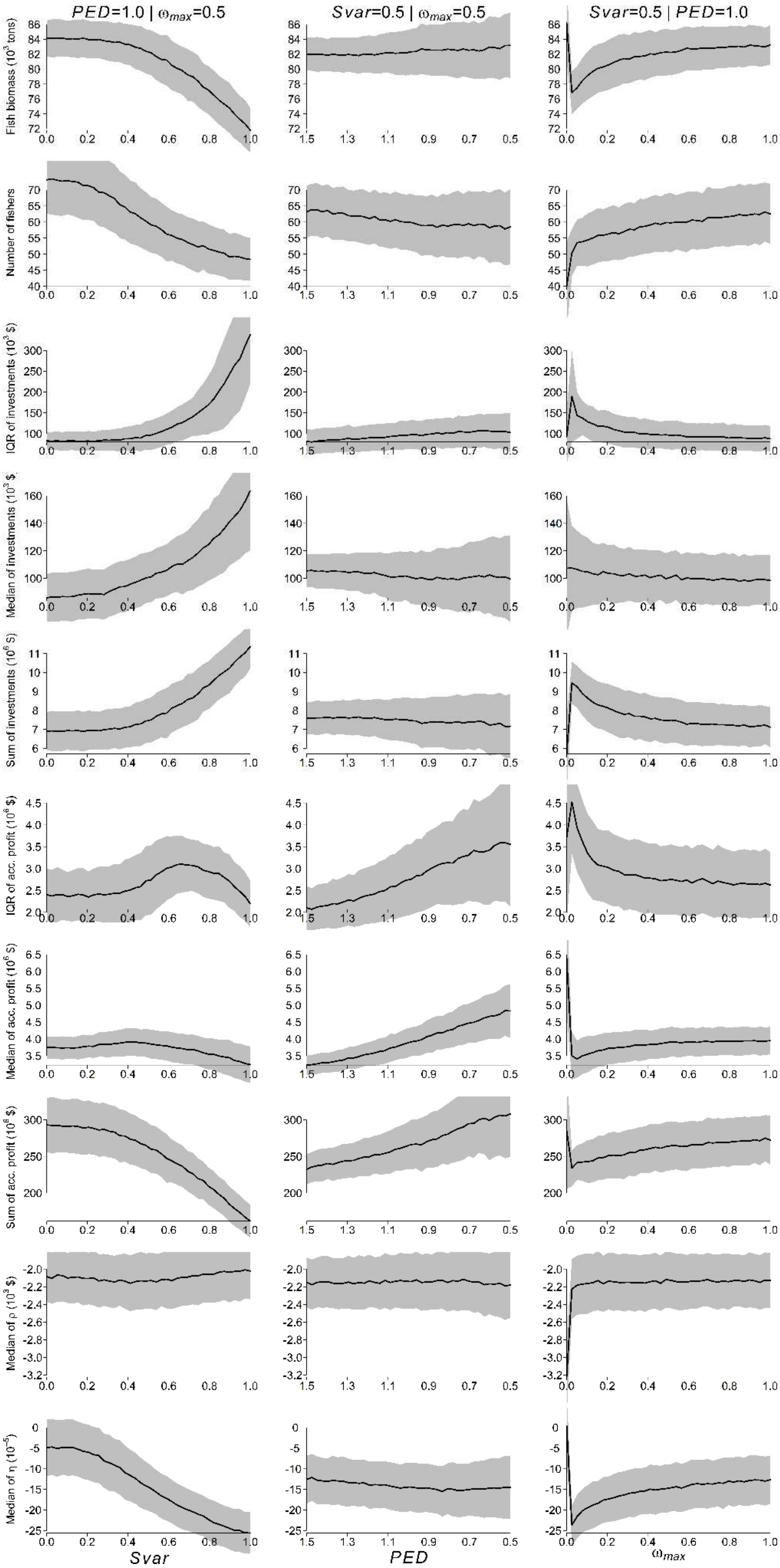

(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
(j)
Parameter change
+20%
-20%
Fish biomass
Number of Fishers
Median of η
Median of ρ
IQR of investments
Median of investments
Sum of investments
IQR of acc. profit
Median of acc. profit
Sum of acc. profit
Bi
Cf
Cb
Cm
Pmid
PTL
Pmax
PED
b
a
d
c
VCint
VCsl
Svar
No_Change

Figure S2.2



(a)
Cf
Base
+20%
-20%
Profits ($)
6000
4000
2000
0
-2000
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
(b)
PED
Profits ($)
(c)
VCint
Profits ($)
(d)
VCsl
Profits ($)
(e)
Inv
Profits ($)
Years

Figure S3



PED=1.0 | ω_{max}=0.5
$Svar$=0.5 | ω_{max}=0.5
$Svar$=0.5 | PED=1.0
Fish biomass (10^3 tons)
Number of fishers
IQR of investments (10^3 \$)
Median of investments (10^3 \$)
Sum of investments (10^6 \$)
IQR of acc. profit (10^6 \$)
Median of acc. profit (10^6 \$)
Sum of acc. profit (10^6 \$)
Median of ρ (10^3 \$)
Median of η (10^{-5})
$Svar$
PED
ω_{max}

Model component	Parameter	Description	Value	Equation
Fish stock				
	Bi	Initial fish biomass (replenished every January 1st)	100,000 t	-
Individuals				
	Svar	Fishing success variability	0.5	5
	Cb	Basic costs rate	0.168	7
	Cm	Cost rate of maintenance	0.504	7
	Cf	Cost rate of fishing	0.5	7
	VCsl	Slope of the relationship between vessel capacity and investments	0.037	3
	VCint	Intercept of the relationship between vessel capacity and investments	-352.72	3
	ω_{max}	Upper bound of ω	0.5	-
	a	Probability of leaving port parameter (starting slope)	0.2	4
	b	Probability of leaving port parameter (starting time)	100	4
	c	Probability of leaving port parameter (ending slope)	0.2	4
	d	Probability of leaving port parameter (ending time)	240	4
	$\bar{\eta}$	Mean response to variance in expected profits	0	-
	σ_η	Standard deviation of the response to variance in expected profits	$3.86 \cdot 10^{-4}$	-
	$\bar{\rho}$	Mean opportunity costs / preference toward fishing	-1,828 $	-
	σ_ρ	Standard deviation of opportunity costs / preference toward fishing	1,828 $	-
Market				
	Inv	Investment costs	$36,560	1
	PED	Price Elasticity of Demand	1.0	6
	Pmax	Maximum price of fish	10 $/kg	6
	Pmid	Mean price of fish	5 $/kg	6
	PTL	Potential Total Landings	143,750 kg	6
	Ddep	Depreciation parameter (duration)	360 days	2
	TDr	Decay rate of the weight put on past economic outcomes	0.005	11