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Triggering the tragedy: The simulated effects of alternative fisher goals on marine fisheries and fisheries policy

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ABSTRACT

Avoiding the 'tragedy of the commons' remains a challenge in many natural resource systems, and open-access fisheries are well-studied in this context. Here, an agent-based model is used to investigate how variation in fisher goals change what policies best solve the tragedy. When fishers' goals are easily satisfied, commons problems are avoided without management interventions, but the imposition of quota limits triggers the tragedy. Thus, commons problems are not necessarily inevitable and sophisticated governance institutions or regulations are not always required to manage them; the same policy may prevent the tragedy or trigger it, depending on the fisher's goals. Given that it is difficult to ascertain them, by using a simulation model we can find patterns that help us identify fishers' goals and incorporate these patterns within our management procedure. This can assist adaptive management to better incorporate behaviour into policy evaluation.

1. Introduction

The 'tragedy of the commons' (Hardin, 1968) remains an on-going problem in many natural resource use contexts. In a characteristic description, open access resources become overexploited when users are difficult to exclude and no user has any incentive to conserve the resource in the face of competition (Hardin, 1968). This makes natural resource management necessary to ensure sustainability. Fisheries classically suffer from 'commons problems' (Ostrom, 2008) where it may take the following form: fishers are motivated to invest in fishing capacity (e.g. larger boats, improved detection technology, increased effort), and join a 'race to fish', creating a depleted fishery (Emery et al., 2014). From this relatively simple perspective, and in the absence of additional factors such as group cooperation (Ostrom 2015) the system is inherently flawed, requiring management intervention to curtail 'inevitable' tragedy.

It is well-acknowledged that 'fisheries management is the management of people, not fish' (Jentoft, 1997), yet the majority of management research focuses on the biological side of the system, despite long-standing calls for a better understanding of fisher behaviour and strategy (Wilen et al., 2002; Wilen, 1979). Behaviour and strategy, in this context, are principally decisions and actions pertaining to gear choice, distribution of effort and trip durations, employed to achieve objectives under the constraints of regulation and other conditions (Béné, 1996; Salas and Gaertner, 2004). Individual goals clearly contribute significantly to the decisions driving these behaviours. Thus, fishers' personal goals are an important aspect to incorporate into fishery management research to better understand the implication of policy changes.

In this paper, we investigate the effect of individual goals on fishing behaviours, using an agent-based model (ABM). ABMs are numerical models that incorporate autonomous, interacting agents, and have been used to simulate real-world systems (Axtell and Epstein, 1994; Axtell, 2000; Rauch, 2002; Crooks and Heppenstall, 2012). This is a bottom-up modelling approach, whereby individual agents can be assigned heterogeneous behaviours and objectives (Railsback and Grimm, 2011; Scott, 2016). Agents can be placed in spatially and temporally explicit landscapes and interactively perform actions that may lead to emergent behaviours not present in more prescribed top-down models. ABMs can also potentially capture agents' adaptive (and heterogenous) responses to changing policies. As such, these models are useful tools for investigating the effects of alternative fisher behaviours and policy interventions (Little et al., 2004).

While studies show fishers may consider a number of factors when

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they decide how to behave, including in-group fairness, conservation, and compliance with social norms (see 'discussion' for a presentation of some of these studies), bio-economic models typically conceptualise fisher behaviour as profit maximising (e.g. Clark 2010; Anderson 2015). In this paper, we are exploring the behavioural consequences of varying economic goals (see below). This simplification allows for model runs to test the specific behavioural impact of economic concerns.

This paper explores a stylised, homogenous agent concerned solely with a particular economic goal. To reflect different concepts of economic satisfaction, we implement three types of goals in the model: (i) to maintain a consistent and sufficient income; (ii) to maintain a relative income in comparison to one's peers; (iii) profit-maximisation. These have been identified as prominent fisher goals through interviews (Holland, 2008), and economic and psychological research (Hoff and Stiglitz, 2016). For example, Holland (2008) shows fishers in Maine prefer to fish known areas with a projected moderate, consistent income than move to unknown sites with potentially higher payoffs. This is exemplified by the following interview extracts:

> "I'm a consistency person. I'd rather come in with a little bit less and have it every day than go for the risky, pound your chest, I caught 'em all" (p.332) (Holland, 2008)

Critically, in the simulations we explore economic goals as independent factors. That is, fishers do not pursue multiple goals at the same time. Instead, one simulation run implements fishers who maintain a consistent and sufficient income while another simulation run implements fishers who maintain a relative income in comparison to one's peers. In other words, simulations are compared where every constraint is kept constant (biology, number of agents, spatial distribution, etc.) except for the economic goal each fisher targets.

In pursuing their goals, the fishers choose between exploring (gaining information) and exploiting (gaining returns). Exploration can be thought of, following Wilson (1990), as a production of knowledge problem (Wilson, 1990). In generating information (exploration) a fisher is forfeiting action (fishing), however they are also learning and using inference to generate potentially higher yields. There are multiple ways to model exploration (Hutniczak and Münch, 2018; Little and McDonald, 2007; Dorn, 2001; Bastardie et al., 2013). One way, is to see it as a 'bandit problem', invoking a choice to balance trade-offs (Kuleshov and Precup, 2000). Algorithms for simulating 'multi-armed' bandit problems (where there are many competing choices) are used to simulate fisher behaviour in this study (see Methods). Similar behaviour algorithms have been used in lab experiments to understand how humans learn and search in spatial environments with a vast set of possible actions, as well as how social learning coupled with bandit problems affects outcomes (Wu et al., 2018; Toyokawa et al., 2019).

Interviews with fishers in the US Pacific groundfish fishery and the Indonesian mixed snapper fishery[1] suggested that fishers aim to match their peers' incomes, or at least a portion of it. This aligns with the theory of social comparative processes, which argue that people evaluate their social context by comparison with others of similar socio-economic circumstances, and judge their subjective well-being accordingly (Fetsinger, 1954; Campbell et al., 1976; Smith et al., 1989; Parducci, 1995; Diener and Lucas, 2000).

The existence of profit-maximising behaviour by fishers has found empirical support in commercial fisheries (Robinson and Pascoe, 1997; Pascoe and Tingley, 2006; Bockstael and Opaluch, 1984; Lane, 1988). For example, Pascoe and Tingley (Pascoe and Tingley, 2006) demonstrate that the Scottish fleet tends to operate where marginal revenue equals marginal cost. As such, economic models of fisher behaviour draw on micro-economic theory where individuals are represented as producers and assumed to make decisions based on profit-maximising imperatives (Van Putten et al., 2012). This can be done through the use of random utility models as based upon expected utility theory and discrete choice modelling. This approach has seen a growing number of applications in the past two decades (Bockstael and Opaluch, 1983; Eales and Wilen, 1986; Holland and Sutinen, 2000; Curtis and Hicks, 2000; Smith, 2002; Hutton et al., 2001; Tidd et al., 2011). However, an analysis entitled "Exploring the Validity of the Profit-maximising Assumption" concludes that it is true for some fishers but does not explain all behaviour (Robinson and Pascoe, 1997).

Seeking a consistent income and comparing oneself to the average are forms of satisficing. Satisficing is a decision-making strategy that takes account of the relevant availabilities and pursues options that meet acceptable thresholds required to achieve a goal (Simon, 1947). In this paper, fisher goals are simulated by varying fishers' 'satisficing thresholds' - the point where fishers' goals are satisfied. These 'satisficing thresholds' have been incorporated into a simplified, conceptual level version of the POSEIDON agent based model. This model depicts a spatially explicit near-shore capture fishery. As explained in 'methods', a fleet of 200 fishers target a single species of fish (also modelled as agents who respond to these fishing pressures) in order to make an income and achieve their goals. Their income is made by selling the fish they catch according to ex-vessel prices that are set exogenously and fixed, and offsetting their day to day costs (fuel). Furthermore, policy interventions such as Total Allowable Catch Limits (TACs), Marine Protected Areas or Individual Transferable Quotas can be imposed on the fishery. Here, TACs are used to show how fisher's goals influence the long-term biomass and income of the fishery and how this changes when different quota limits are imposed. This shows that when fishers have certain goals, a tragedy of the commons like situation can be avoided even under an open access fishery and that management interventions aiming to conserve the fishery can perversely 'trigger the tragedy'.

2. Methods

The crux of this study is to understand how various fisher goals bring about different goal-orientated behaviours and how these potentially affect the outcomes of management interventions. To investigate this, scenario modelling using an ABM is employed to show the effects of three alternative fisher goals against different policies (namely open-access and TAC limits). This is achieved by simulating different goals and running experiments where policy and fleet makeup are varied (each experiment, its motivation and parameters are described under Experiments and Results). The performance of goal-orientated behaviours against policy interventions are assessed by noting the final stock biomass and cumulative fishery income. It is expected that alternative goals, other than profit-maximisation (which is commonly assumed in models that incorporate fisher behaviour) are likely to produce different behaviour patterns. This is hypothesised to impact the effectiveness of management such that some interventions are appropriate given certain behaviour but inappropriate otherwise. This is done to show how fisher behaviour is a crucial aspect of fisheries that should not be excluded from modelling and how doing so can help to ensure more successful natural resource management.

A conceptual version of the POSEIDON ABM is utilised in this study (Bailey et al., 2019). The model and the units of its outputs are purely representative. This analysis is interested in the overall effects of different fisher objectives on the simulated system but not in the discrete units themselves. The model illustrates general potential outcomes and key points in the fishery management space. This version of POSEIDON has been chosen to isolate the effects of fisher behaviour from the noise and idiosyncrasies that models of specific real-world fisheries bring.

[1] Dr Richard Bailey and Dr Jens Koed Madsen, members of CoHESyS Lab, at the University of Oxford conducted interviews with fishers in the US Pacific Groundfish Fishery and the Indonesian Mixed Snapper fishery in April 2016 and April 2018 respectively.https://www.cohesys-lab.net/

2.1. The model

The model is an abstract, spatially explicit ABM depicting a stylized map of a near-shore capture fishery (Bailey et al., 2019). The model domain is of a shoreline with a single port, an ocean and a fleet of 200 fishers. A single species of fish, modelled as agents, grow according to a logistic growth function (following Cabral et al., 2010 and Soulié and Thébaud, 2006). They grow locally (per cell) and diffuse spatially in their environment according to the local gradient. The fish biomass responds to and is depleted by fishing pressure (Bailey et al., 2019). Ex-vessel prices are set exogenously and remain fixed. Constant demand is assumed with zero inflation or discount rates. Agents incur input costs in the form of fuel, the price of which remains constant (Fixed costs are not included in this conceptual model). Different policy interventions, such as MPAs, TACs, individual transferable quotas (ITQs) or seasonal closures, can be imposed on the modelled environment with full compliance (Bailey et al., 2019). Here, various TACs are imposed.

Central to the model is a fleet of individual vessels that act as autonomous agents. These agents form social networks and exchange information. Each agent has two 'friends' with which they do this. Decisions are made at the start of and during each simulated day (Bailey et al., 2019). Decisions include whether to fish, where to go and which gear to use (Fig. 1, from Bailey et al. (2019)). Such decisions are made without perfect information but are based on experience and the experience of those in their social network (Bailey et al., 2019). The value of this information implicitly decays as the environment changes and as the biomass is exploited.

Fisher decisions are modelled as 'bandit problems'. These are sequential choice problems where agents must decide between a number of possible actions at each stage (Soulié and Thébaud, 2006; Wu et al., 2017; Berry and Fristedt, 1985; Bubeck and Cesa-Bianchi, 2012). Each choice provides information about the reward for the action taken but not for the alternatives. The goal is to maximise the present value of payoffs by allocating resources (time spent fishing) amongst competing alternatives (fishing locations) (Bailey et al., 2019; Berry and Fristedt, 1985). Agents must decide between exploitation (making the best choice given current information) or exploration (gathering more information) (Wu et al., 2017). A balance should be struck between gaining information and rewards. In POSEIDON this is modelled as the following: initially agents randomly choose a site, evaluate their rewards and compare this with the outcomes of those in their network. Agents then stochastically decide whether to continue exploiting the current site, randomly explore or copy their friend (Bailey et al., 2019). This has been termed explore-exploit-imitate (EEI). An evolving group response that maximises agents' goals is formed. E.g. if the goal is to maximise profits, behaviours that result in larger profits will be reinforced and adopted (Bailey et al., 2019). Bandit algorithms applied to spatial exploitation have been used in Wu et al. (2018). Toyokawa et al. (2019) also augment bandit problems with social interactions. However, these other experiments have not explored the policy implications of these behaviours. In the model, policies do not change the behaviour algorithms but impose different constraints and/or incentives; indirectly altering behaviours. This demonstrates a key feature of ABMs in which 'micro-motives lead to macro-behaviour' (Ferguson, 2016).

For a full list of the parameters and values used, please refer to the Table 1.

2.2. Fisher goals

Three different objective functions within the EEI structure are modelled: maintaining a consistent income (consistent income goal), achieving a proportion of the average fisher income (relative income goals) and profit-maximisation. These goals are simulated as they are mentioned in interviews with fishers (Holland, 2008) and evidence of them from the psychological and economic literature (Hoff and Stiglitz, 2016; Smith et al., 1989). Profit-maximisation is used as a control.

Profit-maximising behaviour is simulated through an ε-greedy bandit algorithm. Agents will always choose the action (fishing locations) with

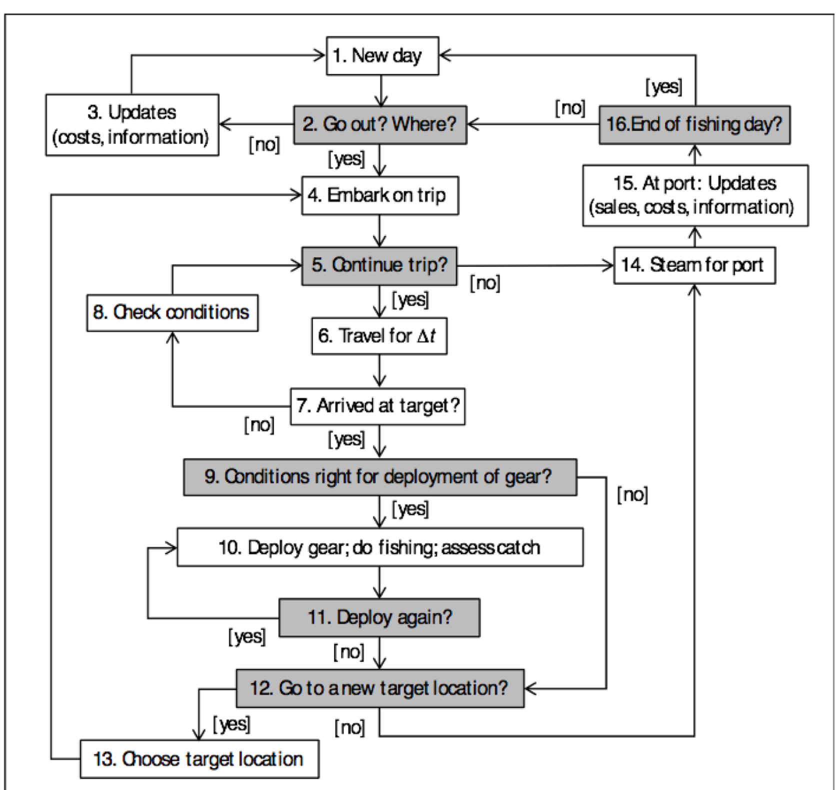

Fig. 1. Flow chart indicating decisions made by autonomous agents in the POSEIDON model.

Table 1
Model parameters.

Parameter	Value	Meaning
Biology	Logistic	
	5000	max units of fish per cell
	0.001	Diffusion rate
	0.7	r (Malthusian growth parameter)
Fisher	Explore-Exploit-Imitate	
rest hours	12	rest at ports in hours
fishers	200	number of fishers
friendships	2	number of friends each fisher has with which to exchange information
max days at sea	5	time after which boats must return to port
Map		
width	50	map size (in number of cells) horizontally. Each cell represents 10 × 10km
height	50	map size (in number of cells) vertically. Each cell represents 10 × 10km
port position	40,25	location of port (cell coordinates)
cell width	10	width (and height) of each cell (in km)
Market		
market price	10	$ per unit of fish sold
gas price	0.01	$ per litre of fuel
Gear		
catchability	0.01	% biomass caught per tow hour
speed	5.0	km/h
hold size	100	max units of fish storable in boat
litres per unit of distance	10	Litres of fuel consumed per km travelled (each cell is 10 × 10 km)
litres per trawling hour	5	litres of fuel consumed per hour trawled

the 'best' outcome (based on previous experience) except when a uniformly random action is selected instead. Here an adaptive parameter of ε=0.2 is selected. At each step the location with the highest mean reward is 'greedily' played with probability 1- ε and a random location is chosen with probability ε (Wu et al., 2017). The parameter is adaptive in that the ε value increases or decreases by 2% each time an exploratory trip is successful or unsuccessful respectively. The algorithm assumes that agents are not risk averse and are not given any additional information beyond that received from their 'friends' or their experience. An ε-greedy bandit algorithm is selected over other bandit algorithms as it was found to perform better than others in this model (Schelling, 1978). Altogether this was deemed an appropriate means to simulate profit-maximising behaviour.

To simulate the aims of different satisficing behaviours (achieving a consistent income and/or achieving a percentage of the mean income), the exploration-exploitation procedure of fishers is modified. Agents still choose between exploring and exploiting but do so depending on different satisficing thresholds (i.e. points at which agents' goals have been achieved and they are satisfied) rather than each trip with probability ε. For different consistent income goals, a profit threshold is set, measured as dollars made per hour ($/hr). I.e. a threshold of 4 indicates that fishers are satisfied when they are making $4/hr. For relative income goals, a proportionate threshold is set, measured as the fraction of the average income. I.e. a threshold of 0.4 indicates that fishers aim to achieve 40% of the average income (Kuleshov and Precup, 2000). Fishers then explore or exploit based on whether they are achieving a given threshold. They will exploit if they are at or above it (satisfied) and explore otherwise (dissatisfied).

2.3. Optimization methods

In some of this study's experiments, a Bayesian Optimiser determines the 'optimal' policy under alternative goal-orientated behaviours. The 'optimal' policy is defined with respect to an objective function. It is essential to define the objective carefully as the optimiser is unable to make judgement calls. E.g. if the optimiser is programmed to maximise profits within a 10-year period, it may suggest the best policy to achieve this, but in such a way that biomass reaches zero by year 10. Thus, additional constraints must be set and modellers should be cognisant of the way the optimiser interprets 'best' practice.

Bayesian optimisation (Wilson, 1990) "works by creating a meta-model of the simulation outcomes, iteratively simulating new policies and using the outcomes to update the meta-model" (Bailey et al., 2019). The optimiser then indicates the policy (in this case, quota limit) that achieves this 'best' response (Bailey et al., 2019). An advantage of combining the optimiser with the ABM is that the agents are adaptive and thus the 'optimal' policy takes the counter-measures potentially employed by agents into account. For a full explanation of the optimisation technique as utilised in this model, please see Bailey et al. (2019).

2.4. Classification

In Experiment 5, a logistic regression is run to estimate the association between average distance form port and exploration rate and relative income satisficing thresholds to identify indicators of goal-orientated behaviours. Average distance from port and exploration rate were chosen based on the way that relative goals have been modelled and on the results from experiments 1–3. The fitted logistic regression model was used to generate predicted probabilities for relative income satisficing thresholds. Predicted probabilities were then used to generate a binary variable where satisficing thresholds less than 0.6 indicated easily satisficed agents and values greater than 0.5 were used to indicate agents that were not easily satisficed ('greedy'). This binary variable for predicted satisficing threshold was then compared to the observed data to generate a predicted success rate for classifying relative income satisficing thresholds.

3. Experiments and results

To explore the impacts of alternative goal-orientated behaviours on the fishery, from an income and biomass perspective, multiple experiments, described below, were run. Each experiment is simulated using the POSEIDON model (Bailey et al., 2019). A summary of the conditions for each experiment is provided in Table 1. All experiments held effort, catchability, and all other parameters constant. Only the fishers' goals (satisficing goals (i.e. aiming for a consistent income, or relative income) or profit maximization) and management interventions (quota and quota limits) were varied. Each simulation experiment was run 100 times, as multiple runs are required to estimate the outcome distributions. In preliminary tests, results stabilised after 100 runs (the means of fish biomass and income, our dependant variables, remaining largely unchanged outside of uncertainties). Each model run covered 30 years to observe the full dynamic responses of the model and allow the simulations to stabilise.

Experiment 1 investigates the effects of consistent income, relative income and profit maximisation goals on an open-access fishery. This provides a baseline to understand how fisher goals effect behaviour without confounding management interventions. Experiments 2 and 3 investigate how the goal of maintaining a proportion of the average income effects fish biomass and income when quotas are limited (by a fishery-wide TAC limit). The experiments show that some management interventions can be inappropriate given different fisher goals. Following this, experiments 4 and 5 explore whether adaptive management is an effective way to manage fisheries when fisher behaviour is uncertain. See Fig. 2 for the logical flow of the experiments.

Income comparisons are conducted at the end of each trip. Specifically, upon returning to port, the fisher computes their income (units of harvest fish * market price – litres of fuel spent/hour * numbers of hours at sea * gas price). Thus, while fishers have hourly costs (e.g. litres of fuel/hour they travel), the fisher computes their total income for that trip upon arrival in the port. At this point, the fisher compares their income with that of other fishers to determine whether the trip was satisfactory.

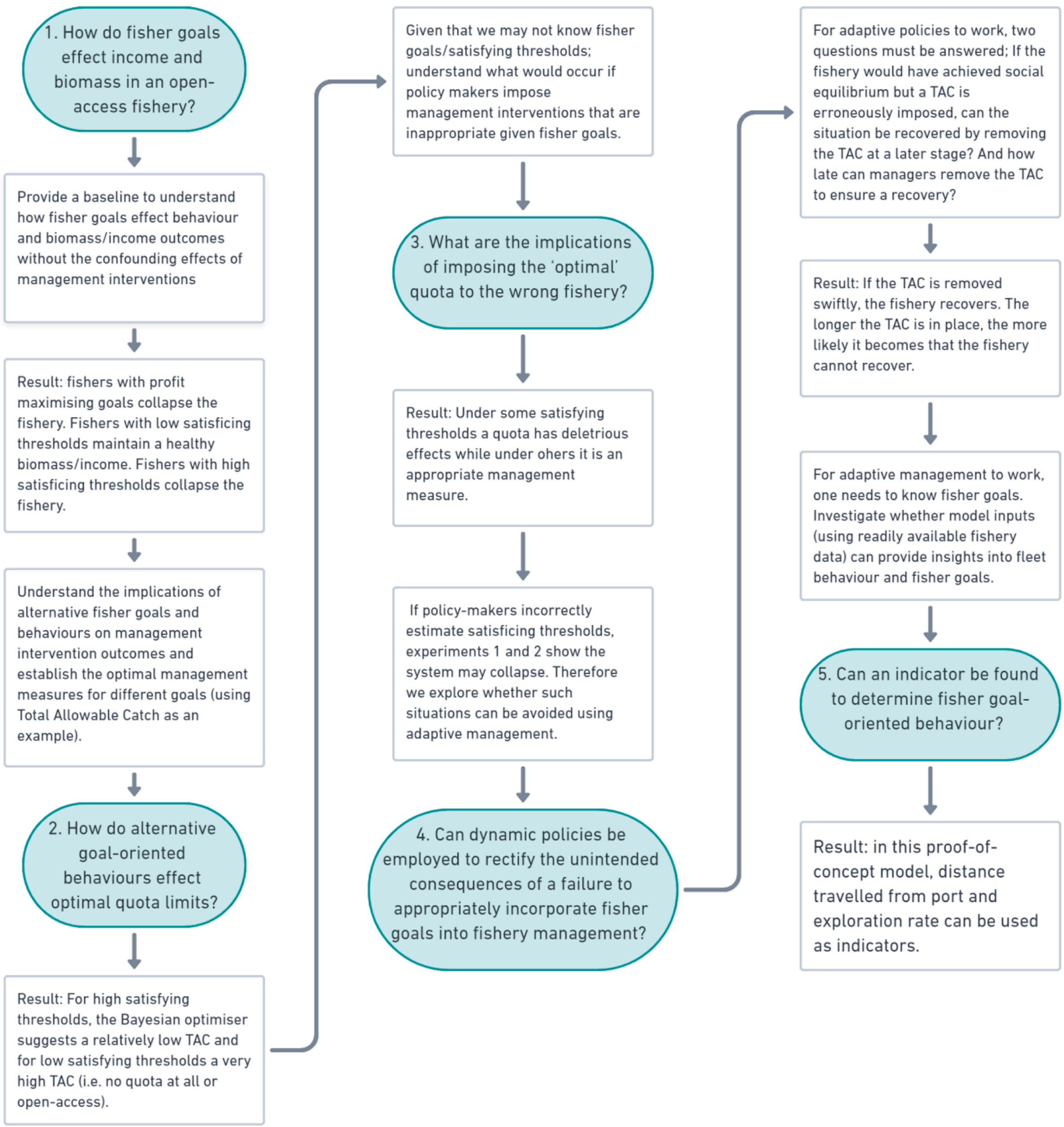

Fig. 2. Description of the logical progression from one experiment to the next. It shows the high-level results of each experiment and the reasoning for the following experiment.

As described, to simulate satisficing behaviour, different satisficing thresholds (i.e. the point at which an agent is satisfied) are set. For relative income goals, satisficing thresholds (relative income goal) are set from 0.1 to 2.5, indicating the proportion of the average income that fishers are satisfied with achieving (e.g. for relative income goal=0.1, a fisher is satisfied with 10% of the average income). Thus, for relative comparisons, a fisher may have a positive income, but may consider this unsatisfactory if fishers in their social network are making more money. If this is the case, the unsatisfied fisher will explore on the next trip.

For consistent income goals, satisficing thresholds were set from $1/hr to $35/hr. Thus, if a fisher has a goal of $5 earns $5.24/hour, they will be satisfied and will return to that area on the following trip, but will explore new areas if they earn less than the required amount on that trip. Table 2 gives a summary of the different experiments, satisficing behaviours and management interventions that are simulated.

Table 2
Fisher goals and management interventions in the experiments.

Experiment	Fisher Goal	Management Intervention
1	Aiming for consistent income (1–35); relative income (0.1–2.5); profit maximisation	Open-access
2	Aiming relative income (0.1–1)	TAC
3	Aiming relative income (0.1–1)	TAC
4	Aiming relative income (0.7)	TAC imposed at year 0 and removed at years 1, 3, 5 and 10 years after imposition
5	Aiming relative income (0.7)	TAC imposed at year 0 and removed at years 1, 3, 5 and 10 years after imposition

3.1. Experiment 1: how do alternative fisher goals effect income and biomass in an open-access fishery?

For relative income goals, satisficing thresholds (relative income goal) from 0.1 to 2.5 were set. For consistent income goals, satisficing thresholds were set from $1–35/hr. For each simulation, we measure the final biomass (i.e. the total quantity/weight of fish remaining in the simulated environment at the end of the year) and cumulative annual fishery income (i.e. the total income across all agents for one year of fishing). In the model, fish biomass grows according to a logistic function in each cell and diffuses from one cell to the next (for more information, see Section 1.2 Appendix of Bailey et al., 2019). Fishers incomes are made according to their catch (which is sold for an exogenous fixed market price) and costs (which comprises of fuel used whilst fishing).

3.1.1. Experiment 1: results

Fig. 3 shows final simulated biomass and cumulative fishery income resulting from different satisficing thresholds, with agents aiming for a relative income shown in blue and agents aiming for a consistent income represented in pink. In both simulations, we compare their outcomes with profit maximizing agents. Each box plot shows the results of 100 simulations compared with the profit maximizing agents (baseline). Notably, the profit maximizing agents deplete the fishery within 30-years. As we can see from Fig. 3, agents who are easily satisfied (relative income goal≤0.5 and consistent income goal ≤5) conserve biomass and achieve higher cumulative income than profit maximisers. This is due to the fact that agents in these simulations do not find the most effective places to fish, as there are happy with less catches. Comparatively, agents with medium thresholds satisfaction collapse the fishery like profit maximisers, generate higher levels of competing, which in turn makes them highly effective fishers. Finally, agents who are very hard to satisfy (relative income goal≥2.1 and consistent income goal ≥7) generate extreme levels of competing, which in turn makes them explore too much and fish ineffectively, as they are almost never satisfied with their current trip. This causes over-exploration, which eventually maintains biomass but with lower levels of income. In sum, experiment 1 shows that fishers who are easy to satisfy maintain high levels of biomass and have higher income than profit maximisers (who collapse the fishery), fishers with medium satisfaction thresholds collapse the fisher due to competition while fishers who are difficult to satisfy earn very little and maintain the biomass because of over-exploration due to extreme levels of competition.

Fishers' goals influence the long-term biomass and income of the fishery even when effort, gear and fleet are kept constant. This is because different goals generate different spatial allocations of effort. Profit maximisers and satisficers with high thresholds congregate near port, fishing intensely, and slowly fish further from port as resources are depleted. Satisficers with low thresholds tend to spread out with each vessel focussing on a specific fishing location (cell).

Fig. 4 shows intensity and spatial configuration of fishing effort (number of tows) per cell for relative income goal=0.4 and relative income goal=1 respectively. The 'checkerboard' appearance when relative income goal=0.4 demonstrates that some cells are heavily exploited while the rest see little effort. When relative income goal=1, fishers 'fan-out', starting close to port and spreading over time. As stated, fish biomass grows according to a logistic function in each cell and diffuses from one cell to the next. The logistic growth model responds badly to the concentrated effort exhibited by profit maximisers because these fishers serially deplete areas near port without allowing for the biomass to grow and diffuse to neighbouring cells (for more information on the diffusion rate, see Section 1.2, Appendix, Bailey et al., 2019).

Satisficing agents on the other hand, distribute their effort with

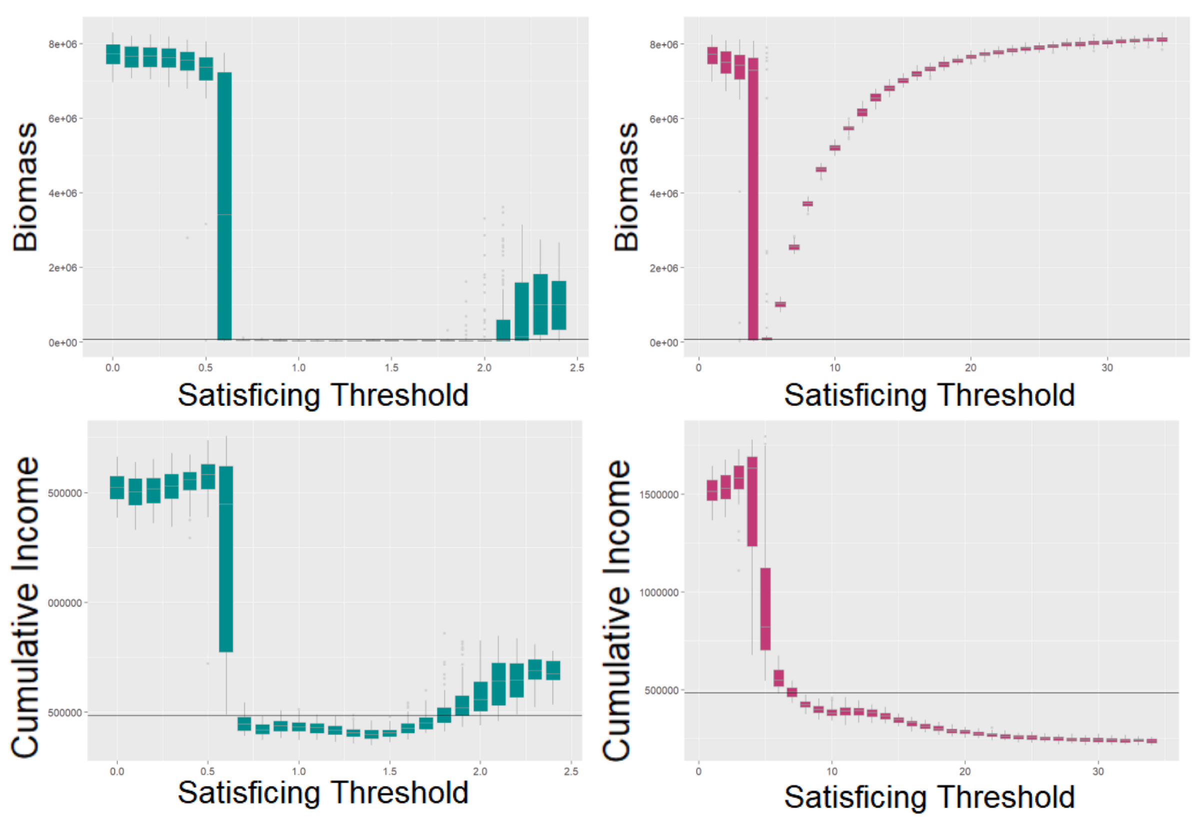

Fig. 3. Final biomass and cumulative income over a 30-year period for relative income satisficing thresholds from 0 to 2,5 (blue/left) and consistent income satisficing thresholds from 0 to 35 (pink/right) in an open-access regime. The horizontal line indicates the cumulative income/biomass outcome under a goal of profit-maximisation. Note that the outcome under profit maximisation is 'constant' in comparison to the satisficing thresholds. This allows for a comparison to understand if the outcomes under different satisficing thresholds is above/below the outcome achieved under profit maximisation.

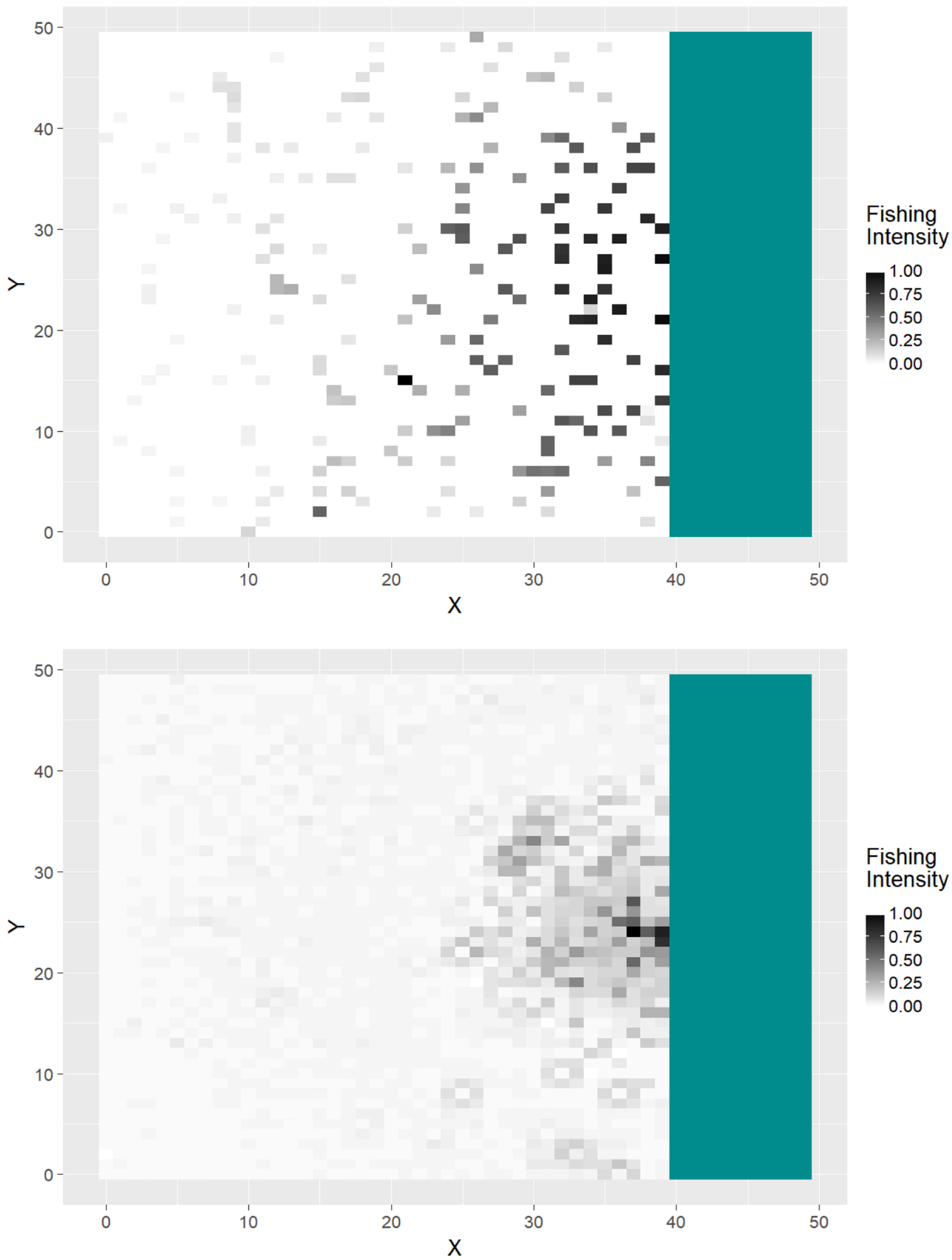

Fig. 4. Spatial distribution and intensity of fishing effort under a relative income satisficing threshold of 0.4. (top) and 1 (bottom). The intensity of fishing effort is calculated as number of tows per cell over the maximum number of tows in a single cell over the 30-year period. Green indicates land mass.

rarely more than one boat fishing one cell at a time. This effort is not enough to deplete the biomass in the cell but enough to leave space for further growth and movement of fish from the fished cell to unfished areas surrounding it. The exploration rate (the number of exploratory trips over the total number of trips) drives configuration of the effort. At lower thresholds, fishers are satisfied and so do not explore, staying in a single cell. If another fisher (or more) were to join them in that cell, they are more likely to become dissatisfied and leave, until eventually fishers are broadly distributed with one boat in a cell. At higher thresholds fishers are seldom satisfied whereas at lower thresholds it is the opposite. Dissatisfaction triggers exploration, which distributes effort (see Fig. 4), and drives biomass (and income) down.

Counter intuitively, even though fishers with lower thresholds (i.e. below 0.5 or 5 for relative or consistent income goals) are satisfied with less profits or smaller proportions of the average income they perform better in aggregate, as behaviours at these thresholds create a social equilibrium. As each fisher returns time and again to fish in the same preferred cell, they reduce the biomass in their preferred cell and their generated income. However, if the fisher is easily satisfied, the initial depletion may not be enough to prompt the fisher to explore, and the spill-over effect from unexploited cells ensures that exploited cells are never fully depleted; in the long run this spill-over will increase in magnitude eventually raising the income of the fisher beyond the original level. This scenario also occurs when agents have relative income goals.. This establishes a state where all fishers target a single area and receive a consistent relative level of income. For the same effort and exploitation levels, agents with low satisficing thresholds conserve the fishery while profit maximisers or agents with higher thresholds collapse it.

3.2. Experiment 2: how do alternative goal-orientated behaviours effect optimal quota limits?

Given the impacts of alternative fisher goals on biomass and income observed in Experiment 1, Experiment 2 investigates the implications of fisher goal behaviours on management intervention outcomes and establishes 'optimal' management measures for different goals using Bayesian Optimization (Smith et al., 1989; Van Putten et al., 2012; White and Mace, 1988; Kolody et al., 2008; Fulton et al., 2011). Total Allowable Catch limits (TACs) (Karagiannakos, 1996) are used as the management tool in this case. The optimal TAC under relative income satisficing thresholds from 0 to 1 is set by the Bayesian Optimiser. Here, the 'optimal' TAC is the quota that maximises total cumulative income across the fleet over the 30-year simulated period.

3.2.1. Experiment 2 results

Results are shown in Fig. 5, where satisficing thresholds and optimal quotas are non-linearly associated. When relative income satisficing thresholds are less than 60% of the average income (relative income goal≤0.6) having no TAC at all is optimal (which the optimiser reports as 2 million units). As explained in relation to Fig. 3, this is due to the fact that fishers who are easy to satisfy do not generate a highly competitive environment, meaning that they are likely to be content to fish on areas they have fished on previous trips due to the low nature of competition. As they are unlikely to ever reach a TAC of 2 million units, thus it is equivalent to having no fishing limits. Comparatively, as illustrated in the above, agents who are more difficult to satisfy are likely to generate competitive and highly effective fishing behaviours, which eventually collapses the fishery. Thus, when relative income goal=0.7, a relatively conservative TAC of 580,811 units is identified. Fishers aiming for higher proportions of the average income warrant more conservative TACs (to counter their tendency to over-fish for profit). The difference in optimal quotas between relative income goal=0.6 and relative income goal=0.7 suggests policy outcomes are sensitive to alternative fisher goals. This substantiates the claim that understanding fisher decision-making and fisher goals is crucial to managing the fishery.

3.3. Experiment 3: what are the implications of imposing the 'optimal' quota to the wrong fishery?

As illustrated in experiment 2, fisher goals and behaviour significantly affect optimal TAC settings. Thus, it is important to investigate the implications of imposing what is optimal under one satisficing threshold to a fleet with a different satisficing threshold. In other words, what would occur if policy-makers impose interventions that are not appropriate to a given fishery?

To explore this, relative income goal=0.7 optimal quota (580,811 units) was imposed on fleets with relative income goal=0.1–1. relative income goal=0.7 was chosen as it is the point where social equilibrium does not emerge (see Experiment 1). At this threshold, the system shifts from exhibiting high, stable biomass and income levels to lower, less stable levels of each. To understand how TAC alters the system and its sensitivity, the simulation was compared to open-access conditions.

3.3.1. Experiment 3 results

For fishers who are easy to satisfy, the imposed TAC breaks the social equilibrium and causes collapse of fisheries that would have otherwise settled into a high-biomass high-profits equilibrium (see Fig. 6). In an open-access regime, fishers settles into the social equilibrium after 5 years for values relative income goal=0.1–0.5. However, when a TAC is imposed on the same fishery, biomass declines rapidly. This is due to the fact that the quota produces inequality and competition between fishers, which in turn unsettles the social equilibrium and causes increasing exploratory trips. This reinforces the findings of Experiment 1: low exploration rates are a driver of the social equilibrium.

This finding is primarily driven by the emergence of inequality, as the TAC creates an inequality-driven 'exploration race'. When the TAC is reached, the fishery closes for the season. Thus, only agents fishing close to port land their catches before the quota is exhausted, resulting in increased income inequality as agents who fail to land catches receive reduced incomes. As such, these agents fail to satisfy their income threshold (a function of the average income) and react by exploring new fishing grounds. Under an open-access regime (relative income goal=0.1–0.5) exploration rate is 0. When the TAC is introduced the exploration rate never falls to 0 but instead steadily increases from year 5 in conjunction with falling biomass. Fishers start fishing closer to port to increase income (by reducing fuel costs) and decrease the chance of being unable to land catches when the quota is exhausted. Fishers are thus pushed to fish more efficiently to keep up with their neighbours and/or their income thresholds in ways they weren't compelled to under open access. Thus, average distance from port declines for relative income goal=0.1–0.5. Fishers exhibiting this behaviour achieve higher income, pushing average income up further. This causes further inequality, triggering a consecutive round of exploratory behaviour with still more vessels fishing closer to port. An inequality driven feedback

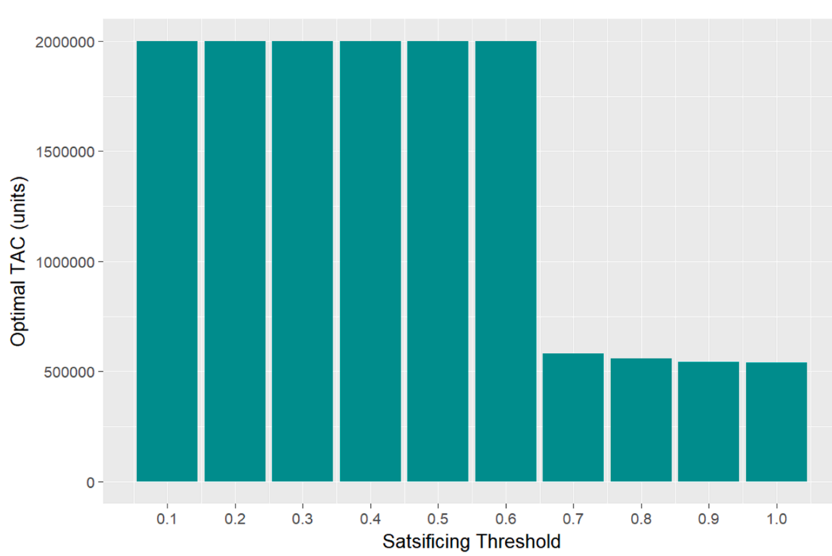

Fig. 5. Optimal TACs calculated by the Bayesian Optimiser under relative income satisficing thresholds from 0.1 to 1.

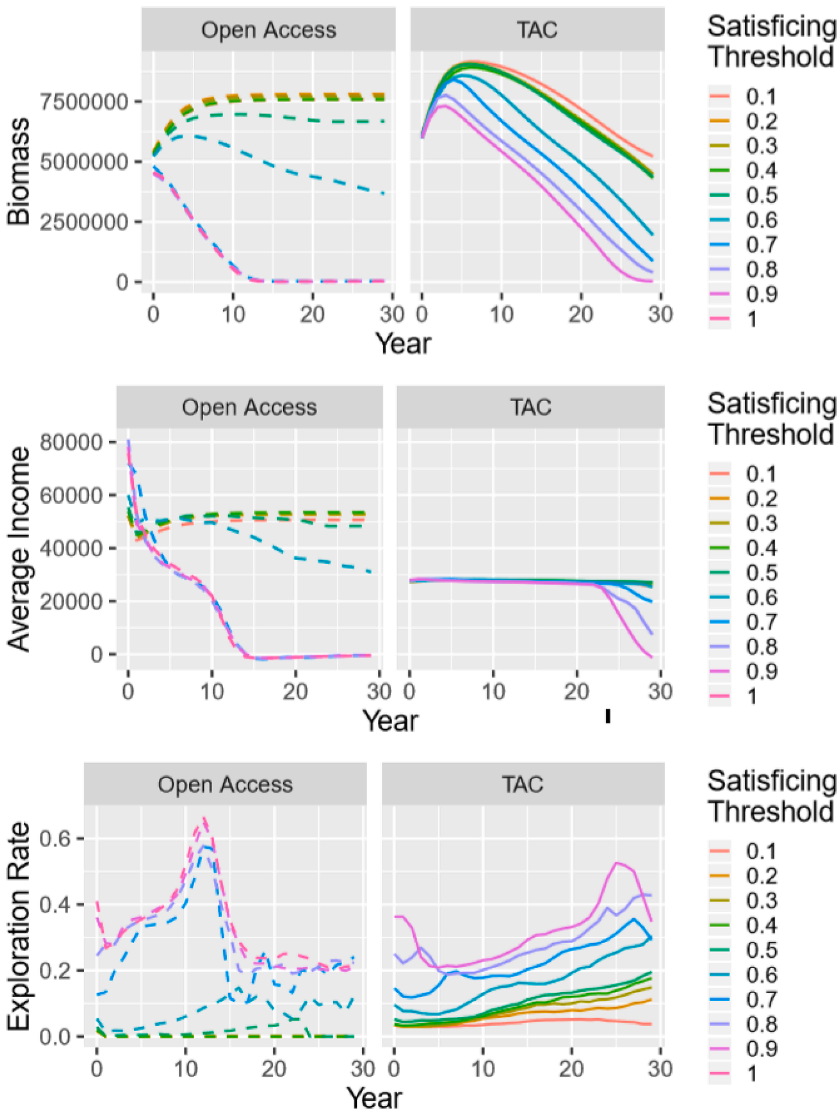

Fig. 6. Biomass, income and exploration rates over a 30-year period for relative income thresholds from 0 to 1 under an open-access regime (left) and a TAC of 580,811 units (right). Under the TAC, incomes are limited by catch restrictions and so stabilise at approximately $30,000.

loop is created, reinforcing this behaviour. By conglomerating nearer to shore in a 'fishing front', fishers negatively affect the biomass, exhibiting similar behaviour to that generated in Fig. 4 by profit maximisers. Effectively, the TAC produces the effect of agents with medium satisfaction parameters from Experiment 1 who collapsed the fishery due to increased competition. In other words, via emergent inequality, the TAC introduces competition in simulations where fishers would otherwise be in a competitive equilibrium. Thus, the TAC destabilises the social equilibrium achieved at lower thresholds under open-access with negative impacts on both fish biomass and income.

Conversely the TAC has positive impacts under situations where fishers have higher satisficing thresholds as the limit ensures stocks are not decimated. Under open-access, when relative income goal>0.6 vessels already congregate in a 'fishing front' and deplete biomass (Fig. 4). Thus, the TAC does not directly alter the spatial distribution of effort as it does under lower thresholds.

3.4. *Experiment 4: can dynamic policies be employed to rectify the unintended consequences of a failure to appropriately incorporate fisher goals into fishery management?*

Under some satisficing thresholds the TAC has deleterious effects while under others it is an appropriate management measure. Therefore, understanding fisher goals is important as it directly influences adaptation and, as a consequence, policy optimisation. Unfortunately, policy-makers are unlikely to know fisher goals explicitly. If policy-makers incorrectly estimate satisficing thresholds, experiments 1 and 2 show the system may collapse. Here, we explore whether such situations can be avoided using adaptive management. Adaptive management are flexible measures that alter given new information regarding systems.

For adaptive policies to work, two questions must be answered; If the fishery would have achieved social equilibrium but a TAC is erroneously imposed, can the situation be recovered by removing the TAC at a later stage? And how late can managers remove the TAC to ensure a recovery?

To test these questions, 4 experiments were run. The optimal TAC for relative income goal=0.7 (580,811 units) is imposed but then removed after 1, 3, 5 and 10 years respectively. A homogenous fleet of 200 fishers (relative income goal=0.4) was used. relative income goal=0.4 was chosen as the social equilibrium is secured 100% of the time under this threshold and the imposition of the TAC 'breaks' the equilibrium as described under Experiment 3 (due to the increased competition caused by the emergent inequality). Each experiment was run for 60 years with 100 runs. Running it 100 times allows for a good understanding of the probability of collapse and 60 years of simulation allows for slow recovery rates, as stock recovery can take a significant amount of time (Britten et al., 2017). The system is considered 'collapsed' if final biomass is below 1 million units and recovered otherwise (Shahriari et al., 2016).

3.4.1. Experiment 4 results

As mentioned, we chose model settings where Open Access fishing reached equilibrium, but where the introduction of a TAC triggered a collapse due to increased competition. The following measurements describe whether the fishery can return to equilibrium following the removal of the TAC or if the damage is irreparable. Fig. 7 illustrate yearly biomass outcomes following the TAC's removal at different periods. The recovery likelihood is 100%, 81%, 37% and 0% for removing the TAC in years 1, 3, 5 and 10 respectively. In other words, if the TAC is removed swiftly, the fishery recovers. However, the longer the TAC is in place, the more likely it is that the fishery cannot recover again. Removing the TAC restores social equilibrium if done early, but only if the fishery achieves social equilibrium under open-access.

Thus, employing adaptive policies may be a means to avoid a fishery collapse if inappropriate TACs can be removed in time. The current result is directly informed by the behavioural component. As described in the above, agent satisfaction levels are relative income goal=0.4, which was chosen as this condition reached equilibrium, yet collapsed under a TAC. For different economic goals and different parameter settings, the impact of the introduction and removal of the TAC would be different. Thus, aside from providing an interesting exploration of a particular type of agent, the experiment points to the deeper point that we must have a good understanding of fishers aims and behaviours in order to understand how they will adapt and respond to economic, policy, and biological changes.

3.5. Experiment 5: can an indicator be found to determine fisher goal-orientated behaviour?

In the experiment described above, for adaptive policy management to work, policy-makers would benefit from determining whether a fishery would achieve social equilibrium by estimating fishers' motivations. Furthermore, they must be able to do so in time to remove the TAC to allow for a chance of recovery.

Determining the goals of fishers would entail resource-intensive social surveys. Given the nonlinearity of satisficing thresholds, even small errors in surveys could spoil their effectiveness and result in collapse (which can occur rapidly, see Fig. 5). The model may provide variables that estimate fisher's goals and satisficing thresholds. Such lessons from representational models may then be translated to real world fisheries with readily available fishery data (such as data on average trip duration, landings, catch per unit effort etc.). Modelling this provides a cost-effective strategy that allows policymakers to analyse existing data to provide insights into fleet behaviour and dynamics.

Distance from port and exploration rates were investigated as potential indicators of fishers satisfaction goals. A logistic classifier was trained on 1000 runs of each of the experiments for relative income goal=0.1–1. The classifier was trained to discover if relative income goal≤0.5 by looking only at distance from port or exploration rate. Two regressions were run for each potential indicator at year 2 and 4. This allows hypothetical policy-makers to decide whether to remove the TAC at year 3 or 5 respectively (giving the fishery an 81% and 37% chance of recovery respectively, see Experiment 4).

Prediction quality is expressed as a percentage of the number of times the classifier predicts correctly over the total number of times the experiment was run.

3.5.1. Experiment 5 results

At both years 2 and 4, if the average distance from port is approximately greater than 200 km then it is predicted that relative income goal≤0.5 (Fig. 5). The same can be said if exploration rate is 0.1 or lower. Prediction quality for average distance form port is 99% and 84% at years 2 and 4 respectively. For the exploration rate the quality of out of sample prediction is 99.8% at year 2 and 100% at year 4. That classifier precision is best when done early indicates that chance of the system returning to the social equilibrium following the TAC removal is greater the sooner it is done.

4. Discussion and conclusion

The results shown above demonstrate, as might be expected, that fishers' goals influence long-term biomass and fishery income even when effort levels are kept constant. More importantly, 'tragedy of the

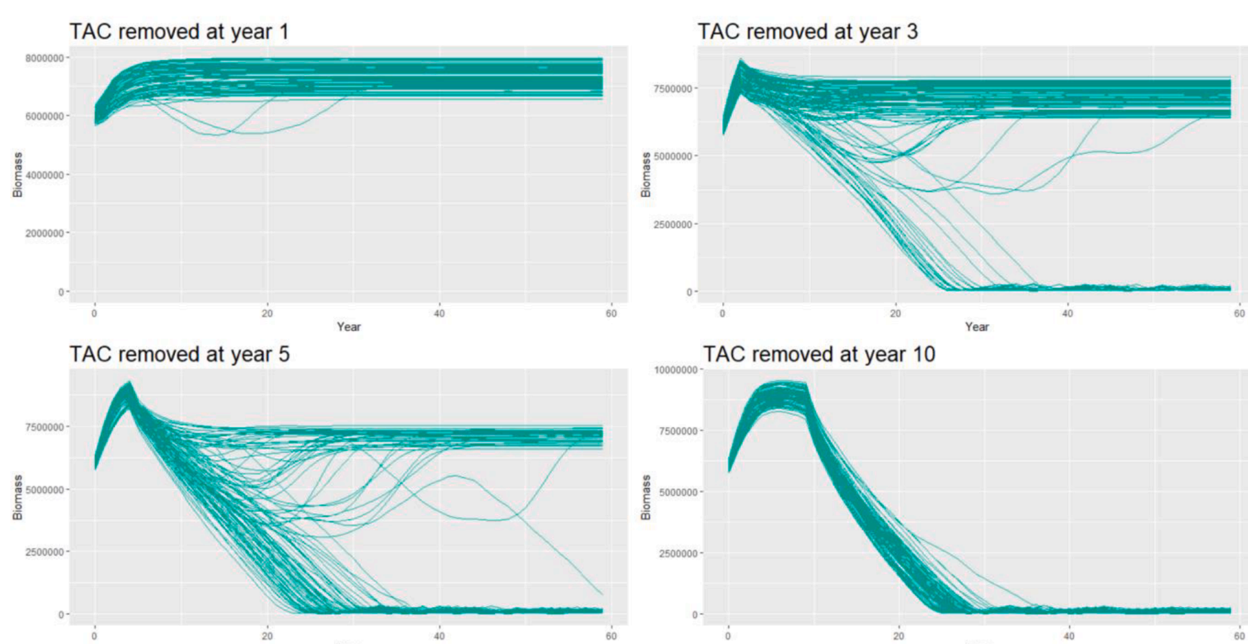

Fig. 7. Yearly biomass outcomes over 100 runs, TAC removed at year 1, 3, 5 and 10, respectively. 0%, 19%, 37% and 100% of the simulation runs end in biomass collapse, respectively.

commons'-type problems are not inevitable under open access regimes. Rather, given certain goal-orientated behaviours, a stable situation where biomass is protected, and fishers receive relatively high, stable income levels can be achieved. Further, inappropriate management interventions that fail to take fisher goals into account can trigger a resource collapse. The simulations illustrate that fisher's goals and the strategies they employ to achieve them affect how they react to management and thus are an important factor to include in modelling exercises. The simulations demonstrate that, through modelling, readily available fishery-dependant data (e.g. distance travelled from port, average trip duration, landings, catch per unit effort) can be used to indicate the likely goal-orientated behaviours which can inform management and policy intervention. Such information can facilitate the efficient use of adaptive management and avoid the need for time consuming and resource intensive surveys to determine harvester behaviours. It also provides an argument for incorporating cognitively realistic goal-orientated behaviours when designing interventions for 'managing the commons'. Of course, resource managers should carefully monitor changes in fleet behaviours and the environment as any shifts may mean adaptations in fisher goals. While these observations are drawn from a single species proof-of-concept model, care should always be taken to understand to ensure management is reflective of real-world circumstances.

Scholars have argued that the only means to curtail the tragedy of the commons is through public control or private property rights (Pinsky et al., 2011; Carruthers and Stoner, 1981; Smith, 1981). According to Hardin (1968) 'ruin is the destination toward all men rush' when rival and non-excludable (common pool) resources are left to the devices of self-serving harvesters. Yet, when fishers are easily satisfied, commons are maintained at relatively high levels (Experiment 1) and a social equilibrium is created. By maintaining low exploration rates, fishers concentrate effort in a few locations. The system stabilises with fishers seldom vacating their fishing spots whilst harvesting consistently and not significantly reducing biomass (Fig. 4). In this case, neither top-down control nor private property rights are required to protect common-pool resources (CPR).

Showing that the tragedy is not inevitable is not a novel result; Ostrom (2015), Berkes (1986), San Martín et al. (2010) and Dietz et al. (2003) have documented cases where CPR was preserved through binding contracts or cooperative strategies. Indeed, a situation remarkably similar to the outcomes of experiment 1 occurred in Alanya, Turkey (Berkes, 1986) where fishers were assigned fishing locations, spaced to optimise production capacity. After 10 years of experimentation, negotiation and cooperation, Alanya devised a strategy reflecting the spatial allocation of effort, exploration rates (i.e. zero exploration) and stability, which emerges in the POSEIDON model when fishers have low relative income goals. The difference between Alanya and the model is that the social equilibrium is achieved without institutions. Ostrom (2015) argues that the capacity to communicate, develop trust, social norms and share a common future contribute to the success of self-governing institutions. However, in our model, none of these factors exist. The agents do not communicate (beyond sharing catch information within their social networks to allow for imitation), have no social norms and cannot develop trust. They cannot create agreements or negotiate strategies. Furthermore, the agents have no concept of these. The tragedy is avoided without any cooperation or regulation whatsoever.

There is a growing literature that questions whether fishers are purely driven by economic and profit maximising features. For example, Polania-Reyes and Echeverry Perez (2015) show that fishers may forego some profit due to deference to in-group fairness, similarly, Holland (2008 p. 339) reports concerns about conservation, and Cárdenas et al. (2000) and Hatcher et al. (2000) show that fishers consider compliance with social norms. Further, Klein et al. (2017) suggest consistency, sustainability and neighbourliness may be as important as income to some fishers. However, as discussed in the above, the current paper focuses exclusively on different concepts of economic considerations. Future research and simulations should explore how competing choice considerations that go beyond economic concerns impact behaviour and management.

The model outputs presented above, together with empirical case studies already published, suggest behaviour and goals of individuals are essential components in the analysis of management effectiveness. Inappropriate management interventions can trigger a 'tragedy of the commons', where previously none existed. It is shown that the results of models, such as this proof-of-concept ABM can highlight relatively simple metrics (e.g. distance travelled from port) that can (if the ABM is representative of the system it is simulating) substitute for resource-intensive social surveys necessary to understand the true fleet make-up with regard to goals. Goal-orientated behaviour can be incorporated into fisheries models, and we argue that without it, such models (which make other implicit assumptions about goals) may be systematically erroneous in their predictions of management intervention effects as context-specific solutions to commons problems.

CRediT authorship contribution statement

Ashleigh Arton: Conceptualization, Formal analysis, Investigation, Visualization, Writing – original draft. **Ernesto Carrella:** Conceptualization, Methodology, Software, Formal analysis, Validation, Writing – review & editing. **Jens Koed Madsen:** Conceptualization, Methodology, Investigation, Writing – review & editing. **Richard M. Bailey:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that there is no conflict of interest.

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