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The role of behavioural flexibility in a whole of ecosystem model

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The predictive accuracy of complex fisheries models developed to anticipate the effects of changing fishery regulations appears to depend on a solid understanding of the processes and feedback systems linking biological and physical information to resource user. Many fisher decisions are modelled in the human component of the models, including inertia, or location choice flexibility. We unpack a whole of ecosystem system model and explore how location choice flexibility in fleet behaviour (sticking to the same seasonal and spatial distribution of fishing) affects outcomes such as catches and income levels and variability. Our analysis shows that the interpretation is not straightforward, and the relationship between behavioural flexibility and income level and income variability has to be considered in the context of three main fleet characteristics: profitability; how diversified the fleet is; and growing or declining target species biomass. We contend that making behavioural flexibility sensitive to the health of the stock and fleet profitability could potentially improve accuracy of large whole of ecosystem models such as Atlantis.

Keywords: behavioural flexibility, ecosystem modelling, fisher decision-making, risk perception.

Introduction

It is now well accepted by most fishery scientists and managers that effective and efficient management policies depend on not only a good understanding of marine biology but also knowledge of decision-making and fisher behaviour (Hilborn, 1985; Fulton *et al.*, 2011a). Understanding feedback processes between human and biological systems is particularly important in the context of ecosystem-based management, as this entails an increasing focus on adaptive, rather than prescriptive, approaches (Pascoe *et al.*, 2008; Symes and Hoefnagel, 2010; Tallis *et al.*, 2010).

Over the past three decades, fishery models have been developed for many regions in the world to help policy-makers in their endeavours to manage fisheries sustainably (Fulton, 2010). The form and application of fishery models has evolved from largely single species to an increasing number of ecosystem models (Watt, 1975; Halfon, 1979; Sainsbury *et al.*, 2000; Plagányi *et al.*, 2011). The focus of the models has also broadened from tools for assessing fish abundance to include models that allow testing of hypothetical management scenarios, or Management Strategy Evaluation (MSE) (Smith, 1994). This allows the prediction of management change outcomes prior to implementation, and can minimize and potentially avoid unintended consequences of change (Fulton *et al.*, 2011a).

A key part of the expansion of the MSE approach to ecosystem-level questions has been the evolution of operating models, which has seen a broader set of potential processes considered; with regard to both the biological and physical components of marine systems, but also to the human elements that describe resource user behaviour and interactions. The models in the human domain largely rely on traditional and established theory and modelling techniques mostly drawn from economics (van Putten *et al.*, 2011). Even though empirical research suggests that fisher behaviour is frequently best explained by variables related to profit (Eales and Wilen, 1986; Larson *et al.*, 1999; Armstrong and Sumaila, 2001; Cabrera and Defeo, 2001; Dorn, 2001; Bjørndal and Lindroos, 2004), it is also well known that many non-economic and non-observable fisher characteristics, such as attitudes (van Putten *et al.*, 2011, and references therein), knowledge and beliefs (Kennedy, 1987; Abernethy *et al.*, 2007; Del Valle *et al.*, 2008), and risk perception (Mistiaen and Strand, 2000; Eggert and Tveteras, 2004; Haynie *et al.*, 2009), can also contribute to explain observed behaviour (Strand, 2004).

Over the past 20 years, there have been many papers published that voice concern over the disregard and essential failure to incorporate social and psychological knowledge into integrated models (Fulton *et al.*, 2011a). Currently, even though social sciences have added important theoretical bases for studying fisher decision-making and provided additional insights into their behaviour (Hatcher *et al.*, 2000; Cinner *et al.*, 2009), quantitative fishery models often do not fully incorporate these important decision variables (Koeller, 2008; Symes and Hoefnagel, 2010), or only do so implicitly, using default parameters without considering alternative functional relationships (Plagányi, 2006). Using all available information sources to model and understand how fishers may change their behaviour in the context of a dynamic and adaptive management scenario may significantly improve model predictions (Hicks and Schnier, 2006; Valcic, 2009). Assessing the extent to which common representations of individual behaviour in simulation models capture these processes adequately, and suggesting new approaches where they do not, is also important to improve the predictive capacity of decision support tools.

Inertia is one such variable commonly incorporated into fleet dynamics models (Bockstael and Opaluch, 1983; Holland and Sutinen, 2000). Inertia is interpreted as the resistance to moving between fishing areas, with low inertia representing a more mobile fleet (Fahrig, 1993). In this study, we examine the way in which location choice decisions are modelled (Fulton *et al.*, 2007) at the fleet level and consider the impact of inertia on catch and income levels and variability. We refer to inertia as the relative responsiveness of fishing operations to new information when deciding on the location of their fishing activities. We contrast cases in which historical information [e.g. information on new spatial distribution of catch per unit effort (CPUE)] is weighed heavily and the fleet is slower to respond to changing circumstances with cases in which recent information is weighted more heavily in location decisions. Slow responses, resulting from a greater relative weight granted to historical information, are interpreted as being less flexible. This flexibility is then reflected in day-to-day location choice. Flexible fishers are more likely to select locations identified as productive in the new information, while those who more heavily weight historical information will persistently return to the same locations (and so display higher spatial inertia).

In our study, we link the concepts of inertia, responsiveness to information, and location choice flexibility, but acknowledge that a wide range of interpretations have been given to 'inertia patterns', including technological constraints related to change, skill, social capital, the difficulty in venturing into unchartered territories, and information asymmetries due in part to social networks (Holland and Sutinen, 1999). Inertia can also be partly explained by the behavioural implications of different aspects of risk perception. Risk has been defined in a number of ways, but generally involves the probability or likely occurrence of an uncertain outcome or adverse event (Sjöberg, 2000; Sjöberg *et al.*, 2004). Psychological determinants of behaviour in the face of risks have been shown to play an important role in explaining what people do when they are uncertain about the outcomes of their decisions (Kahneman and Tversky, 1979; Hogarth and Reder, 1987; Kahneman *et al.*, 1991).

We use the application of the Atlantis modelling platform for the Australian Southern and Eastern Scalefish and Shark Fishery (SESSF) as a case study (Figure 1) to investigate the impact of location choice and species targeting flexibility assumptions in a whole of ecosystem model.

Figure 1 shows the area that is the subject of the Atlantis modelling case study as represented by 71 polygonal boxes. The box boundaries are determined through a combination of physical and ecological properties and information from the demersal bioregionalization by IMCRA (1998), Butler *et al.* (2001), Lyne and Hayes (2005), and the CSIRO's Atlas of Regional Seas dataset. Within each box, there are up to five layers, depending on the total depth of the box (Fulton *et al.*, 2007).

Many different species occur in this region—including invertebrates (e.g. abalone, rock lobster, prawns, and squid), fin fish, such as the very long-lived orange roughy (*Hoplostethus atlanticus*), and species caught in shallow water (e.g. King George whiting captured in Port Phillip Bay) and on the open ocean (e.g. broadbill swordfish). The commercial SESSF comprises > 20 major commercially important species and stocks. The fishery has been managed using a mix of input and output controls, including individual transferable quotas (ITQs), since 1992 (Fulton *et al.*, 2007).

In this study, we use the existing model of the fishery to examine the influence of alternative assumptions regarding the inertia in fishing patterns on outcomes of modelled fleet dynamics with respect to the levels and variability of catch and income in the fishery. We discuss the implications of the variability of catch and income in the context of the empirical reality that fisher behaviour is often explained by their desire to moderate the risk of income variability (Holland, 2008; van Putten *et al.*, 2011).

As background to this analysis, we first provide an overview of the literature on fisher behavioural modelling, focusing on the empirical literature regarding the role of risk perceptions in fisher behaviour. The Atlantis ecosystem model of the SESSF is then outlined prior to presenting and discussing the results of our simulations.

Fisher behaviour modelling and risk

A broad range of drivers have been considered in explaining fisher behaviour (Holland, 2008). In the modelling literature, rational choice theory (von Neumann and Morgenstern, 1944; Becker, 1976; Hogarth and Reder, 1987; Raiffa, 1997) has mostly been the basis on which formal description of the behaviour of individual fishers has been developed in bioeconomic fishery models. Rational choice theory outlines that individuals select a preferred course of action based on an ordering of the alternative options they face, according to their preferences over the expected outcomes and consequences of these alternative options. In the economic literature, this is formally captured by a utility function which associates a number with each choice, such that the ranking of these numbers reflects the agent's preferences over the consequences of the choices (von Neumann and Morgenstern, 1944).

This approach has led to the development of a large literature on the determinants of decision-making under risk (Friedman and Savage, 1948; Savage, 1954; Kahneman and Tversky, 1979; Ramsey, 1990; Raiffa, 1997). A core result of rational choice theory is that individual choice ranking will usually depend on the mean or expected value of the potential outcomes associated with alternative choices, which is a function of the value of these outcomes if they prevail, moderated by the anticipated variability in the outcomes (or level of uncertainty as to which of the outcomes will eventuate), this being subject to the individual's subjective perceptions of, and attitudes towards, risks.

Standard models of fisher behaviour follow the above theory and assume some form of profit or utility maximization through the inclusion of variables such as relative catch rates, CPUE, or other proxies for the returns associated with different fishing options (van Putten *et al.*, 2011). There are a number of proxies for income variability, such as revenue (Holland and Sutinen,

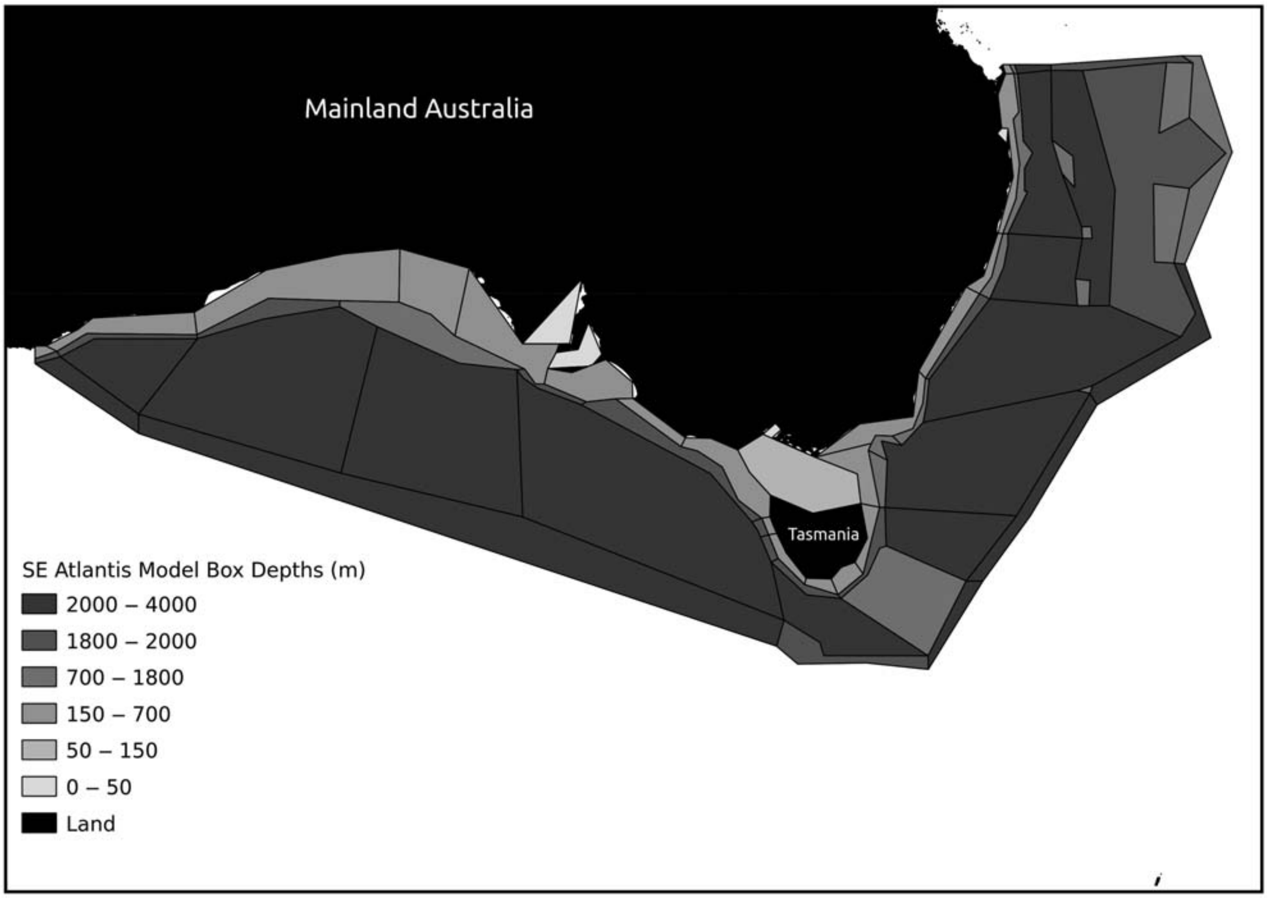

Figure 1. Map of research area and the boxes in Atlantis for the Australian Southern and Eastern Scalefish and Shark Fishery.

1999; Mistiaen and Strand, 2000; Pradhan and Leung, 2004) profit, and wealth (Bockstael and Opaluch, 1983; Dupont, 1993), which are used as explanatory variables in fisher location choice decision models. In econometric studies, the sign of the coefficient on income variability is often interpreted as an indicator of average risk preference (Holland and Sutinen, 2000).

In empirically based models, many other variables are included to explain location choice decisions. In a large number of applications, these variables are not described in detail, but rather included in an "inertia" variable which more often than not is presented as a "black box". Inertia is taken to reflect the variable propensity of operators to respond to new information, capturing the empirically observed patterns of "habitual" behaviour which models of rational agents operating with perfect information do not predict well. Many different drivers have been considered in attempting to explain such habitual behaviour, including combinations of deliberate and non-deliberate decision-making. Although past fisher behaviour is usually the basis on which subsequent behaviour is predicted, in reality past behaviour is not a causal factor in itself. According to the theory of Azjen (1991; Azjen, 2001) behaviour depends on beliefs, subjective norms, and intentions, and it is past experience, in conjunction with a reasoned response, which leads to subsequent behaviour.

Inertia (or sticking with the status quo) is a commonly discussed characteristic of observed behaviour in the context of risk. The treatment of risk in the expected utility framework of analysis was previously mentioned. Three behavioural concepts, developed in the psychology and behavioural economics literature, are relevant in relation to inertia and risk: loss aversion, risk aversion, and ambiguity aversion. Loss aversion (Kahneman *et al.*, 1991) is the tendency to prefer avoiding losses to acquiring gains (Kahneman and Tversky, 1979), making the loss of the status quo option loom larger than the gain of an alternative option (Gal, 2006), thus driving inertia. Risk aversion is the tendency to prefer more certain but possibly lower outcomes to a bargain with a potentially higher but more uncertain payoff. Sticking with a known alternative that performs reasonably well thus appears a good risk-averse decision strategy, thus driving inertia. Ambiguity aversion describes a preference for known risks over unknown risks, suggesting retention of the status quo as a preferred course of action (Hogarth and Kunreuther, 1995; Epstein, 1999), again driving inertia.

All three risk-related explanations of behaviour and the link to inertia are relevant in a fisheries context. However, in fisheries, inertia related to ambiguity aversion may emerge due to a learning-based lock-in effect (Chorus and Dellaert, 2012) as the qualities of alternatives are only revealed upon usage.

While the above explanations from psychology and behavioural economics relate to location choice inertia, fishers face a wide range of other decision problems; for instance, compliance with fishing regulations, exit from and entry into particular fisheries, and investment.

Empirically, fisher behaviour is often partially explained by their desire to moderate the risk of income variability. In a study of this, Salas and Gaertner (2004) find that fishers are by and large risk averse. Risk-averse fishers are likely to fish in areas where the variability in catch and profit is low (Holland and Sutinen, 1999; Pradhan and Leung, 2004). Risk aversion is also considered as a factor leading to visiting the same fishing locations if they have been successfully fished in the past (Strand, 2004; Pascoe and Mardle, 2005), thus contributing to inertia in fishing effort allocation. However, the opposite is found by Holland and Sutinen (1999) who indicate that fishers were more likely to go to areas with higher variance in response to information received about high revenue rates.

Empirical research on fisher decision-making and risk has been carried out using econometric and other social science approaches. There has been less attention paid to process-based or mechanistic models, though a few examples exist (Allen and McGlade, 1986; Holland and Sutinen, 2000; Soulie and Thebaud, 2006).

Allen and McGlade (1986) incorporate empirically determined risk profiles into a single-species fishery model for the Nova Scotia Groundfish Fishery. In this model, the "attractiveness" of a location depends on expected profit, information exchange between fishers and fleet, and the response of the skipper to the information received. The skipper's response to the information is a function of their aversion to uncertainty or ambiguity. According to the model, so-called *stochasts*, described as risk takers, are not explicitly choosing options with higher expected value, but rather options with higher variance on returns. *Stochasts* make their location choice random and thus discover new areas that lead to switching in the investment of fishing effort. As *stochasts* explore areas with previously low catch rates, they thus display a "willingness to take risks". *Cartesian* fishers believe all information they receive and respond accordingly. *Cartesians* concentrate their effort wherever catches were highest in the last period.

Having both fisher types in their model ensures that progress and adaptation occur smoothly and not only by catastrophic collapse and replacement.

Model description

Allen and McGlade's (1986) single-species model assumes some randomness in fisher location choice, which drives the discovery of new opportunities, soon adopted by fishers with a follower, low-risk, behaviour. We investigate the effects of behavioural assumptions related to inertia and behavioural flexibility on the patterns of catch, effort, income, and income variability in the Atlantis ecosystem model, using the SESSF as a case study.

The Atlantis modelling framework is a whole of ecosystem model used to support marine ecosystem-based management, system understanding, and MSE (Fulton *et al*., 2007). The biophysical component of Atlantis is a deterministic (differential equation), spatially resolved, three-dimensional spatial model (Fulton *et al*., 2005), which spans physical drivers, habitats, and foodweb-associated interactions and population dynamics (shown in the top left-hand box in Figure 2; for a detailed version see Fulton *et al*., 2011b). In total, Atlantis has six linked submodels and, as the variables within each submodel are internally and externally linked, the flow on effects can be assessed for the other submodels. The focus in this study is on the changes in the industry submodel as a consequence of different parameter assumptions in the socio-economic submodel (in this study only parameters in the socio-economic submodel were varied).

In Atlantis, the fishing fleets each have their own characteristics, including gear selectivity, habitat association, targeting, effort allocation, and management structures (Fulton *et al*., 2007, 2011b; Hutton *et al*., 2010). A hierarchical effort allocation model and planning scheme is used for determining the scale and distribution of fishing effort. Boats of similar size with common home ports, gear type, target species, and socio-economic characteristics are referred to as subfleets. Effort allocation (Figure 3) for these subfleets is stepwise, based on past conditions, current economic conditions, distance to fishing grounds, and management regulations [i.e. total allowable catch (TAC)].

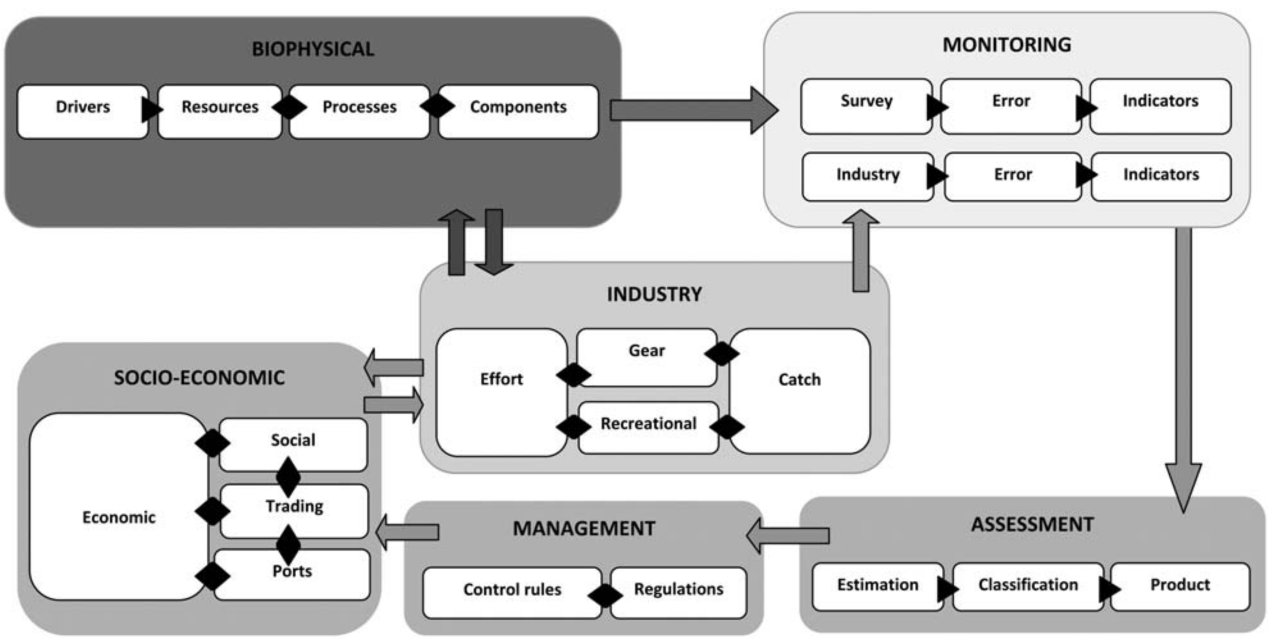

Figure 2. Schematic representation of the six linked submodels of Atlantis (the arrowhead is one-way interaction and the diamond shape indicates that feedback exists). (For a detailed version, see Fulton *et al*., 2011.)

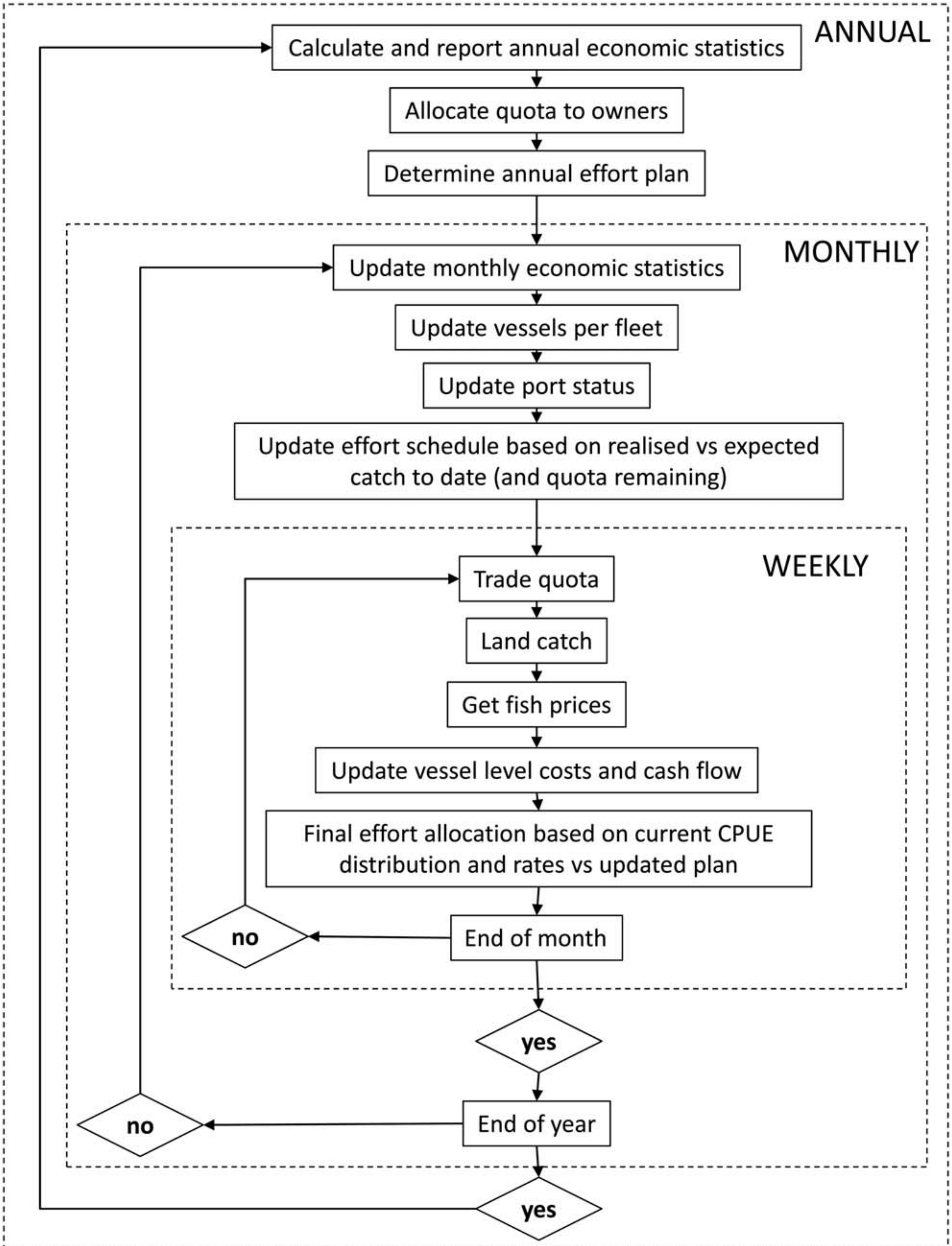

Figure 3. Description of the assumed decision-making process for the fleets in the SESSF in Atlantis.

A subfleet's effort allocation plan is first calculated annually and updated on a monthly basis. At the finest scale, fleets will allocate their effort on the basis of their knowledge of CPUE, expected return per target species, and quota available on a weekly basis. At the end of 4 weeks (a month), economic statistics are updated and effort scheduling is updated based on realized vs. expected catches to date and quota remaining. After 12 months, at the end of the year, the annual effort plan for the next year is determined.

More formally, the first step in planning effort includes, calculating expected return (R_e) per month (m) per target species (s). Expected revenue per unit of effort is calculated by multiplying the price per species per fleet (i) and subfleet (j) per month ($P_{s,j,m}$) and the expected catch (H_e, see below) per unit of effort (E_h) less the per unit of effort costs by species ($\gamma_{s,i,j,m}C_{e,i,j,m,y-1}$).

$$R_{e,s,i,j,m} = P_{s,j,m}\frac{H_{e,s,i,j,m}}{E_{h,i,j,m}} - \gamma_{s,i,j,m}C_{e,i,j,m,y-1} \quad (1)$$

The expected revenue per unit of effort per year for the subfleet is summed over all months of that year and all target species (*tot*) of that subfleet [Equation (2)].

$$R_{e,tot,i,j,y} = \sum_{1}^{m}\sum_{1}^{s}\left(P_{s,j,m}\cdot\frac{H_{e,s,i,j,m}}{E_{h,i,j,m}} - \gamma_{s,i,j,m}C_{E,i,j,m,y-1}\right) \quad (2)$$

The next step is to calculate expected monthly gross effort allocation ($E_{e,i,j,m}$) over a particular commercial species. The historical (h) monthly effort data ($E_{h,i,j,m}$) are scaled depending on the expected monthly returns ($R_{e,tot,i,j,m}$). The expected monthly returns are proportional to last year's ($y-1$) revenue ($R_{tot,i,j,y-1}$) and quota availability [θ_{effort}; Equation (3)].

$$E_{e,i,j,m} = E_{h,i,j,m}\cdot\frac{R_{e,tot,i,j,m}}{R_{tot,i,j,y-1}}\cdot\theta_{effort} \quad (3)$$

Quota availability is a scalar used to ensure that the expected harvest does not exceed quota in hand ($Q_{i,j,y}$). The expected proportional value for each species relative to the total expected value in the fishery is used to weight the effort scaling function. The proportional value matches the value of that species in the subfleet's take [Equation (4)].

$$\gamma_{effort} = \max\left(1.0, \sum_{s}\frac{Q_{i,j,y}}{H_{e,s,i,j,y}}\cdot\frac{R_{e,s,i,j}}{R_{e,tot,i,j}}\right) \quad (4)$$

After monthly gross effort is planned, subfleets update their target species to match those with the highest expected returns.

Key to the model is the way in which expected harvests are represented, as a function of past information, and of the way in which this information is used by fleets to revise their predictions of future catch opportunities. Flexibility is modelled on the basis of the knowledge of the fishery system built up at the fleet level. In the annual effort scheduling, differential fisher knowledge is captured in the expected harvest per unit effort, which is updated per trip based on willingness to accept new subfleet-level information using the simple interpolation of new information and the existing historical view held by that fisher [e.g. as in Equation (5) for harvest per unit effort L].

$$L_{e,s,i,j,m,y-1} = \delta_{i,j}(L_{o,s,i,j,m,y-1} - L_{h,s,i,j,m,y-1}) + L_{h,s,i,j,m,y-1} \quad (5)$$

where L_e is equivalent to H_e/E_h; L_o was the new observed information, and L_h is the historical view. Fishers' flexibility is defined by a heuristically tuned flexibility coefficient (δ) which dictates how the fishers weigh their more recent catches and effort over longer term patterns (Holland, 2008, and references therein). A low flexibility coefficient indicates a heavier reliance on historical information. In contrast, those with a high flexibility coefficient have the capacity to be more responsive and display more flexible behaviour as new information becomes available. This behavioural assumption differs from that in Allen and McGlade (1986) who assume a single pattern of behavioural response for Cartesian operators, alongside randomly driven behaviour for the stochasts.

The expected effort schedule in Atlantis is spatially allocated in proportion to the monthly effort applied by the subfleet to each spatial box. Boxes in Atlantis are not of a uniform size (see Figure 1), but based on biophysical properties. In areas where the properties change rapidly, the boxes are smaller, while in large relatively homogenous areas (like patches of open ocean) the boxes are larger. Planned effort in box b by subfleet ($E_{plan,i,j,b,m}$) is:

$$E_{plan,i,j,b,m,y} = E_{e,i,j,m,y}\frac{E_{h,i,j,b,m}}{E_{h,i,j,m}} \quad (6)$$

With $E_{e,i,j,m,y}$ the monthly resolved scheduled effort for the subfleet, $E_{h,i,j,m}$ historical levels of monthly effort, and $E_{h,i,j,b,m}$ the level of monthly effort by the subfleet historically seen in box b.

However, fishers' annual effort scheduling is also affected by the ability to move to other areas (boxes). Movement may be constrained by onshore social and economic issues or technical availability. For all types, the effort updating is calculated using Equation (7) [this second inclusion of inertia and historical distributions is because interviews with fishers (see Fulton *et al.*, 2007 for more detail)] indicated that for inflexible fishers, not only did historical data heavily influence planned trip locations, but, once at sea, a plan to visit new locations was often impulsively dropped in favour of returning to a known historical site].

$$E_{i,j,m,current,b} = \delta_{i,j}(E_{e,i,j,m,b} - E_{h,i,j,m,b}) + E_{h,i,j,m,b} \quad (7)$$

where $E_{e,i,j,m,b}$ is effort per box (b) based on expectations created using recent experience and conditions; and $E_{h,i,j,m,b}$ is the pattern of effort based on historical patterns and memory.

Methods

We used the Atlantis model to run a base case and two scenarios with different flexibility coefficient (δ) values. For our base case, the flexibility term was parameterized by retrofitting the effort allocation model to reproduce the shifts in allocation and targeting as observed during the 1990s; the skill of this parameterization was assessed by checking predictions vs. effort distributions through the early 2000s (Fulton *et al.*, 2007). While the fishery is a moveable feast in terms of the fine details of management, the general form of effort allocation behaviour has persisted (based on repeated unpublished interviews with fishers participating in the fishery).

For the base case, the coefficient is set individually for each subfleet within a fleet. For instance, the demersal trawl fleet has five subfleets. These fleets target deep piscivorous and demersal fish, such as ling (*Genypterus blacodes*), blue grenadier (*Macruronus novaezelandiae*), and gemfish (*Rexea solandri*), as well as bycatch species (including deep-water sharks and dogfish, and miscellaneous deep-water invertebrates). The flexibility coefficient for the 26 fleets of smaller vessels was set at 0.1. The flexibility coefficient increased to 0.15 for the six fleets of medium-size vessels, and to 0.2 and 0.225 for the fleets of slightly larger and largest vessels, respectively. Larger vessels are assumed to be better equipped for exploratory fishing.

The first scenario, which we labelled the *traditional fisher* scenario, characterizes the fishery by a low flexibility coefficient of 0.05 as the fleets are assumed to rely mostly on historical information to make decisions. In the second scenario, the flexibility coefficient was set at a high value (0.95). We labelled this the *flexible fisher* scenario as the fleets were assumed to be mostly responsive to new information and conditions. We model expected and realized effort, expected and realized catch, and expected and realized CPUE, and present differences in outcomes for the base case and the two scenarios for the whole SESSF. We also detail the outcomes for five selected fleets in the SESSF fishery (target species and detailed information for the five fleets are shown in Appendix 1).

Results

Each fleet annually adjusts their expected catch for each species up or down, or retains it at the same level, on the basis of catches in the previous year(s) and assumptions made as regards their flexibility. On average over the entire period in the base case, realized catches are 25% higher than expected catches at a whole of SESSF level. In the flexible fisher scenario, however, expected catch is overestimated by the fleets, indicating that flexible fishers are "overoptimistic", and that elements of uncertainty and risk may exist at fleet level in a complex, whole of ecosystem fishery model, even if this model is based purely on deterministic assumptions.

When considering the whole SESSF, cumulative realized catches over the 20-year period are 6% lower (~52 000 t) for flexible fishers than for the base case and traditional fishers. Realized catch and effort and derived CPUE for the base case and the traditional fisher scenario ($\delta = 0.05$) and flexible fisher scenario ($\delta = 0.95$) are shown in Table 1.

There is little difference between the base case and traditional fisher scenario. However, for flexible fishers, both realized catches and realized effort are lower, resulting in a higher CPUE. In a fishery that is only marginally profitable, greater flexibility in reducing effort pays off. In terms of realized CPUE, flexible fishers in the SESSF are ~30% more efficient (2817 as opposed to 2165). Given this greater efficiency (based on realized CPUE), although the cumulative gross value of landings over the 20-year period is 6% lower for flexible fishers, the total economic rent increases under this scenario, while it decreases for both the base case and traditional fisher scenario (see also Figure 4).

Changes in biomass levels of the main commercial fish species modelled, according to the different scenarios, are shown in Appendix 2. Targeting behaviour changes over the 20-year period, as the biomass of some species changes and as new fishing opportunities arise. The catches of the main species by all fleets in the SESSF are shown in Figure 5 for the base case.

Table 1. Cumulative catch and effort, and CPUE for the SESSF fishery modelled for the base case, and two scenarios with traditional ($\delta = 0.05$) and flexible fishers ($\delta = 0.95$).

Indicators of efficiency for the whole SESSF	Base case ($\delta = 0.20$)	Traditional fisher scenario ($\delta = 0.05$)	Flexible fisher scenario ($\delta = 0.95$)
Cumulative realized catch ('000 000 kg over 20 years)	878	877	826
Cumulative realized effort ('000 days fished over 20 years)	406	405	293
CPUE (kg d^{-1} fished)	2163	2165	2817
Cumulative gross value (undiscounted US$'000 000 over 20 years)	42 720	4284	40 482
Cumulative economic rent (undiscounted US$'000 000 over 20 years)	−227	−217	436

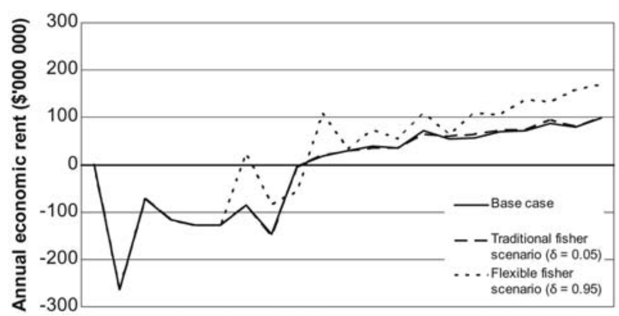

Figure 4. The annual economic rent for the base case and two scenarios with traditional ($\delta = 0.05$) and flexible fishers ($\delta = 0.95$) for the SESSF fishery.

The largest relative fall in catch in the base case is observed for blue grenadier and orange roughy, even though the biomass for both species increases from about year 10 onwards (see Appendix 2), by which time the fishing fleets are targeting different species. In contrast, the catch and biomass of flathead and ling increases over the 20-year period (Appendix 2). Catch changes in the flexible fisher scenario (not shown in Figure 5) are similar to those shown above except for greater variability in rock lobster catch. Flexible fishers switch targets, temporarily moving from targeting mainly piscivorous fish into high value rock lobster (despite the costs of the quota leases which such switches in target species involve), which does not seem to affect rock lobster biomass significantly (Appendix 2). The biomass of most species increases over time in all scenarios (although at different rates). However, prawns and commercial crabs show a decline, as well as some of the bycatch species such as school shark.

At the scale of the entire SESSF, fishing patterns and species targeting under the traditional and flexible fishing scenarios seem to conform to expectations. Flexible fishers are able to switch species, and their capacity to reallocate their effort rapidly allows them to benefit from opportunities as they arise. Even though cumulative realized catches are lower for flexible fishers, their realized CPUE

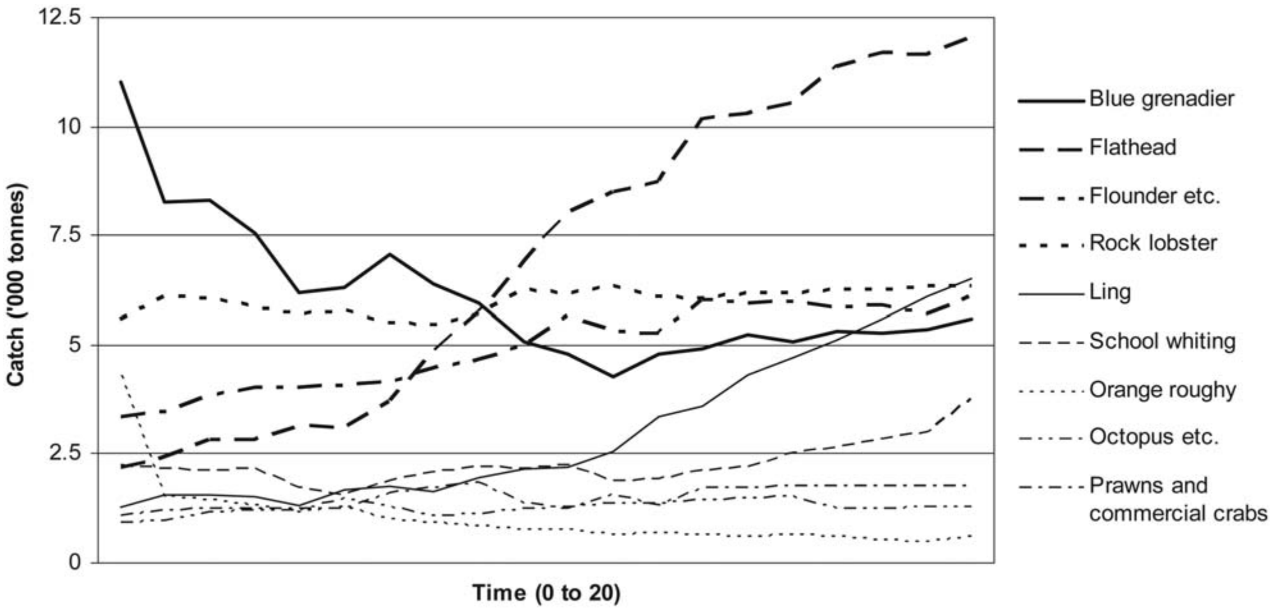

Figure 5. Catch of the main species for the SEFFS fishery (20 years – base case).

Table 2. Characteristics of the five main fleets in the SESSF fishery in terms of relative diversity, biomass target species, and profitability (averages over the 20-year run for the base case scenario).

Fleet characteristics	Danish seine for flathead	Bottom trawl for deep demersal fish	Bottom trawl for flathead	Bottom trawl for orange roughy	Prawn trawl
Diversity	66% dependence on one species	Highly diverse set of target species	71% dependence on one species	Diverse set of target species	Specialized
Catch target species	↑ (flathead)	→	↑ (flathead)	↓ (orange roughy)	Temporary ↑ then ↓ (rock lobster) →
Profitability	Highly unprofitable	Marginal	Marginal	Unprofitable	Profitable

is significantly higher as they are able to reduce their total effort more easily, in an only marginally profitable fishery.

A detailed examination of five individual fleets provides insights into the importance of flexibility assumptions in explaining the performance of these fleets. Details for each fleet are presented in Appendix 1 and their main characteristics are summarized in Table 2.

With the catch changes for target species in mind, in particular the decrease in the target species of the bottom trawl for orange roughy, and the increase in target species of the bottom trawl and Danish seine for flathead, we assess the effect of different assumptions with respect to fisher responsiveness on catch, effort, and CPUE of fleets (Table 3). We define "gross value" as the sum of the total landings per species multiplied by the price per species, and the "profit" as the gross value minus the total cost of fishing.

In all fleets, flexible fishing is more efficient, with an average CPUE between 1% (for the bottom trawl for deep demersal fish) and 69% (for the Danish seine for flathead) higher than average CPUE for traditional fishers. A similar advantage is observed with flexible fishing in the bottom trawl for the flathead and prawn trawl fleet. In the prawn trawl fleet, flexible fishers are able to benefit from a one-off lobster biomass opportunity, while traditional fishers cannot benefit from this opportunity to the same extent. Even though the prawn trawl fleet is profitable in all three scenarios, flexible fishers realize 5% higher catches and profit over the 20-year period.

Similarly, flexible fishers in the bottom trawl for flathead fleet are better able to exploit increasing biomass of flathead. Their cumulative realized catches are higher (59 000 t) than those of traditional fishers (50 000 t). This fleet is only marginally profitable, however, and flexible fishers also experience negative profits in the first 15 years of the simulation. Overall, the losses are ~10% lower for flexible fishers than for traditional fishers.

Flathead is also targeted by the seine fleet. In this fleet, flexibility of the fishers does not pay off in terms of total catches (46 000 t as opposed to 60 000 t). However, by significantly reducing their effort (by 53%), flexible behaviour does pay off in terms of profit (US$24 million profit for flexible fishers as opposed to a US$40 million loss for traditional fishers). A 69% higher CPUE is realized by flexible fishers compared with traditional fishers in the Danish seine fleet.

In the bottom trawl for deep demersal fish fleet, the difference in CPUE between flexible and traditional fishing is smallest (3304 and 3271, respectively). This fleet is very diverse in terms of the number of target species, of which there are 11, with an additional six potential target species that remain unfished. The ability to make quicker and greater annual adjustments does not pay off for flexible fishers in this highly diversified fishery. This is due to the cost structure of this fleet which is only marginally profitable. Flexible fishers are able to avoid only 6% less losses than traditional fishers in this fleet.

The bottom trawl fleet for orange roughy is characterized by a decline in the catch of its main target species. In this fleet, flexible

Table 3. Cumulative catch and effort, and average CPUE for the five main fleets in the SESSF fishery modelled for the base case, and two scenarios with traditional ($\delta = 0.05$) and flexible fishers ($\delta = 0.95$).

Indicators of efficiency	Base case ($\delta = 0.20$)	Traditional fisher scenario ($\delta = 0.05$)	Flexible fisher scenario ($\delta = 0.95$)	Value ($\delta = 0.95$) divided by value ($\delta = 0.05$)[a]
Cumulative realized catch ('000 000 kg over 20 years)				
Danish seine for flathead	58	60	46	0.77
Bottom trawl for deep demersal fish	310	308	282	0.92
Bottom trawl for flathead	49	50	59	1.18
Bottom trawl for orange roughy	39	40	36	0.90
Prawn trawl	190	190	198	1.04
Cumulative realised effort ('000 days fished over 20 years)				
Danish seine for flathead	45	45	21	0.47
Bottom trawl for deep demersal fish	95	94	85	0.90
Bottom trawl for flathead	74	74	63	0.85
Bottom trawl for orange roughy	14	14	11	0.79
Prawn trawl	19	19	16	0.84
Average annual CPUE (kg d^{-1} fished)				
Danish seine for flathead	1278	1321	2238	1.69
Bottom trawl for deep demersal fish	3270	3271	3304	1.01
Bottom trawl for flathead	667	672	936	1.39
Bottom trawl for orange roughy	2755	2907	3415	1.17
Prawn trawl	10049	10049	12121	1.21
Cumulative gross value (US$'000 000 000 over 20 years)				
Danish seine for flathead	1.40	1.44	1.18	0.82
Bottom trawl for deep demersal fish	7.70	7.65	6.78	0.89
Bottom trawl for flathead	1.69	1.72	1.85	1.08
Bottom trawl for orange roughy	1.31	1.33	1.12	0.84
Prawn trawl	23.47	23.47	23.66	1.01
Cumulative economic rent (US$'000 000 000 over 20 years)				
Danish seine for flathead	−0.04	−0.04	0.02	−0.50
Bottom trawl for deep demersal fish	−1.43	−1.42	−1.33	0.94
Bottom trawl for flathead	−0.15	−0.15	−0.14	0.93
Bottom trawl for orange roughy	−0.05	−0.05	−0.03	0.60
Prawn trawl	1.90	1.91	1.99	1.04

[a]The proportion is shown to make explicit the proportional between the two scenarios.

fishers switch to other activities, leading to lower catches, but again achieve a 17% higher CPUE. The higher CPUE pays off in this declining fishery as losses for flexible fishers are 45% lower than for traditional fishers. In summary, we find that the payoff for increased flexibility is dependent on the relative profitability of the fleet, the diversity of targeting by the fleet, and trends in the catch of the target species.

While average and total payoffs are usually seen as important drivers of fleet behaviour, as discussed in the introduction and background sections of this paper, empirical evidence suggests that minimizing the *variability* of returns is an important driver of fisher behaviour (Holland, 2008; van Putten *et al.*, 2011). Table 4 lists measures of the variability (standard deviation) in realized catch and profit for the base case and two scenarios for the SESSF and the five main fleets.

The variability in catch is greater for flexible fishers compared with that of traditional fishers for the SESSF fishery as a whole (cumulative total for all fleets) and at an individual fleet level for the trawl fleets. Given that the behavioural model is based on relative catch rates as a main driver of effort reallocation, more flexible fleets will work to reduce the variability in catches due to ecological and environmental variability, by quickly adjusting relative effort across different stocks. In contrast, traditionalist fleets have a more static behavioural filter to the changes in the ecosystem. The results regarding profits reflect the relative prices of different species as well as the different cost structures of fleets.

As opposed to the trawl fleet, for the flathead seine fishery, which is a highly unprofitable fishery, the catch variability for flexible fishers is lower. A two-tailed Student *t*-test indicates that the difference in the standard deviation for catch between the base case and the flexible fishers ($p = 0.074$) and the traditional and flexible fishers ($p = 0.100$) is significant (at the 10% level).

There is greater variability in profit for flexible fishers in all fisheries except for the orange roughy trawl fishery, which is characterized by a decline. However, the difference in the standard deviation for profit is not significant at the 10% level.

Discussion

In our study, we focus on the consequences of alternative assumptions regarding inertia, or location choice flexibility, in a whole of ecosystem model (Fulton *et al.*, 2007). We apply three different scenarios to investigate if, in accordance with theoretical assumptions and empirical evidence, flexible behaviour pays off in terms of higher catches and income, while traditional fishers who stick to past routines and fishing patterns are expected to have lower catch and income levels. At the same time, flexible fishers are expected to incur greater, and traditional fishers lower, variability in their income.

Table 4. Variability in annual realized catch and economic rent for the five main fleets in the SESSF fishery modelled for the base case, and two scenarios with traditional ($\delta = 0.05$) and flexible fishing ($\delta = 0.95$).

Indicators of variability	Base case ($\delta = 0.20$)	Traditional fisher scenario ($\delta = 0.05$)	Flexible fisher scenario ($\delta = 0.95$)	Value ($\delta = 0.95$) divided by value ($\delta = 0.05$)[a]
Standard deviation on realized catches (US$'000 000)				
Whole SESSF	6.82	6.73	8.51	1.26
Danish seine for flathead	1.20	1.43	1.06	0.74
Bottom trawl for deep demersal fish	2.05	2.07	2.67	1.29
Bottom trawl for flathead	0.68	0.68	0.98	1.44
Bottom trawl for orange roughy	0.82	0.81	1.06	1.31
Prawn trawl	2.07	2.09	3.99	1.91
Standard deviation on economic rent (US$'000 000)				
Whole SESSF	99.25	100.07	117.10	1.17
Danish seine for flathead	4.35	4.33	5.57	1.29
Bottom trawl for deep demersal fish	59.50	60.00	61.90	1.03
Bottom trawl for flathead	5.62	5.78	7.05	1.22
Bottom trawl for orange roughy	2.05	1.97	1.82	0.93
Prawn trawl	23.08	23.19	41.42	1.79

[a]The proportion is shown to make explicit the proportional difference in the variability in catch and economic rent.

Our analysis shows that the interpretation of fishing choice flexibility and its impacts on fishing outcomes is not straightforward and has to be considered in the context of three main fleet characteristics: whether the fleet is profitable; how diversified the fleet is; and what the status and variability of the target species biomass is.

Flexible behaviour pays off in terms of higher catches in fleets that are at least marginally profitable and are characterized by growing biomass or by biomass spikes (such as the deep trawl for flathead fleets and prawn trawl fleets in our case study). As expected, flexible fishers also experience significantly greater variability in their catches. [Even though flexible fishers also experience relatively greater variability in profit, statistically it is not significantly different (at the 5% level) from that of traditional fishers.] In this same situation, traditional fishers, who tend to stick to their existing fishing patterns, obtain lower but less variable returns. Thus, for fleets that operate on improving and/or less variable stocks, the outcomes of fishing in terms of catch and income are as expected for both flexible and traditional fishers.

In unprofitable fleets, regardless of whether biomass is increasing (e.g. the Danish seine fleet for flathead) or in decline (e.g. the bottom trawl for orange roughy), a flexible fisher's payoff must be interpreted in terms of avoided losses. Having greater "flexibility" to reduce effort and thus decrease relative cost or increase CPUE, flexible fishers are "better off" than their traditional counterparts. The ability of flexible fishers to reduce effort radically and immediately also reduces catch variability in highly unprofitable fisheries.

In highly diverse fleets, characterized by multiple target species (in our case the bottom trawl for demersal species), little income benefit can be derived from being flexible, most probably due to the cost structure of those fleets, making it financially unattractive to change fishing behaviour.

In our simulation model, we have assessed the adequacy with which the common representation of location choice, by means of flexibility or inertia, captures expected catch and income levels and their variability. By systematically exploring the effects of an important behavioural characteristic of fishing fleets captured in the model, we seek to gain better understanding of the complex dynamics at play in the human behavioural part of the model. For the purpose of MSE, model reliability with respect to the human behaviour component is of ultimate importance, not least because of the high uncertainty in this dimension of many models (Fulton *et al.*, 2011a). MSE models are increasingly used by policy-makers to precede the implementation of new management approaches and thus to minimize unintended consequences (e.g. Plagányi *et al.*, 2012).

Interestingly, while Atlantis is a deterministic model, the simulation experiments undertaken in the present study allow identification of cases in which individual fleets experience a divergence between their expectations and realized outcomes. This divergence results from the combined effects of complex biophysical interactions captured in the ecosystem components of the simulation model, as well as multiple responses from the different fleets, and their interactions at the local level. This raises the question of the potential links that could be established between the question of flexibility of behaviour, and that of attitudes towards risk, as mentioned above. Given that the expected choice outcomes can be described in terms of levels and variability of income (or catches), it should be possible to develop an analysis of the preferences fishers may have for alternative behaviours, including in terms of flexibility in adapting to new information, depending on the degree to which they are risk averse.

The empirical literature suggests that risk seekers are willing to take risks in terms of higher variability in their income, but they expect to get higher average returns from risk seeking over time (Das and Teng, 1988). In contrast, risk-averse operators will prefer certain outcomes, even if these are expected to be lower. In the context of fisheries with positive profits and new opportunities due to growing stocks, risk-seeking behaviour could be seen as attempting to achieve higher payoffs by exploring options other than already profitable ones, even if this entails a risk of missing out on the income that would be guaranteed by sticking to existing fishing activities. Thus, risk-prone operators in such contexts could be expected to display flexible behaviour (and risk-averse operators could be expected to maintain traditional fishing patterns). In a fishery with negative or near-zero profits, or with highly variable returns, risk-seeking behaviour could be seen as refusing to change fishing pattern, based on an expectation that there could be a turn of luck, rather than trying out alternative options even if these are expected to yield only small but relatively certain extra gains or lower losses. That is, for fishers that operate in fisheries that are degrading and where stocks are variable, risk-prone behaviour would imply being relatively inflexible.

The links between flexibility in behaviour and attitudes towards risks have been examined in studies undertaken in other fields, such as agricultural economics. In these studies, risk-averse behaviour is often interpreted as moving away from strategies with high variance of income (e.g. Hansson and Lagerkvist, 2012). However, in relation to tactical adjustments in extreme years—where a tactical and dynamical response (i.e. being flexible) to unfolding opportunities and threats is used to generate additional income or avoid losses—flexible behaviour is sometimes also interpreted as risk-averse behaviour (e.g. Pannell *et al*., 2000).

This leads to envisaging new ways of implementing differing flexibility in simulation platforms such as Atlantis that include a significant human behavioural component. This could be done, in particular, by doing away with the assumption that flexibility profiles should be stable. Indeed this assumption has been challenged in the literature (Isaac and James, 2000; Frechette, 2005) and it has been empirically shown that flexibility profiles are not stable over time. Fishers of all types may display different behavioural flexibility in good and bad years. For instance, in a bad year, there may be a preference for an immediate resolution of uncertainty due to the negative consequences associated with delaying the resolution. This is not dissimilar to biological models where there is a trade-off between being hungry and the need to leave cover to feed, thereby changing risky behaviour (Walters *et al*., 1997). As fishers are not meeting their income targets in bad years, they may behave as if they were in a non-profitable fishery, thus decreasing the level of inertia in a fishery.

Similar considerations also apply to the assumption that fisher's weighting of past catch rate information is linear and diminishing over time. Anecdotal information suggests that fishers may, in fact, weigh catch and effort information from extreme years more heavily. For instance, fishers will more "vividly" recall their location choices for years with catches that were significantly above (and below) average. If current catches resemble those of an extremely good year, fishers are more likely to repeat the location choice patterns of the "past good year". Fishers will also weigh location choice decisions made in bad years differently. After all, they will seek to avoid repeating decisions that, in their minds, led to outcomes that were significantly below average. Addressing the differential weighting of "extreme" years in catch rate information over time, and making flexibility coefficients relative to the context, could potentially improve the human behaviour component of large whole of ecosystem models such as Atlantis.

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Appendix 1

Over the 20-year period the biomass level changes in one of five ways: is stable (→), increases (↑), increases a little (→↑), decreases (↓), or decreases a little (→↓) with respect to year 1 (% increase or decrease shown for the main species where change was large or the species makes up a large proportion of the catch).

Table A1. Total catch (in tonnes) of main species and proportion of catch by fleet modelled for the SESSF for the base case scenario.

Species	Total catch	(Change from year 1 in year 20)	DseineFDB (Danish seine)	DtrawlFD (bottom trawl for deep demersal fish)	DtrawlFDB (bottom trawl for flathead)	DtrawlFDO (bottom trawl for orange roughy)	PtrawlPWN (prawn trawl)
Morwong	2056	(→)	T[a] 609	T 61	T 757		B 578
Cardinal fish	144	(↓)		T –		B 143	
Gem fish	1387	(↑)		T 1356			30
School whiting	45 320	(↑ 68%)		T 24 664	T 4716	B 8965	B 6566
Mirror dory, oreo, whiptails	18 887	(↓)	T –	T 8426	B 179	T 10 238	5
Blue grenadier	122 790	(↓ 49%)	B[b] 82	T 77 219	B 3652	B 15 422	B 1438
Flounder, gurnard, wrasse, trevally, snapper, king george whiting, latchet	98 922	(↑ 82%)	T 38 837	T 15 245	T 3342		B 1012
Redfish	12 472	(↓)		T 9437	B 1882	B 1066	
Ribaldo	1346	(↓)		T 872		T 474	
Flathead	140 910	(↑ 452%)	T 77 441	T 10 862	T 36 122	B 496	B 13 752
Ling	60 449	(↑ 414%)		T 41 118		B 503	B 11 434
Orange roughy	20 649	(↓ 86%)		T 6574		T 13 207	B 868
Blue-eye trevalla	13 231	(↓)		T –			
School shark	2842	(↓)		T –			
Skates and rays	13 831	(↑)	B 468	T –	B 152		B 12 561
Blue warehou	7767	(↓)		T –		B 269	
Gulper sharks	953	(↓)		T –			B 71
Rock lobster	120 478	(↑ 13%)					T 117 582
Octopus, stomatopods, seastar, gastropod, prawns, non-commercial crabs	25 047	(↑ 42%)					T 13 441
Prawns and commercial crabs	30 104	(↑ 62%)					T 28 923
Total catch (including bycatch species)			117 436	195 838	50 801	50 787	208 262
Number of vessels[c]			27	88	35	22	8
Average crew size[c]			3 or 4	3–7	3–5	3–5	3
Number of subfleets[c]			2	4	3	3	1

[a]T = target species.
[b]B = by catch species.
[c]Adapted from Hutton *et al.* (2010).

Appendix 2

Figure 2A. Biomass for a number of target and bycatch species for fleets in the SESSF as modelled by Atlantis over a 20-year time frame for the base case scenario.