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Comparing proactive and reactive management: Managing a transboundary fish stock under changing environment

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Comparing proactive and reactive management: managing a transboundary fish stock under changing environment

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Abstract. Environmental change in general, and climate change in particular, can lead to changes in distribution of fish stocks. When such changes involve transboundary fish stocks, the countries sharing the stock need to reconsider their harvesting policies. We investigate the effects of changing stock distribution on the optimal fishing policies in a two players' non-cooperative game. We compare reactive management, under which the manager ignores future distributional shifts (knowingly or unknowingly), with proactive management where the manager considers such shifts in his decisions. A dynamic programming model is developed to identify closed-loop Nash strategies. We show that the role of two players is symmetric under reactive management but asymmetric under proactive management where managers anticipate future changes in stock ownership. The player loosing the stock tends to harvest more aggressively compared to the player gaining the stock who acts more conservatively. Strategic interactions show tendency for complementary actions that can change abruptly during the ownership transition. The differences between management regimes vary from quantitative to qualitative; differences are minimal for stocks with little or no schooling, whereas highly-schooling stocks may avoid collapse only under proactive management.

Keywords: Adaptive policy, Climate change, Closed-loop Nash competitive solution, Concentration profile, Discrete-time continuous-state Markov decision model, Dynamic programming, International fisheries management, Non-cooperative game

1 Introduction

Effects of climate change on the distribution of transboundary stocks are receiving increasing attention in fishery management literature (Hannesson et al. [2006], Ekerhovd [2010], Sumaila et al. [2011]). Climate model projections (IPCC [2007]) indicate that during the course of 21st century the atmospheric surface temperature is likely to increase by 1.8-4.0°C. The atmospheric warming has significant effects, one of which is the increase of ocean temperatures, particular in the Arctic areas. For fish rising sea temperatures may have profound effects both for their distribution and abundance (Cheung et al. [2009]). For example, Perry et al. [2005] showed that in the North Sea, two thirds of the studied species had shown distributional responses to warming climate.

Fish distribution shifts impose a new challenge on the management of commercial fish stocks (Hannesson [2007], Cochrane et al. [2009], Johnson and Welch [2010], Sumaila et al. [2011]) and in practice. Transboundary stocks are usually shared using the principle of "zonal attachment" in which countries' shares of the total quota are proportional to the proportion of the stock biomass in their Exclusive Economic Zones (EEZ). Displacement of fish will threaten the stability of existing sharing agreements, as has happened for Atlantic mackerel (*Scomber scombrus*): the extension of mackerel distribution to Icelandic EEZ made the earlier sharing agreement not involving Iceland dysfunctional, and negotiations for a broader agreement have so far not been successful (ICES [2011]).

The problem of shifting zonal attachment in the climate change context was first examined by Hannesson [2007]. The stock was assumed originally to be under sole ownership, and then over time, as temperature rises, start to "spill" into the EEZ of another country. The two countries respond to the changes with a time lag, and the management decisions are non-cooperative. Managers in the model used by Hannesson make their decisions based on their knowledge about past and current conditions: their expectation about the future stock distribution is a weighted average of the previous year's estimate and the currently observed split ratio. The optimal management decisions are based on the assumption that the current estimate of the stock distribution is representative of the future, as if there were no further change in the distribution. We define such manager as "reactive".

Our model builds upon Hannesson's model [2007], but our managers can also be "proactive" decision makers. We take this to mean that the manager takes into account both the current stock distribution as well as an anticipation of future distributional changes. In other words, managers may adapt to climate change, instead of merely coping with it. The distinction between reactive and proactive strategies is usually left implicit in discussions about climate change and fisheries, despite the recognition of this issue in many other contexts (e.g., Petulla [1987], Lin and Carley [1993], Klassen and Angell [1998], Zhen et al. [2011]).

Finding optimal harvest policies for proactive decision makers is much more demanding than for reactive decision makers. We used dynamic programming (DP) to find the optimal policies at each time step in a non-cooperative game. Proactive harvest decision making in absence of a trend in the stock distribution was studied by Golubtsov and McKelvey [2007] using a DP algorithm. In contrast to their work, our model includes a rising temperature trend over time. However, to keep the model simple, we had to assume the trend to be deterministic, whereas Hannesson [2007] assumed a stochastic trend. Furthermore, we also consider general forms of fish stock concentration profiles (Clark [1990]) in order to reveal a more complete picture of the problem. The main research questions of our study are: How will managers' belief about future environmental trend and the consequent distributional shift affect their harvest policies, and what are the implications of those decisions on the biological stock?

2 Model Specification

Solving problem of our interest requires a bio-economic model that combines both biological (stock dynamics in space and time) and economic effects (profit-maximizing harvest policy, constrained by the other player's actions). In general terms, our model is a deterministic, discrete time, two-player dynamic game model with a finite time horizon, one continuous state variable, and one continuous action (policy) variable for each player. We first describe the biological and economic sub-models, before describing the dynamic programming methods that we use to find optimal policies.

2.1 Biological Model

We use a discrete-time logistic population growth model where stock renewal and harvesting alternate. During the part of a season when fishing takes place, the stock occupies the EEZs of two countries. Stock renewal is determined by the combined stock size.

The discrete-time logistic growth function with harvesting is (e.g., Hannesson [2007]):

$$\begin{aligned} R_t(S_t) &= aS_t(1 - S_t) + S_t \\ S_{t+1} &= p_t R_t(S_t), \end{aligned} \tag{1}$$

where R_t is the stock after recruitment at time t, S_t is the stock size after harvest, a is the growth ratio (the greater the parameter, the faster the stock is rebuilt), and p_t is the harvesting strategy, here expressed as the escapement proportion. We assume that stock size is expressed relative to the carrying capacity; this parameter thus disappears in normalization.

The fish stock we have in mind is a migratory stock that moves between spawning and fishing grounds (Figure 1). No fishing takes place during the reproductive season. During the fishing season, the harvestable stock R_t may be found entirely in the EEZ of country 1 or country 2, or split among the two, depending on the ocean temperature. The share of the harvestable stock in the EEZ of country 1 is given by parameter $\theta_t = \theta_t^1$, the split ratio; the rest $1 - \theta_t = \theta_t^2$ spills into EEZ of country 2. Harvest takes place within the country's own EEZ; each country decides its own harvest strategy, the proportion of fish p_t^i to be left behind. As a result of harvesting, the stock size is reduced to S_t^i. Both streams of fish will then unite for reproduction. Next season, the stock will then increase to a new level R_{t+1} due to growth and reproduction of the fish left behind from previous season t. This so-called split stream model was first introduced by McKelvey and Golubtsov [2006].

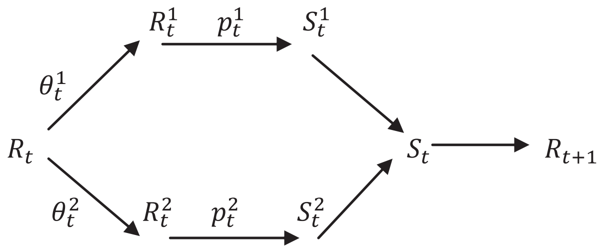


Figure 1: The split stream game of McKelvey and Golubtsov [2006] employed in this paper. R = stock after recruitment; S = stock after fishing; θ = split ratio; p = escapement proportion (the strategy variable).

In this paper we mostly discuss distributional changes driven by the climate change (i.e., the warming of sea water). However, in our formulation of split rule, the actual driver is immaterial, as long as it is predictable for a proactive manager. We assume that temperature increase is a linear function of time and that this leads to a linear decline in split ratio from $\theta = 1$ to $\theta = 0$:

$$\theta_t = \min(1, \max(0, 1 - \delta(t - t_{spill}))) \tag{2}$$

where δ is an annual trend parameter, $\delta = 0.04$, and $t_{spill} = 12.5$ is a parameter determining the timing of the transition. With these parameters, country 1 is the sole owner from initial year to year 12, and from year 38 to terminal year country 2 is the sole owner; in between two countries share the stock (Figure 2). We emphasize that only the proactive manager has full knowledge of δ to estimate his future stock share. For a reactive manager, who believes future split ratio to be the same as the current one, δ does not enter the decision making process. Instead, he updates his estimate of the current split ratio each season.

Because split ratio θ_t is a deterministic function of time, we do not treat θ_t as an independent state variable. Our model has therefore a single state variable, stock size R.

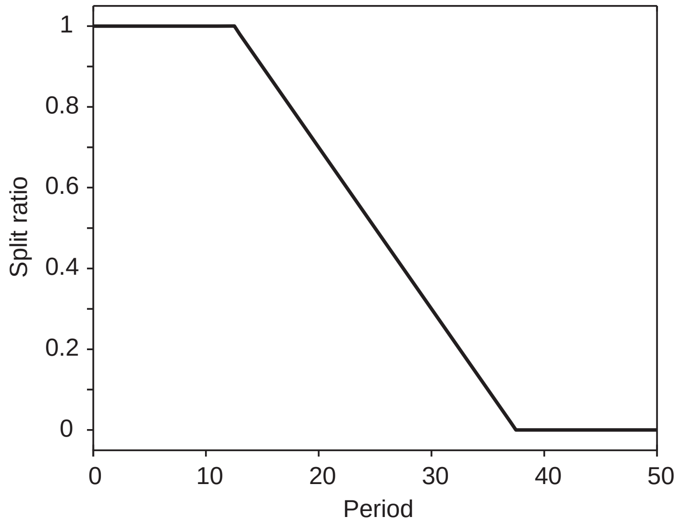


Figure 2: The split rule $\theta(t)$. With the parameters used in this paper, the stock is shared from year 12 to year 38.

2.2 Economic Model

In our model, two countries that share the fish stock play a non-cooperative game over a finite time horizon. We assume they are risk neutral and their goals are to maximize the sums of their current and discounted future payoff, constrained by the actions of the other country. Furthermore, we assume that players are omniscient: they have full knowledge about current state of the stock and its distribution as well each others' rationality.

2.2.1 Revenue, Cost and Concentration Profile

For simplicity, we assume fish price to be exogenous and normalized to 1. The expression for seasonal revenue is then straightforward and depends on the amount of fish (θR) and the player's fishing strategy (p):

$$V_t^i = \theta_t^i R_t (1 - p_t^i). \tag{3}$$

Cost of fishing is a key element for economic decisions. Fish stock density is critical in determining costs of fishing: the lower the density, the more effort is needed to catch a unit of fish. To describe how fish density experienced by fishermen depends on total stock abundance, Clark [1990] introduced the concept of concentration profiles (see also Steinshamn [2011]). A concentration profile describes how average maximum density of fish depends on total stock abundance and is determined by spacing behavior of fish, i.e., by the degree of their schooling behavior; this will vary from species to species.

Let us denote the effective stock density experienced by the fleet of country i at within-season time τ as ρ_τ^i, which is the function of instantaneous sub-stream stock size x_τ^i and split ratio θ_t:

$$\rho_\tau^i(x_\tau^i) = \left(\frac{x_\tau^i}{\theta_t}\right)^b, \ i = 1, 2. \tag{4}$$

Because the stock size is normalized to a maximum of one and we have not included a scaling parameter, this formulation expresses stock density in relative terms, with $\rho = 1$ obtained for an unfished stock. Because fish do not respect country boundaries, two countries are assumed to have the same stock density at the beginning of each fishing season, $\rho_0^i = (\theta^i R/\theta^i)^b = R^b$. This explains why equation (4) has been corrected for split ratio θ. Thus, two countries shall initially face same per unit cost of catching fish. Over time within the season, their sub-stream stock densities will usually diverge.

If $b = 0$ in equation (4), density becomes a stock-size independent constant. This would describe a fish species which is infinitely schooling and when fishermen can easily find these schools and catch the last fish. Under such circumstances, both players face the same cost per unit catch throughout the fishing season, until the stock is exhausted. $b = 1$ is another special case where density is strictly proportional to the stock size; this could happen when the area of fish distribution is unchanged, but the density changes with stock size. $b = 1$ thus represents the case of non-schooling, uniformly distributed fish. However, most of fish stocks behave between these extreme cases, and in our model, we have focused in cases with $0 < b < 1$.

Having understood implications of fish density on the unit costs, we can now derive total costs C_t at season t:

$$C_t = \int_0^1 c_e e_\tau d\tau, \tag{5}$$

where c_e is cost per unit effort and e_τ is fishing effort at time τ. For simplicity, within-season discounting is ignored in equation (5). Effort e_τ is defined as function of instantaneous catch rate y, assumed constant within a season, and catchability coefficient q, describing how easy (or difficult) the fish are to catch:

$$e_\tau^i = \frac{y^i}{q\rho_\tau^i}. \tag{6}$$

By solving equation (5) and equation (6), we get the total seasonal cost for each player as (for details see Appendix A):

$$C_t^i = \begin{cases} \frac{c_e\theta_t^i}{q(1-b)} R_t^{1-b}(1 - {p_t^i}^{1-b}) & \text{, if } 0 \le b < 1, \\ -\frac{c_e\theta_t^i}{q}\log(p_t^i) & \text{, if } b = 1. \end{cases} \tag{7}$$

Equation (7) implies that the greater the value b, the costlier it is to fish. Notice that when $b = 0$, $C_t^i = \frac{c_e\theta_t^i}{q} R_t(1 - p_t^i) = \frac{c_e\theta_t^i}{q} Y_t^i$ where Y is the total catch; the cost is independent of initial stock R. In all other cases, costs are higher when R is lower.

2.2.2 Multi-period Profit Maximization

The objective of a risk neutral manager is to choose his harvest policy such that the net present value of the stock is maximized. Because fishing takes place in a country's own zone, the immediate payoff v_t^i depends on a player's own strategy p_t^i but not on the other player's strategy p_t^{-i}. The immediate payoff is $v_t^i = V_t^i - C_t^i$, or, when $0 \leq b < 1$ (the equation for $b = 1$ is derived similarly):

$$v_t^i(p_t^i, R_t) = \theta_t^i R_t(1 - p_t^i) - \frac{c_e \theta_t^i}{q(1-b)} R_t^{1-b}(1 - p_t^{i\,1-b}),\ i = 1, 2. \tag{8}$$

The future payoffs from $t+1$ to $t_{max} - 1$ are calculated analogously, noticing that the future state of stock depends on harvest policies of both players. For simplicity, when $t = t_{max}$, the future payoff is set to zero. This simplification is warranted because as long as the final payoff is not unnaturally large, the actual value has no implications for the policies during the period when the stock is shared.

The optimal harvest policies satisfy the two players' simultaneous Bellman equations (Miranda and Fackler [2002], p. 208):

$$V_t^i(R_t) = \max_{p_t^i} \left\{ v_t^i(p_t^i, R_t) + \sum_{k=t+1}^{t_{max}} \frac{v_k^i(p_k^i \mid p_k^{-i*}, R_k)}{(1+r)^{k-t}} \right\},\ i = 1, 2, \tag{9}$$

where r is the discount rate. The value functions $V^i(\cdot)$ and optimal harvest policies p^{i*} are solved numerically; once p_t^i are determined for initial state R_t, future policy decisions become automatically decided. Changes in the state of the system are governed by both players' harvest policies together with the biological growth function (1).

2.3 Numerical Methods

We apply dynamic programming (DP) to solve the optimization problem given by the simultaneous Bellman equations (9) (Miranda and Fackler [2002], Chapter 8). Thus, in the process of backward induction, we first identify the players' optimal policies for all subgames during the terminal period; the optimal policies under non-cooperative harvest are Nash equilibria (Clark [1990], Chapter 5.4). When these are known for the terminal period, optimal policies during the previous period can be solved, and so forth. This procedure eventually yields optimal policies for all subgames. These optimal policies are subgame perfect Nash equilibria (Mas-Colell et al. [1995], Miranda and Fackler [2002]).

Because optimal policies are state-dependent and influenced by the players' past actions, we are dealing with closed-loop equilibria (Fudenberg and Tirole [1991], p. 130), irrespective of whether managers are proactive or reactive. However, how future payoffs are determined differs between the management regimes. Under proactive management, future payoffs follow from the value function and are based on correct projection of θ and assuming optimal future policies. Under reactive management, optimal policies are guided by the assumption that θ remains in its current value. In this case we follow Hannesson [2007] and calculate future payoffs as the discounted payoffs that result from both players choosing certain proportional escapements (p_t^i) and then maintaining the resulting absolute escapements ($S_t^i = p_t^i \theta_t^i R_t$) indefinitely.

To find the Nash equilibria in each subgame, we used an exhaustive search on a 100 $\times$ 100 grid, representing escapements p_1 and p_2 evenly spaced in $0.0001 \ldots 1$. In most cases a unique, globally stable Nash equilibrium was identified. However, under proactive regime, the exhaustive search occasionally failed to identify Nash equilibria. By studying the reaction curves[1] for such subgames, we found that a small proportion of failures were caused by numerical inaccuracy introduced by the finite search grid. In the vast majority of failures, however, the absence of Nash equilibrium was genuine. This is possible because in our model reaction curves can be discontinuous, and therefore they may not intersect (thick curves in Figure 3; see Appendix B for further discussion). However, all subgames had at least one local Nash equilibrium. Furthermore, when multiple local Nash equilibria existed, at least two of them were Pareto efficient. To select one equilibrium in a consistent and unambiguous way, we use a gradient ascent algorithm. This can be envisaged as a negotiation process where the players simultaneously adjust their bids in small steps, based on what is advantageous to them at that very moment. The starting point is no fishing, $(p_1, p_2) = (1, 1)$, and the gradient is defined by the partial derivatives of each players' total payoff with respect to their fishing policies for the focal season. This algorithm converges to a point that is a local Nash equilibrium (Figure 3).

In all simulations, we assume two managers/countries in question to be identical in terms of their management regimes (reactive or proactive) and in the economic parameters (price of fish, unit cost of fishing effort, and discount rate). They become asymmetric in the course of fishing season because of different effort expended and because diverging stock densities imply different catch rates per unit effort. Price and the cost of per unit effort are fixed constants in the model. All the results are based on a setting where the fish stock is first under the sole ownership of country 1, then starts gradually spilling into the jurisdiction of country 2, until at some point it enters the sole ownership of country 2 (Figure 2). Stock size is discretized to 50 bins, with a uniform bin density above $R = 0.2$ and doubled density below that; linear interpolation is used to estimate future payoffs for intermediate stock sizes. Minimum stock is set to $R = 10^{-4}$, below which stock is considered extinct.

All simulations were conducted with R (R Development Core Team [2011]), and the code is available from the authors on request.

3 Results

Here we focus in comparing reactive and proactive management. We start with results from the backward induction, focusing in qualitative differences of the policy functions between the two management regimes. We then move on to dynamic path analysis and to describing how knowledge about the future changes the strategic interactions between the players. Finally, we describe how the results depend on the choice of the key parameters in our model.

3.1 Policy Functions

To illustrate the results from backward induction, we present policy functions for both players. These describe the Nash strategy of a player for all combinations of stock size and period. We illustrate these policy functions as grey-scale images in Figures 4–6 that can be seen as "road maps" that give a player's optimal action under all possible conditions. The

[1]A reaction curve is a function that maps a player's best response against his opponent's all possible responses. Intersections of reaction curves are Nash equilibria. Fudenberg and Tirole [1991] discuss reaction curves also under name *reaction correspondence*.

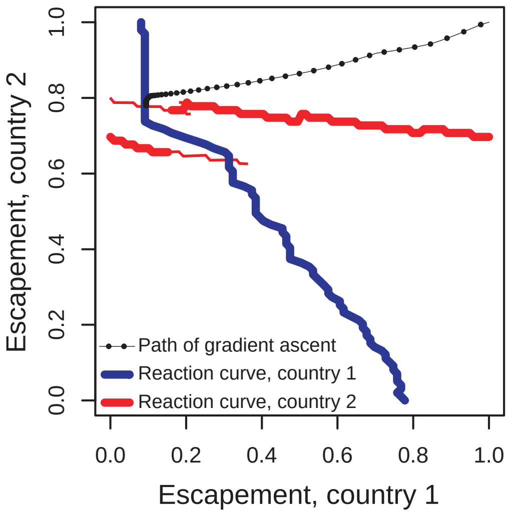
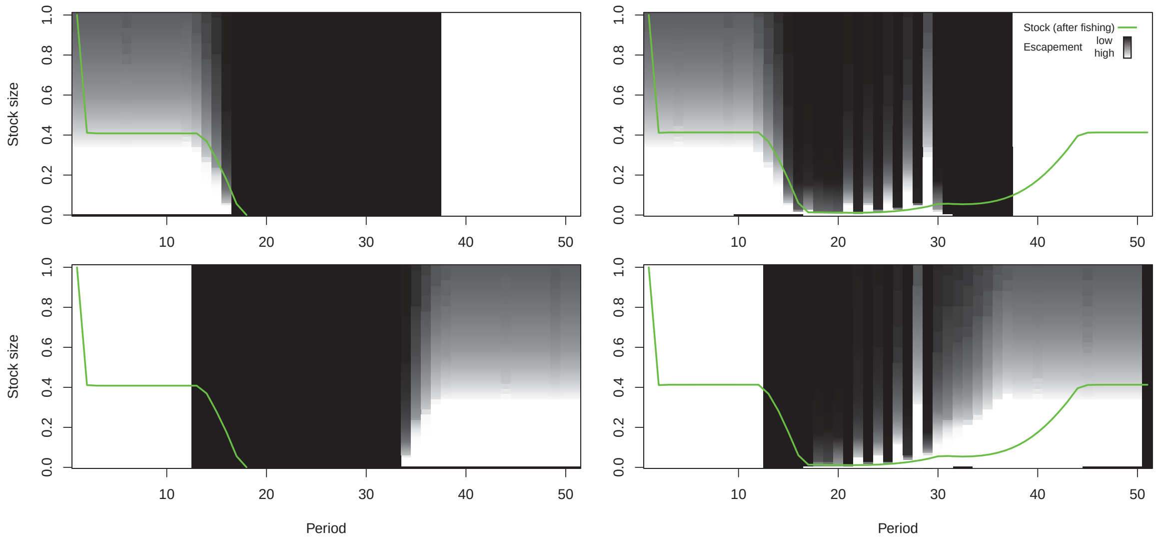


Figure 3: Discontinuity in the reaction curves when $a = 0.6$, $b = 0.4$, $c_e/q = 0.2$, $r = 10\%$, $R = 0.329$, $t = 31$, and $\theta = 0.26$. Red thick curve depicts the best response of player 2 to player 1's strategy, and blue thick curve depicts the best response of player 1 to player 2's strategy. Because these curves do not intersect, there is no global Nash equilibrium. However, thin colored curves that show the local best responses do intersect, and these intersections are local Nash equilibria. Both turn out to be Pareto efficient. One of these is chosen using a gradient ascent algorithm; its path starting from $(1, 1)$ is shown by the black curve.

harvest policies are most conservative (i.e., the escapement is large) under sole ownership and least conservative when the ownership is equal. Under reactive regime, the behavior of player 1 and player 2 is almost symmetric, in a sense that their policy functions are mirror-symmetric with respect to the point of time when the stock is equally shared ($\theta = 0.5$). This symmetry no longer holds under proactive management where knowledge about the future makes the positions of the two players inherently different. Here we first describe the basic patterns; we will elaborate on the underlying mechanism further down.

Policy functions are always different between reactive and proactive management. For some parameter combinations the differences only become apparent under close scrutiny. More typically, however, the policy functions are qualitatively different: under reactive management, the escapement proportion at a certain stock size for the first player (who is losing the stock) is monotonically decreasing with time, whereas under proactive management, the escapement proportion becomes non-monotonic. At weakest, monotonicity is seen as a modest reduction in the harvest of player one that occurs after he has become the minor owner, before his harvest increases again for last years of mutual ownership.

The non-monotonic harvest control can take striking forms. A "zebra" pattern is one special form of non-monotonicity (Figure 4). It occurs only during the stock transition, and is characterized by alternation of a low/nil harvest in one period and a substantial harvest in another period. Moreover, the two players' policies are in almost perfect anti-synchrony. When the zebra pattern occurs, it prevails for most stock levels but is more pronounced for low stock levels before entirely disappearing for very low stock levels. In some other cases, the regular zebra pattern is replaced by apparently erratic harvest. This pattern emerges when reaction curves in individual subgames become discontinuous and there is no global Nash equilibrium in a particular subgame.



A Reactive management B Proactive management

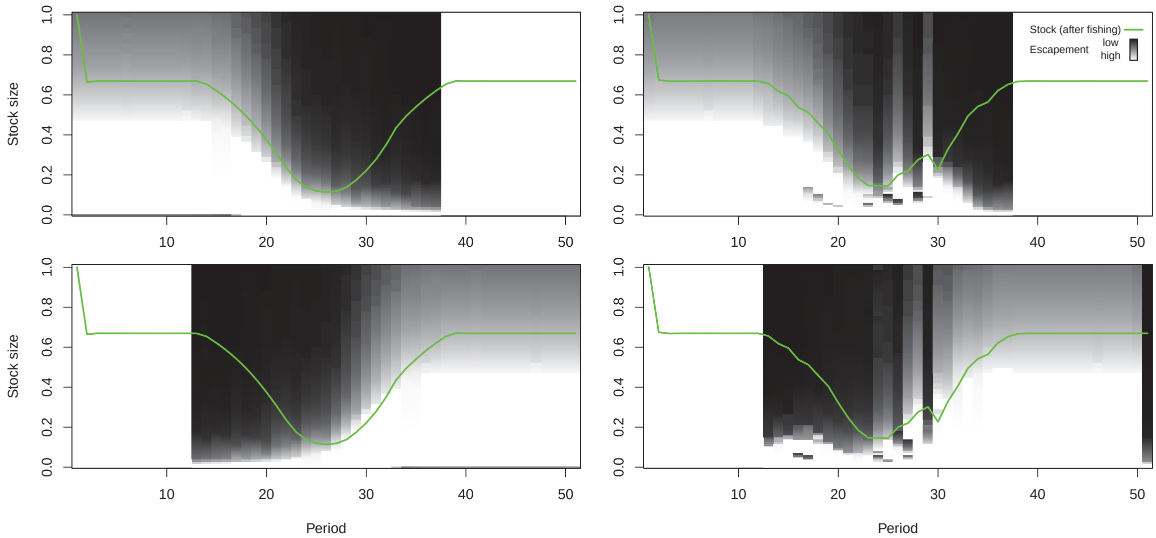
Figure 4: Policy functions under reactive (A) and proactive management (B) for country 1 (top) and country 2 (bottom). Policy here is escapement and is shown with the gray scale, with white corresponding to zero harvest ($p = 1$) and black to zero escapement ($p = 0$). Policy function is defined for all combinations stock and period. Stock trajectory when $R_0 = 1$ is shown with the curve (green). Proactive management reduces risk of stock depletion, and may cause "pulse control". $a = 0.3$, $b = 0.1$, $c_e/q = 0.2$, and $r = 10\%$.

3.2 Dynamic Path Analysis

Policy functions can be used to simulate the paths of optimal harvest and stock level, given a certain initial state. Stock trajectories when the initial stock is unexploited ($R_0 = 1$) are illustrated by the green lines in figures 4-6 . The common observation is that during sole ownership, the policy is to maintain or rebuild the stock to a certain "optimal" level[2]; this applies regardless of i) whether it is ex-ante or ex-post transition, and ii) which one of the two management regimes applies. When the stock becomes shared, it declines to extinction or reaches a minimum level at around the time when the ownership is equal or similar and then starts to recover.

In accordance with the differences in the policy functions, the differences in stock trajectories between reactive and proactive management range from subtle to dramatic. There are three main cases: the stock goes extinct regardless of the management regime (not illustrated), the stock goes extinct under the reactive but not proactive management regime (Figure 4), or the stock goes extinct under neither of the management regimes (Figure 5–6). Thus, the reactive management is more vulnerable to the negative consequences of non-cooperative exploitation.

[2]Because the intrinsic productivity of the stock is not influenced by the distributional change, under cooperative management it would be optimal to keep the stock at this level all the time.



A Reactive management B Proactive management

Figure 5: Policy functions under reactive (A) and proactive management (B) for country 1 (top) and country 2 (bottom). Proactive management can induce complex dynamics. See figure 4 for further explanations. $a = 0.8$, $b = 0.4$, $c_e/q = 0.2$, and $r = 10\%$.

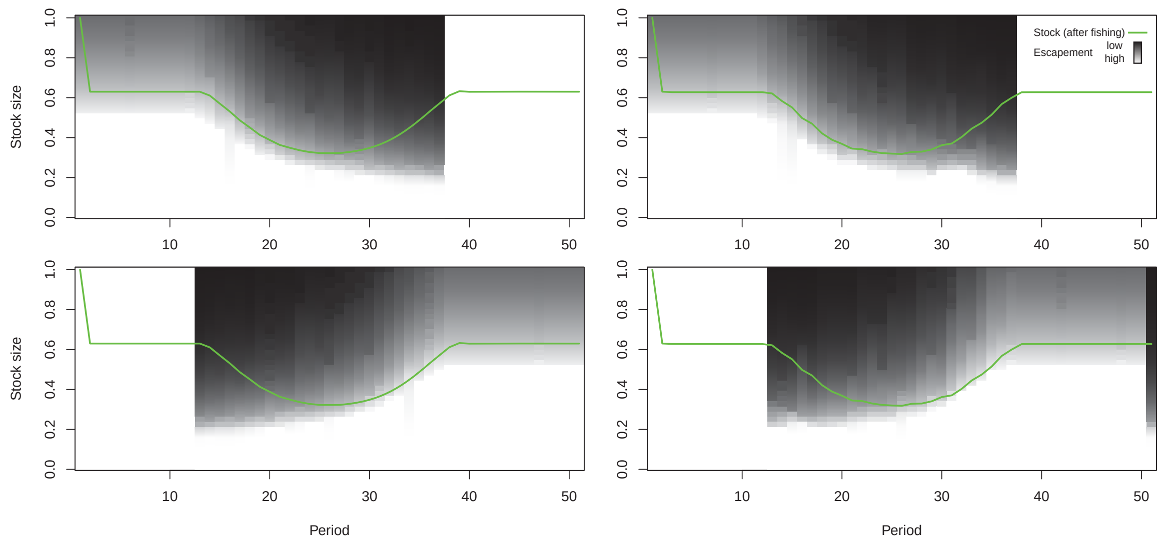
Another observation is increased stock volatility under proactive management. Stock trajectory of reactive management is always smooth and typically nearly symmetric around $\theta = 0.5$; this is a reflection of the monotonicity observed in policy functions: a continuous and gradual change of harvest ensures a smooth stock trajectory. The recovery of the stock, whenever it occurs, is also monotonic. Under proactive management, however, recovery might not be monotonic, and the stock can become fairly volatile (Figure 5B). These patterns are caused by non-monotonicity of the policy functions. The largest volatility is associated with policy functions showing erratic policies. Curiously, however, the pulse control does often not result in noticeable volatility because of the complementarity of the two players' policies, i.e., heavy harvest by one player is associated with little or no harvest by the other.

As b is increased (i.e., stock is more evenly dispersed and more costly to exploit), proactive stock trajectory is gradually smoothed out. The quantitative difference of stock between proactive and reactive management becomes minimal (Figure 6).

In terms of the realized payoff, the proactive management brings slightly higher cumulative payoff (excluding the first and the last period) for both players than the reactive management; the difference becomes large only when the stock collapses under reactive management. An important exception occurs when stock collapses also under proactive management: in this case, reactive management brings higher cumulative payoff for both players (the proactive players race to exhaust the stock).

3.3 Strategic Interactions

A study of the two players' optimal policies under the alternative management regimes helps to understand the mechanisms behind the observed differences in stock trajectories.



A Reactive management   B Proactive management

Figure 6: Policy functions under reactive (A) and proactive management (B) for country 1 (top) and country 2 (bottom). For certain parameters, the quantitative difference between the management regimes is small. See figure 4 for further explanations. $a = 0.5$, $b = 0.9$, $c_e/q = 0.2$, and $r = 10\%$.

Here we limit ourselves to cases where the stock does not go extinct. We summarize the main features of the strategic interactions below; Table 1 includes a schematic summary of the main phases of interactions.

Under reactive management, the strategic interactions are simple (Table 1). We can distinguish three phases: (1) When the stock is under sole ownership of player 1, there is no strategic interaction, and the sole owner aims to maintain the stock at an optimal level; (2) When the stock starts to spill to the jurisdiction of country 2, the non-cooperative harvest starts. The main owner harvests more than he would do under sole ownership, but less than the minor owner who is a free rider. When the original major owner becomes the minor owner, the roles of the players are reversed, but there is no fundamental change in the game; (3) In the end, the stock becomes under sole ownership of player 2, who in turn starts to pursue sole owner optimal management. This may involve first letting the stock to recover to the optimal level.

Under proactive management, the strategic interactions become more complicated (Table 1):

(1a) "Sole owner optimum": Initially, ex ante the transition, the situation is exactly the same as for the reactive manager.

(1b) "Anticipation": The stock is still in sole ownership of player 1 but under the proactive management, anticipation of player 2 entering the game leads player 1 to increase his harvest relative to the single player optimum. In our simple, deterministic model, anticipation occurs just one time step ahead.

(2a) "Mutual race to fish": Both players engage in heavy harvest. This phase is similar

Table 1: Schematic summary of time line of the strategic interactions.

Ownership	Management regime	
	Reactive	Proactive
Sole owner: country 1	Sole owner optimum	Sole owner optimum
		Anticipation
Spilling starts	Mutual race-to-fish	Mutual race to fish
	$harvest_1 < harvest_2$	$harvest_1 < harvest_2$
		$harvest_1 \geq harvest_2$
Equal shares	$harvest_1 = harvest_2$	Pseudo-cooperation
	$harvest_1 > harvest_2$	Loser's race to fish
Spilling ends		$harvest_1 > harvest_2$
Sole owner: country 2	Sole-owner optimum	Sole-owner optimum

under reactive and proactive regimes.

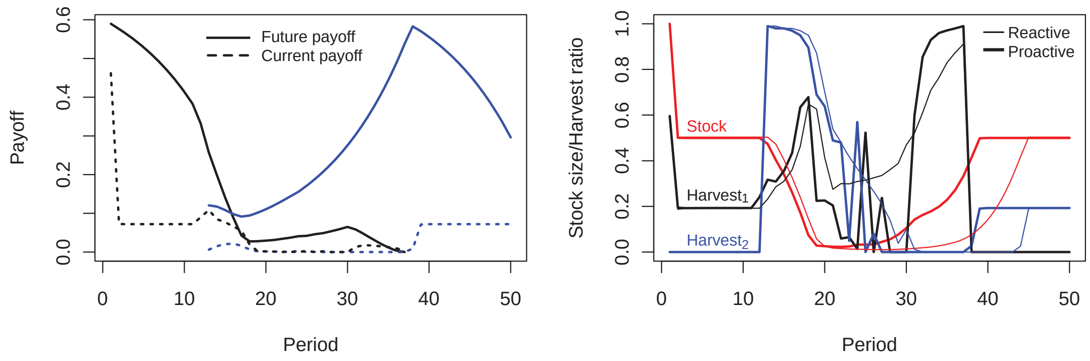
(2b) "Pseudo-cooperation": Under proactive management, the non-cooperative Nash equilibria can involve a period of no or little harvest, as if the players would cooperatively rebuild the stock. Indeed, some rebuilding of stock is in the interest of both players: for player 2 because he is the major owner and approaching the point where player 1 can no longer fish the stock down, and for player 1 because he can benefit from increased stock during the next phase. This phase only occurs when b is low enough to make harvesting a small stock profitable.

(2c) "The loser's race to fish": Player 1 no longer has power to push stock down, so it can pay for player 2 to conserve stock. Player 2 adopts a bang-bang harvest strategy before he reaches optimal stock level. The future value of player 1's stock is diminishing (see Figure 7); he then engages heavily in his terminal harvest.

(3) "Sole owner optimum": Ex post the transition, the situation is similar to that under the reactive management, apart from the terminal effects arising from the finite time horizon of the model.

In summary, we observe that the strategic interactions induced by reactive management are much simpler than those occurring under proactive management. The features we observe under proactive regime, anticipation, pseudo-cooperation, and loser's race to fish, are absent under reactive management. The nature of reactive management (managers are assumed to see future stock ownership being the same as it is today) prohibits any anticipatory behaviors of its players. Under proactive management, anticipation of the change in ownership changes a seemingly robust conclusion about the harvest policies of a shared stock: that the main owner always conserves more than the minor one who free-rides the main owner's conservation efforts (Hannesson 2007). In anticipation of becoming the minor owner, player 1 starts to harvest more than his competitor while still being the major owner, a few years before his stock share goes below 50% (Table 1, Figure 7).

A detailed example of dynamics under reactive and proactive management is presented in Figure 7. It shows that under proactive management player 1 is seen to start increasing his harvest one year earlier than under reactive management; this leads to an earlier stock decline, but otherwise the difference between the regimes is small. However, after a while, "pseudo-cooperation" starts: the harvest of both players is less under proactive compared to reactive regime. This involves a period of pulse fishing. Finally, player 1 starts his aggressive terminal fishing, but the stock is nevertheless recovering. The stock reaches the sole-owner optimal level much earlier under the proactive compared to the reactive regime.



A Current and future payoff

B Strategic interactions

Figure 7: An example of trajectories of current and future payoff (A; under proactive management only) and stock size and escapement policies (B). In (A), dashed and solid lines show respectively the current payoff and discounted future for player 1 (black) and player 2 (blue). In (B), thin solid or dashed lines are for reactive and thick solid lines for proactive management. The harvest ratio of player 1 is shown in black and that of player 2 in blue, and stock size is in red. $a = 0.4$, $b = 0.3$, $c_e/q = 0.2$, and $r = 10\%$.

3.4 Pulse Fishing

We now elaborate on the causes of pulse fishing policy seen under proactive management in Figure 4 and Figure 7. Pulse fishing is a well-known phenomenon in the bioeconomic literature (Clark et al. [1973], Pope [1973], Hannesson [1975]). Explanations mostly fall in two categories, non-linearity of harvest cost (economy of scale) and poor age-selectivity leading to inadvertent catch of young fish, before they realize their growth potential (e.g., Clark [1990], Tahvonen [2009], Steinshamn [2011]). Neither explanation applies here. Pulse fishing in our model is driven by competitive interactions between the two players. It is an expression of complementarity that often characterizes optimal policies of proactive managers: when conserving the stock is in the interest of both players, the best response to the opponent's increased harvest is to harvest less. In an extreme case, the reaction curves are nearly identical with slopes $\sim -45°$; the intersection of the reaction curves is then sensitive to small changes in current or future payoffs. Consequently, Nash equilibria can easily flip between situations where player 1 is harvesting heavily whereas player 2 does not harvest, and the opposite.

The necessary condition for strong complementarity is that both players have significant future value associated with the stock, such that sacrificing current payoff to conserve the stock for future harvest is sensible. This requires that (1) the asymmetry in ownership is not very large and that (2) discount rate is not very high. Furthermore, complementarity is facilitated by low b, such that stock can be profitably harvested even at low stock levels, and consequently, that players have more latitude to choose their policies.

Under certain conditions, complementarity of the reaction curves becomes visible as pulse fishing. Suitable conditions in our model are triggered by the "loser's race to fish"; let us denote the beginning of this terminal harvest by t'. When b is small, the terminal harvest is associated with significant payoffs, creating an incentive for player 1 not to let stock to shrink to very low levels. At the same time, this creates a situation in which player 2 does not benefit from further recovery of the stock. Taken together these conditions lead to a situation in which Nash equilibria (above a certain stock size) in period $t'-1$ involve heavy harvest by player 2 and no or little harvest by player 1. This outcome affects the game in the previous period ($t'-2$): player 2's heavy harvest in period $t'-1$ reduces the conservation incentive of player 1 but increases his own conservation incentive, and the Nash equilibria for this period are mirror images of those for period $t'-1$. This effect can then cascade further back in time, giving rise to the zebra patterns (e.g., Figure 4).

It is worth highlighting that pulse fishing is more prominent in policy functions than in the dynamic path analysis: the optimal stock trajectory often involves so low stock levels that pulse fishing does not occur (were the optimal stock trajectory higher in Figure 4B, pulse fishing would continue until the terminal harvest of player 1). We also emphasize that pulse fishing is not a very robust feature of the model: preliminary results from a stochastic model suggest that uncertainty about future stock state easily eradicates at least the regular pulse control shown in Figure 4.

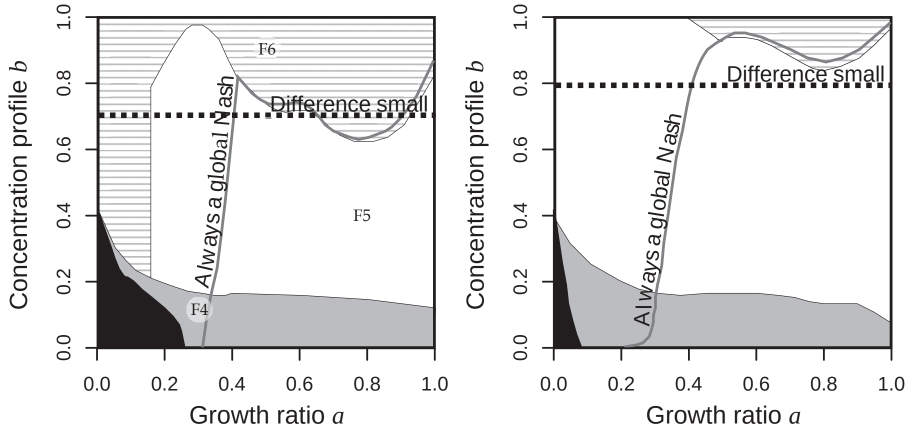
3.5 Sensitivity

In this section, we summarize how growth ratio (a), concentration profile (b) and discount rate (r) influence the model behavior (Figure 8). We first note that the model reproduces the patterns familiar from simpler models: harvesting is most likely to lead to extinction when stock is highly schooling (low b), has low growth ratio (low a), and when interest rate is high ($r = 10\%$).

Whether proactive and reactive regimes differ markedly is most prominently influenced by the concentration profile b. Highly schooling stocks (low b) are harvested to extinction under the reactive regime, whereas sustainable harvesting is often possible under the proactive regime. If the value of b is sufficiently large (i.e., $b \geq 0.7$ when $r = 10\%$), the quantitative differences between reactive management and proactive management become negligible. This result is intuitive: if it is harder and thus costlier to fish down a small stock for player 1 in the end of stock transition, player 2 has better control of the stock. Players' strategic interactions then become much simpler and close to those under the reactive regime.

Growth ratio (a) has a major influence on complexity of reaction curves and policy functions. Discontinuous reaction curves (see Section 2.3 and Appendix B) tend to become visible as non-existence of global Nash equilibria during the pseudo-cooperative phase if the growth ratio $a \gtrapprox 0.4$. When $a \lessapprox 0.4$, pulse control (policy functions) and pulse fishing (dynamic path analysis) prevail; discontinuities may still exist but they no longer lead to absence of a global Nash equilibrium.

What is the role of discount rate? Figure 8B shows that the effect of a smaller discount rate is two-fold: (a) a more diffuse bifurcation area, and (b) a shrinking area of monotonic policy control. As we explaining earlier, bifurcation is induced by the non-convexity of payoff function. The smaller the discount rate, the greater non-convex the total payoff function will become. This explains the more complex system dynamics we observe here.



A Discount rate $r = 10\%$ B Discount rate $r = 1\%$

Figure 8: Schematic illustration of the dynamic behavior of the model with respect to growth ratio a (x-axis), concentration profile b (y-axis), and discount rate r (panel (a) and (b)). Black area: both reactive and proactive regime lead to extinction. Gray area: only reactive regime leads to extinction. Horizontal stripes: monotonic control. Below and to the right of the solid gray curve, global Nash equilibrium may not exist under the proactive regime. Below the dotted black line, the quantitative difference between reactive and proactive becomes significant. Parameter combinations corresponding to Figures 4–6 are also shown. $c_e/q = 0.2$.

4 Concluding Remarks

Our model has attempted to simulate how stock displacement induced by climate warming may affect international fishery management. Significant changes in stock distribution do occur, although at present it can be difficult to judge the degree to which these are related to climate change (Brander [2010]). For example, mackerel used to be an occasional visitor to Icelandic waters, but in the recent years it has become abundant enough to support a sizeable Icelandic commercial fishery (ICES [2011]). The earlier agreement for sharing the mackerel stock did not involve Iceland and broke down. The current situation can be characterized as a non-cooperative game where the parties regulate their mackerel fisheries based on their own perceptions of their rightful shares. Even though the presented split-stream model certainly is a gross simplification of the reality, it does capture some essential characteristics of managing a migratory stock.

Results from comparison of reactive and proactive management regimes show that two players are approximately symmetric under reactive management, but anticipation about the changing future makes the role of the two players inherently asymmetric under proactive management. The differences between two alternative management regimes can be seen in following aspects:

- For any given stock size, the optimal harvest rate under reactive management is monotonically increasing with respect to time for the player losing the stock and monotonically decreasing for the player whose stock share is increasing. Under proactive management, the pattern is replaced by non-monotonic harvest control which can take complex forms.

- Stock trajectory under reactive management is always smooth and typically nearly symmetric; the trajectory under proactive management shows various degrees of volatility. Under sole owner equilibrium, the stock level is the same regardless of who the sole owner is or which management regime applies.

- Reactive managers can always find a unique, global Nash equilibrium. Proactive management can sometimes result in non-existence of a globally stable Nash equilibrium; instead, two or more local Nash equilibria appear.

- Proactive management induces complex strategic interactions between players. Typically these involve more aggressive harvesting by the player that is loosing the stock, whereas the player gaining the stock acts more conservatively. However, there is also often a short period when even the competitive solution is to allow the stock to grow.

- Proactive management can save a stock from a stock collapse caused by competitive, non-cooperative harvest.

We emphasize that choice of concentration profile can influence the degree of variations between two management regimes. Our model shows that fixing the concentration profile to an extreme case ($b = 0$ or $b = 1$) can be misleading (see also Steinshamn [2011]). With a general formulation of concentration profile, the quantitative difference between two alternative regimes increases as b decreases, becoming subtle only for low-schooling stocks ($b \sim 1$). This suggests that reactive management can be a good approximation of proactive management only if the stock in question shows little schooling behavior.

In comparison to the noticeable changes in harvest policies caused by shifting the management regime from reactive to proactive, often the impact of the regime shift on total stock level and realized payoff is more subtle. This is possible because the two players' harvest policies often show "complementarity": it is not in interests of either player to let the stock become very small, such that the best response to other player's aggressive policy is conservative policy, and vice versa. This complementarity mitigates the stock-level effects of volatile policies that may occur under proactive management.

We would like to emphasize that our model is deterministic and our managers have perfect knowledge. This was necessary to keep the model as simple as possible. Some features we observed in the model such as pulse fishing are intriguing, yet they may not be robust and can ease or even disappear in a stochastic world. Extending the model into stochastic version and incorporating cooperative games into model will be natural next steps forward.

While the distinction between reactive and proactive strategies to decision making is well established in many contexts (e.g., Petulla [1987], Lin and Carley [1993], Klassen and Angell [1998], Zhen et al. [2011]), in the literature about climate change and fisheries this distinction is typically left implicit. Adaptation to climate change can involve proactive strategies that aim to anticipate important future changes (Tompkins and Adger [2004], Cochrane et al. [2009]), or reactive strategies where adaptation is passive and happens to change that has already occurred (Hannesson [2007], Cochrane et al. [2009], Coulthard [2009]). Theoretical research on the issue has been lacking, despite calls for proactive policies (Herrick et al. [2009], Johnson and Welch [2010]). Our results highlight that reactive and proactive approaches can give rise to very different policy responses, with the proactive approach allowing avoiding some of the worst outcomes.

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Appendix A: Fishing Costs and Concentration Profile

We assume that a uniform catch rate y_t^i is maintained within a season. Total catch Y during season t of length one then becomes:

$$Y_t^i = \int_0^1 y_t^i d\tau = \theta_t^i R_t - S_t^i, \tag{10}$$

where θ_t^i is the split ratio at season t for country i, R_t is total stock before harvesting, and S_t^i is the stock size in country i's zone after harvesting. The sub-stream stock size x_τ^i at time τ within a season can be written as:

$$x_t^i(\tau) = \theta_t^i R_t - \tau y_t^i. \tag{11}$$

The concentration profile ρ, giving the effective stock density, is a function of stock size x:

$$\rho(x_\tau^i) = \left(\frac{x_\tau^i}{\theta_t^i}\right)^b, \tag{12}$$

where b is a non-negative parameter. If $b = 1$, stock is uniformly distributed and reducing the stock will proportionally affect density but not the distribution area; if $b = 0$, stock density remains constant, representing a stock of "super-schooling" type. In our model, we look at the more generic case $0 < b < 1$.

The decision variable is p_t^i, the escapement proportion, i.e., the proportion of fish in his stream the manager of country i decides to leave behind at season t:

$$p_t^i = \frac{S_t^i}{\theta_t^i R_t}. \tag{13}$$

Costs are proportional to fishing effort. Effort by country i at time τ is:

$$e_\tau^i = \frac{y_t^i}{q\rho(x_\tau^i)}, \tag{14}$$

where q is the catchability, a parameter relating effort to catch rate, i.e., how easy to catch the fish are. Now we can derive the total seasonal costs:

$$C_t^i = \int_0^1 c_e e_\tau^i d\tau = \frac{c_e}{q} \int_0^1 \frac{y_t^i}{\rho(x_\tau^i)} d\tau = \frac{c_e \theta_t^{ib} Y^i}{q} \int_0^1 x_\tau^{i\,-b} d\tau. \tag{15}$$

where c_e is the cost per unit of effort, assumed to be constant and the same for both countries in the game. We know also that:

$$\int_0^1 x_\tau^{i\,-b} d\tau = \int_0^1 (\theta_t^i R_t - \tau y_t^i)^{-b} d\tau = \frac{(\theta_t^i R_t)^{1-b} - S_t^{i\,1-b}}{Y_t^i (1-b)} = \frac{(\theta_t^i R_t)^{1-b}(1 - p_t^{i\,1-b})}{Y_t^i (1-b)}. \tag{16}$$

Replacing the integral in equation (15) with equation (16), we obtain total seasonal cost for country i:

$$C_t^i = \frac{c_e \theta_t^i R_t^{1-b}(1 - p_t^{i\,1-b})}{q(1-b)}, \tag{17}$$

which is a function of the decision variable p_t^i and state variables θ_t^i and R_t.

Appendix B: Discontinuous Reaction Curves

We highlighted in section 2.3 that the reaction curves in our model may become discontinuous, i.e., they may display a bifurcation. We elaborate on this issue here.

In a two players' game, Nash equilibria are intersections of reaction curves. With continuous reaction curves, such an intersection is bound to exist. However, this is no longer true if a discontinuity is present; thus the corresponding subgame may not have a global Nash equilibrium.

Example in Figure 3 shows a discontinuity in player 2's reaction curve. Player 2 has two locally optimal responses to a certain range of player 1's harvest policies. These are shown as local reaction curves, i.e., curves of policies that are better responses than immediately adjacent responses. When player 1 is harvesting aggressively (low p_1), the best response for player 2 is given by the lower, more aggressive local reaction curve. However, if player 1 is leaving a larger proportion of his stock behind, player 2 gets better off by shifting to the upper local reaction curve, corresponding to a more conservative harvest policy. This discontinuity occurs such that global reaction curves never intersect, i.e., there is no global Nash equilibrium. There are, however, two local Nash equilibria, one of which is reached if the players find the Nash equilibrium by local gradient search starting from no catch (Figure 3).

Mathematically, the discontinuity arises due to non-convexity of payoff function that allows multiple local optima to exist. This is due to introducing concentration profile into managers' decision problem. Study of current and future payoff landscapes show that the current payoff surface is approximately linear when b is sufficiently small but convex when b increases further. The future payoff surface can become very ragged, the more so the faster the stock grows.

Complex future payoff landscapes arise because a player can achieve high net present value by being conservative while accepting the cost of the other player free-riding, or by being aggressive and therefore making the future stock so small that the other player cannot profitably fish. Which solution is the local Nash equilibrium reached by the local search algorithm can change abruptly as a function of stock size. Such abrupt changes then make the future payoff landscape of the previous period more complex, and the effect propagates backward. It is worth noting that discontinuities never appear under the reactive management regime where future payoff landscape is inherently simple.

The bifurcation brings interesting dynamics to the model, but we should interpret this with caution. The presence of discontinuities during the last period when they occur is a robust and real feature of the modelled system. However, the way they back-propagate is influenced by numerical limitations arising from discretizing a continuous state variable, stock size. The back-propagation is also enhanced by the assumption of determinism, which implies that both players can predict the stock level next year perfectly. The tendency for bifurcations is lessened in the real world where uncertainty prevails.

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