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Authors
Boettiger, Carl
Bode, Michael
Sanchirico, James N
et al.

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Optimal management of a stochastically varying population when policy adjustment is costly

Carl Boettiger[a,*], Michael Bode[c], James N. Sanchirico[b], Jacob LaRiviere[e], Alan Hastings[b], Paul R. Armsworth[d]

[a] *Department of Environmental Science, Policy and Management, University of California, Berkeley, 130 Mulford Hall #3114, Berkeley, CA 94720-3114, USA*

[b] *Department of Environmental Science and Policy, University of California, Davis*

[c] *School of Botany, University of Melbourne, Australia*

[d] *Department of Ecology and Evolutionary Biology, University of Tennessee, Knoxville*

[e] *Department of Economics, University of Tennessee, Knoxville*

Abstract

Ecological systems are dynamic and policies to manage them need to respond to that variation. However, policy adjustments will sometimes be costly, which means that fine-tuning a policy to track variability in the environment very tightly will only sometimes be worthwhile. We use a classic fisheries management question – how to manage a stochastically varying population using annually varying quotas in order to maximize profit – to examine how costs of policy adjustment change optimal management recommendations. Costs of policy adjustment (here changes in fishing quotas through time) could take different forms. For example, these costs may respond to the size of the change being implemented, or there could be a fixed cost any time a quota change is made. We show how different forms of policy costs have contrasting implications for optimal policies. Though it is frequently assumed that costs to adjusting policies will dampen variation in the policy, we show that certain cost structures can actually increase variation through time. We further show that failing to account for adjustment costs has a consistently worse economic impact than would assuming these costs are present when they are not.

Keywords: optimal control, fisheries, ecological management, adjustment costs,

Introduction

Ecosystems are dynamic and exhibit rich patterns of variability in both time and space (Durrett and Levin 1994). In designing management policies for ecosystems, managers need to decide how much of that variation to respond to. Managers could try to track variations

*Corresponding author
Email address: cboettig (at) berkeley.edu (Carl Boettiger)

in ecosystem dynamics very closely by setting policies that are extremely responsive to the environment. Many theoretical studies that seek to identify optimal policies for exploited populations and communities adopt this approach and largely ignore the challenges that would be involved in implementing such recommendations (e.g., Reed 1979, Neubert 2003, Sethi et al. 2005, Halpern et al. 2011). However, the policy process can often be much more sluggish to respond to variations in ecosystem dynamics (Walters 1978, Armsworth et al. 2010). Moreover, stakeholders impacted by ecosystem management may prefer some stability and not want to deal with continually changing management recommendations (Biais 1995, Armsworth and Roughgarden 2003, Patterson 2007, Patterson and Resimont 2007, Sanchirico et al. 2008). In other words, whatever gains are available from fine-tuning a policy prescription to more closely reflect environmental variation should be traded off against potential costs associated with the more responsive approach to management this would require.

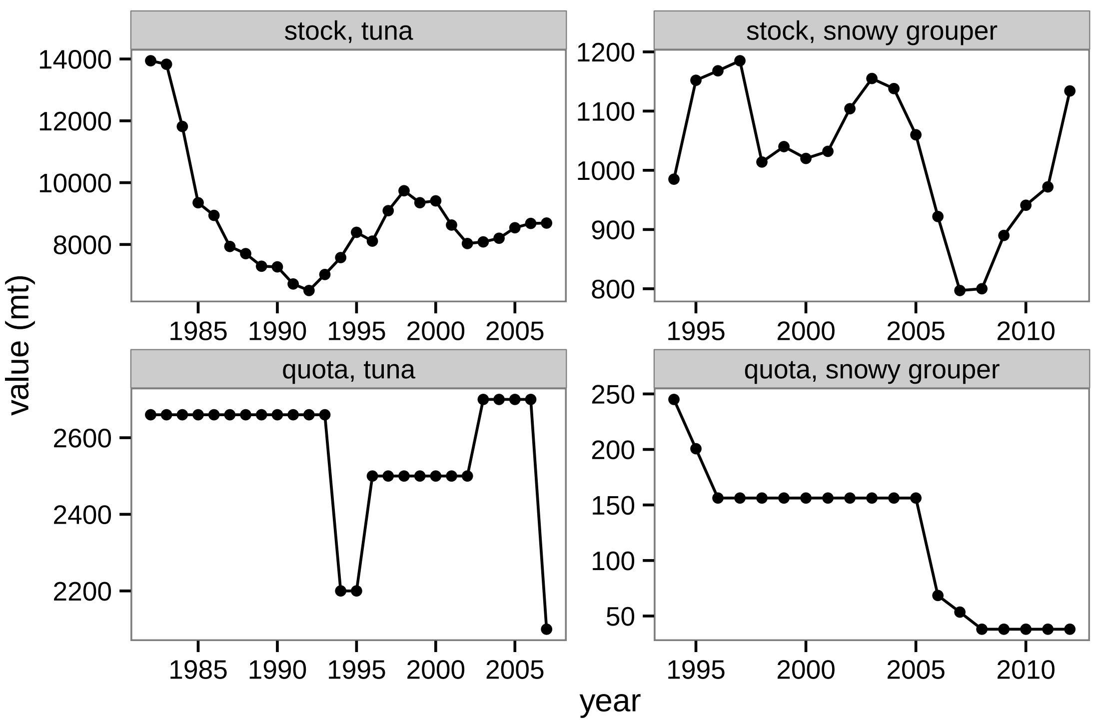

Figure 1: Estimated stock abundances (top panels) show much greater variation than the corresponding harvest policies (bottom). Left panels: ICCAT Stock assessments and Total Allowable Catch (TAC, before adjustments for national underages and overages) for bluefin tuna, 1982 - 2007. Right panels: SEDAR stock assessments and annual quotas for south Atlantic snowy grouper, 1994-2012.

To illustrate this tradeoff, we use an example from fisheries management. Figure 1, top-left panel, shows a time series for the estimated population size, represented as spawning stock biomass, of west Atlantic bluefin tuna (*Thunnus thynnus*, henceforth bluefin) from a recent stock assessment (International Commission for the Conservation of Atlantic Tunas (ICCAT) 2009). The bottom-left panel shows the catch quota (Total Allowable Catch or TAC, before being adjusted for overages or underages in the catch of each country in the previous year) for the stock as set by the relevant management agency (International Commission for the Conservation of Atlantic Tunas (ICCAT) 2009). Despite the estimated population size declining by 53.3% between 1982 and 1991, the quota was not changed during this period. Instead, the quota only changed occasionally and in between times was left unaltered. Fishery management decisions regarding this species can be highly contentious (Safina (1998), Sissenwine et al. (1998), Porch (2005)). Moreover, the stock is fished by fleets from many nations with quotas being set by a multilaterial management agency through a process of negotiation. As such, we might reasonably anticipate that for this species there could be substantial transaction costs involved in reaching agreement over any quota change, or constraints on the frequency with which the those changes could occur. Either could contribute to the observed quota stability.

Such patterns of variable stocks managed under far less variable quotas are extremely common, as in the instance of the management of south Atlantic snowy grouper (*Epinephelus niveatus*) shown in the righthand panels (SEDAR 2013). Though the stock assessment shows similarly frequent variation between 1994 and 2012, the quota has only been adjusted twice during this period. In contrast to the adjustment in the bluefin quotas, both adjustments in snowy grouper quotas were phased in through steps over several years: 1994-96 and 2005-08. More generally, reviews by Biais (1995) and Patterson (2007) document many cases where changes in catch quotas that a management agency set were more modest than changes that would be recommended just by considering variations in stock abundance.

We use a classic fisheries management question to examine how accounting for costs of policy adjustment can change optimal policies (see also Ludwig (1980), Feichtinger et al. (1994), Wirl (1999)). We focus on how harvest quotas for a stochastically varying fish population can be chosen to maximize the net present value of a fishery. Our formulation and solution method largely follow Reed's classic treatment on this question, a treatment repeated widely in bioeconomic textbooks. We note that while later work has extended this treatment to deal with a variety of other issues (e.g. Sethi et al. (2005); Singh et al. (2006); McGough et al. (2009)), we start from the classical model for simplicity of presentation and analysis.

With his formulation, Reed (1979) showed that a constant escapement policy could be optimal under certain conditions. Such a policy involves choosing annual quotas that are perfectly responsive to recruitment variation in a fish stock. In poor recruitment years, the quota is set to zero and no fishing is allowed. Any time a recruitment pulse exceeds the escapement threshold, a quota is set that allows the fishery to exactly compensate through harvesting, thereby maintaining the optimal escapement level. However, in that analysis, Reed did not account for any costs of policy adjustment, which for such a responsive management strategy potentially could be large.

As the examples in Figure 1 make clear, management policies will rarely be as responsive as this constant escapement policy assumes. In this paper, we consider a case where managers seek to balance the benefits in terms of increased profits from fishing from more finely tracking recruitment variations with the growing costs associated with adjusting policies frequently to do so. The policy adjustment costs involved could reflect pure administrative transaction costs or preferences held by fishermen, fish processing plants or other stakeholders, for less variable quotas. In seeking to account for these policy adjustment costs, we recognize that we do not know just what functional form they should take and that it will require substantial empirical work to estimate that. Therefore, we investigate three candidate functional forms that represent qualitatively different assumptions about how these costs operate to determine whether the results we obtain are sensitive to such differences.

Methods

Fish population dynamics (state equation)

We will assume Beverton-Holt dynamics with multiplicative environmental noise

$$N_{t+1} = Z_t \frac{A(N_t - h_t)}{1 + B(N_t - h_t)}, \tag{1}$$

where N_t the stock size, h_t the harvested level, Z_t gives the stochastic shocks, which we assume are log-normally distributed and A and B are positive constants.

We assume managers set an annual quota for harvesting h_t (the control variable) after observing the stock size that year N_t (the state variable), but while still being uncertain about future environmental conditions and stock sizes. Through time, this gives a time path of management actions $\mathbf{h} = (h_1, h_2, \dots)$ that depend on the stock sizes that were observed (a state dependent control rule).

We assume that managers choose annual quotas to maximize the expected net present value (NPV) of the fishery. We take as a base case the situation where there are no costs associated with policy adjustment and the managers' objective is

$$\max_{\mathbf{h}} \mathbf{E}(NPV_0) = \max_{\mathbf{h}} \sum_{0}^{T_{\max}} \mathbf{E}\left(\frac{\Pi_0(N_t, h_t)}{(1+\delta)^{t+1}}\right) \tag{2}$$

where $\mathbf{E}$ is the expectation operator, $\delta > 0$ is the discount rate and Π_0 is the net revenue from operating the fishery in a given year. In this base case, we assume the annual dockside (that is, before accounting for any adjustment costs that may be incurred) net revenue from fishing is

$$\Pi_0(N_t, h_t) = p h_t - c_0 E_t \tag{3}$$

where E_t represents fishing effort. We assume catch is proportional to stock size and effort expended fishing that year, $h_t = q E_t N_t$ and constant $q > 0$ is the catchability coefficient. In Eqn. (3), p is the price per unit harvest and c_0 the cost of fishing per unit effort and, to simplify the presentation of results, we assume that these are constants with $p > 0$ and $c_0 > 0$.

To simplify presentation of the results, we will illustrate cases where the growth parameters are chosen so that the equilibrium biomass for the equivalent deterministic model without harvesting is 10; (specifically, $A = 1.5$ and $B = 0.05$ in Eqn (1)). To characterize environmental variability, we assume multiplicative shock Z_t is distributed log-normally with log standard deviation $\sigma_g = 0.2$. In addition, we show cases where $p = 10$, $\delta = 0.05$ and $c_0 = 30$. In the supplement we illustrate that the qualitative patterns observed here are not sensitive to the specific choices of these parameter values.

Taken together this objective function (2) and the state equation (1) define a stochastic dynamic programming problem that we solve using backwards recursion via Bellman's equation. We denote the resulting state-dependent, optimal control as $\mathbf{h}_0^*$. We solve this problem on a finite time horizon of $T = 50$ using value iteration (Mangel and Clark 1988, Clark and Mangel 2000).

R code for implementing the dynamic programming algorithm in this context is provided as a supplementary R package to the paper, (github.com/cboettig/pdg_control, Boettiger et al. (2015)), along with scripts for replicating the analyses presented here. To address concerns about computational reproducibility (Boettiger 2015), a Docker container image of the software environment is also provided.

Costs of policy adjustment

We compare this base case to three alternative problem formulations, each reflecting different plausible functional forms that costs of policy adjustment could take. In each, we assume managers can adjust the quota set in the fishery h_t in a given year and that any policy adjustment costs are associated with changes to this control variable. In each case, we assume there is no cost in initially setting the harvest policy at time 0.

First we assume that policy adjustment costs are directly proportional to the magnitude of the change in policy being proposed, such that larger changes to annual harvesting quotas incur greater policy adjustment penalties. Specifically, we replace Π_0 in the NPV_0 equation with

$$\Pi_1(N_t, h_t, h_{t-1}) = \Pi_0 - c_1|h_t - h_{t-1}|\,. \tag{4}$$

Next we continue to assume that policy adjustment costs depend on the magnitude of the change in policy being proposed. However, we consider a case where this dependence is nonlinear with big changes in policy being disproportionately expensive:

$$\Pi_2(N_t, h_t, h_{t-1}) = \Pi_0 - c_2(h_t - h_{t-1})^2\,. \tag{5}$$

Finally, we assume instead that there is a fixed cost associated with any adjustment of policy, regardless of how large that adjustment might be

$$\Pi_3(N_t, h_t, h_{t-1}) = \Pi_0 - c_3(1 - \mathbf{I}(h_t, h_{t-1}))\,, \tag{6}$$

where indicator function $\mathbf{I}(h_t, h_{t-1})$ takes the value 1 if $h_t = h_{t-1}$ and zero otherwise. For each Π_i, we can then define a new objective function NPV_i similar to that in Eqn. (2). We note that the fixed cost has conceptual analogues to the set-up cost of Reed (1974) and

Spulber (1982) but here the fee is associated with a change in harvesting ($h_t \neq h_{t-1}$) and not with harvesting *per se* ($h_t > 0$) as in those studies.

Taken together with the state equation Eqn. (1), each of these new objective functions defines a different stochastic dynamic programming problem. Again, we solve them numerically using backwards recursion. To include costs of policy adjustment, we expand the state space to include both the current stock size and the management action taken on the previous time step (N_t, h_{t-1}). For each new objective function $\max NPV_i$, we denote the corresponding optimal control policy as the vector $\mathbf{h}_i^*$.

Note that this problem is much larger computationally than the classic formulation of this stochastic dynamic programming problem for a single stock. Whereas the classic problem considers each of Q possible discrete quotas for S possible stock values at each time t, for a search space of size $S \times Q$ per timestep; this formulation must also consider all possible values of quota in the *previous* time step: since the costs that will follow depend on whether and by how much the harvest policy will change. This creates a total of $S \times Q \times Q$ configurations.

In the Supplementary Material, we compare our results with more conventional fisheries economic formulation in which additional costs are applied to the control variables themselves, as opposed to adjustments to the controls: $\Pi_4(N_t, h_t) = ph_t - c_0 E_t - c_4 E_t^2$. Additional costs of this form tend to have a smoothing effect on optimal quotas, but also change the long-term average stock size or quota size that is optimal.

Comparing apples to apples

Each policy adjustment cost function is characterized in terms of a cost coefficient c_i. However, c_i takes different units for each functional form. Therefore, if seeking to compare the relative effect of each penalty function on optimal management, it is unclear what parameter values should be used. To address this issue, we calibrate choices of c_i so that each has a comparable impact on the optimal fishery NPV. Fortunately, the optimal control framework provides a completely natural way to make this comparison: in terms of the *economic value* (measured by NPV) of the stock in each case. We will calibrate our realized economic value under each policy relative to economic value of the stock when adjustments to the policy are free (NPV_0).

Figure 2 shows the calibration graphically. Each curve plots the change in maximum expected NPV for a given cost structure as the c_i coefficient is increased. In each case, the figure shows maximum expected NPV with policy adjustment costs as a proportion of the maximum expected NPV available in the basic problem $NPV_0(\mathbf{h_0^*})$ without policy adjustment costs.

To compare the impact of penalty functions on optimal management across the different functional forms, we select penalty cost coefficients that induce the same reduction in maximum expected NPV. For example, the dashed vertical line in Figure 2 maps the needed cost coefficient c_i, for each penalty function, such that the fishery is worth 75% of its unconstrained value when optimally managed. To demonstrate that the results shown here are independent of this choice of calibrating to a 75% reduction, we conduct the same

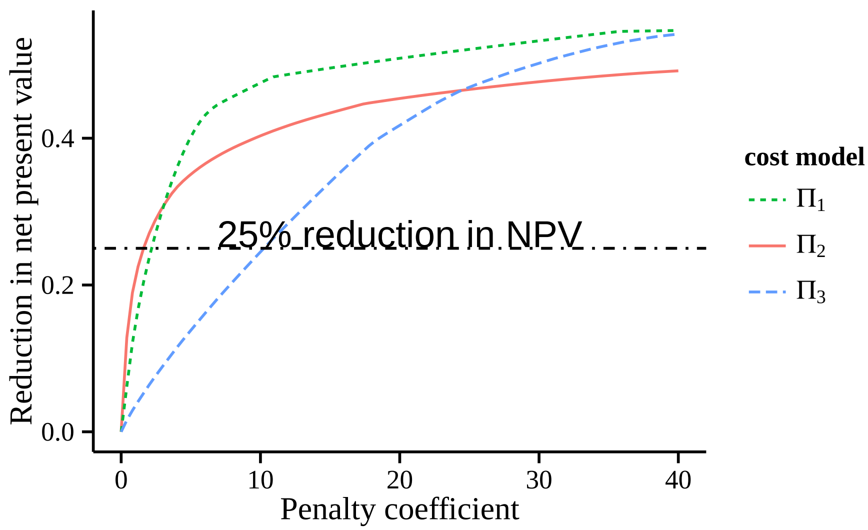

Figure 2: Expected net present value by functional form of penalty. Horizontal axis shows the coefficient c_i governing the magnitude of the policy cost, while vertical axis shows fraction of the maximum expected net present value dissipated by the policy cost, $\frac{NPV_0 - NPV_i}{NPV_0}$. The horizontal line indicates a value of the stock that is reduced by 25% from the maximum expected value in the absence of policy adjustment costs, $NPV_0(\mathbf{h_0^*})$. Selecting the coefficient c_i corresponding to this value in each functional form allows us to make consistent comparisons across the different functional forms of policy costs.

analysis with a 10% and 30% reduction rate as well. The corresponding figures can be found in the Supplemental Materials.

Results

Effect of policy adjustment costs on optimal quotas and stock sizes

Figure 3 illustrates how the different forms of adjustment cost can impact the dynamics of the optimal harvest policy. Corresponding stock sizes can be seen in the supplement. Each panel is generated against the same sequence of environmental variability so that they can be compared directly. The harvest policy chosen shows a systematic deviations from the adjustment cost free optimum, depending on the structure of the cost function.
In each case, the optimal solution without any adjustment cost is shown by the dashed grey line, with the policy induced by optimization under the given cost structure (equivalent to a 25% reduction in maximum expected NPV) overlaid in solid blue.

The first panel shows a typical pattern resulting from linear adjustment costs (Π_1). The optimal policy tends to avoid very small policy adjustments, resulting in periods of a constant policy followed by sudden bursts of adjustment. This results in a relatively step-like policy pattern. In contrast, the second formulation (quadratic costs, Π_2) disproportionately penalizes large policy adjustments. The corresponding optimal policy is typified by the middle panel, responding to each of the fluctuations in stock, made by the cost-free policy, but with smaller magnitude response than the equivalent cost-free optimal solution. This

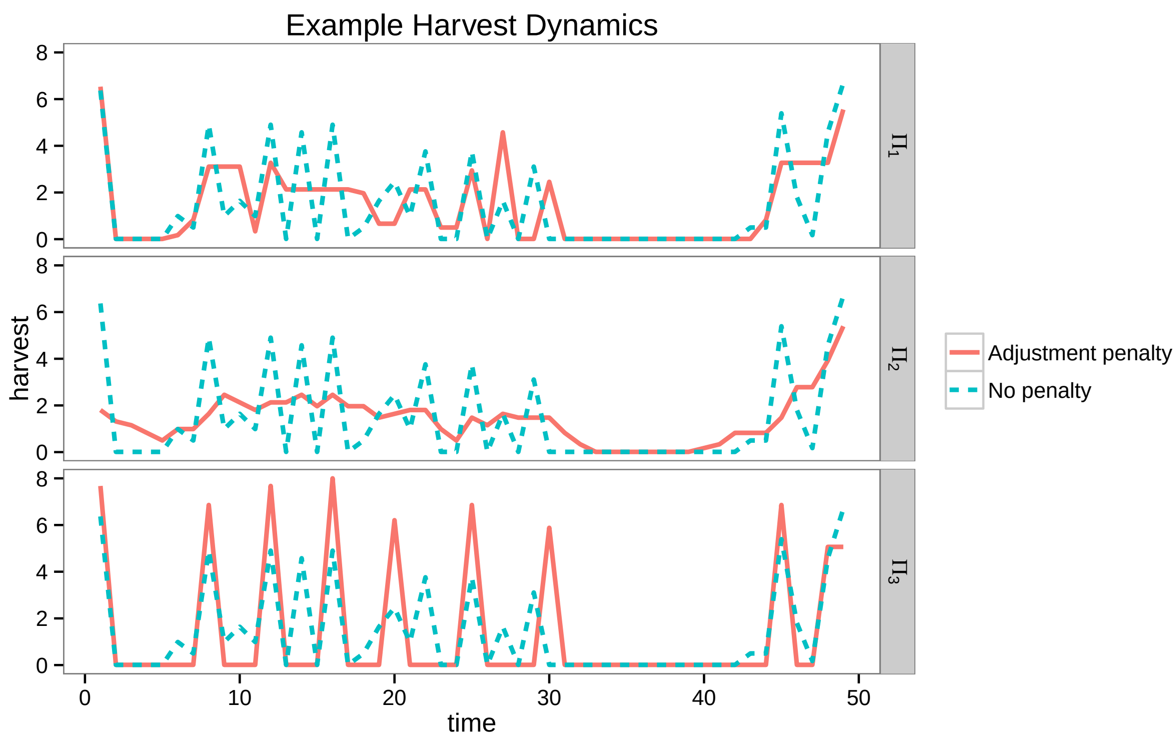

Figure 3: Example realization of optimal harvesting strategy under the different functional forms of adjustment costs. When costs vary linearly with the size of the adjustment (Π_1), periods with no adjustment are more common than if adjustments were free. When costs vary quadratically with adjustment size (Π_2), small adjustments are relatively cheap and thus the resulting optimal policy always changes, but by a smaller amount than if adjustments were free. When adjustments incur a fixed fee independent of size (Π_3), the optimal strategy either remains unchanged or overshoots the cost-free optimum.

results in a smoother h_t curve, one that undershoots the larger oscillations seen in the cost-free optimum in favor of a policy that changes incrementally each year. Finally, the optimal policy for the third, 'fixed fee' formulation (Π_3) only makes large adjustments, as one might expect, because the magnitude of the adjustment made is not reflected in the resulting cost.

These patterns are consistent across stochastic replicates over a range of penalty magnitudes. The comparisons shown in Figure 3 are for one realization (i.e. a particular sequence of random number draws representing environmental variability) and are made for one particular magnitude of policy adjustment costs, which have been calibrated to equal to 25% of $NPV_0(\mathbf{h_0^*})$. To demonstrate this, we solved for the optimal policy under each of the three adjustment cost scenarios for 100 different c_i coefficients. For each resulting policy, we then simulated 500 stochastic replicates of the stock dynamics managed under that policy. To summarize the patterns shown in Figure 3 and characterize the impact of increasingly large fraction of the economic value (NPV) being consumed by policy adjustment costs, we examine the response of several summary statistics to increasing adjustment penalties (as a fraction of the adjustment-free value) in Figure 4. We show the impact of policy adjustment costs on the variance & autocorrelation of the harvests through time.

Despite summarizing across such a large ensemble, Figure 4 confirms the patterns we observed in the individual realizations shown in Figure 3. For example, when small policy adjustments cost little but large adjustments are expensive (Π_2), we see the smoothing signal that we might have expected (see also Ludwig (1980) for this particular case). As cost penalties increase in severity (moving right along the horizontal axis, larger fractions of the economic value are consumed by adjustment costs), the variance in quotas through time decreases and the autocorrelation of quotas through time increases. When adjustment costs are zero, all policies are slightly negatively autocorrelated: this reflects the fact that a high harvest year is usually followed by a low harvest year that allows the stocks to recover. However, as adjustment costs increase, the quadratic policy tends to undershoot when stocks jump to very high or low levels, adjusting to compensate over multiple years, as seen in Figure 3. As a result, autocorrelation increases.

Interestingly, as suggested by the realization in Fig. 3, including a fixed cost (Π_1) of policy adjustment increases the variation in harvests through time. This is the opposite of a smoothing effect.

Finally, the case where policy adjustment costs scale linearly with the size of the adjustment (Π_1) appear to be something of a middle of the road strategy, in that increasing the severity of policy adjustment costs. To reveal the particular impact of policy adjustment costs of this type requires a more targeted summary statistic. Specifically, for each run we calculated the frequency with which the optimal policy involved maintaining a positive quota across multiple time steps unaltered. This type of policy is arguably the most commonly observed behavior in TAC management, but is one that is very rarely observed to be part of the optimal management strategy in the basic model without policy adjustment costs (Eqn. 3) or when optimizing against Π_2 or Π_3.

Figure 4 shows these qualitative patterns still hold at when the models are calibrated to a range of different reductions in NPV, from 0% to 30%, though naturally the magnitude of

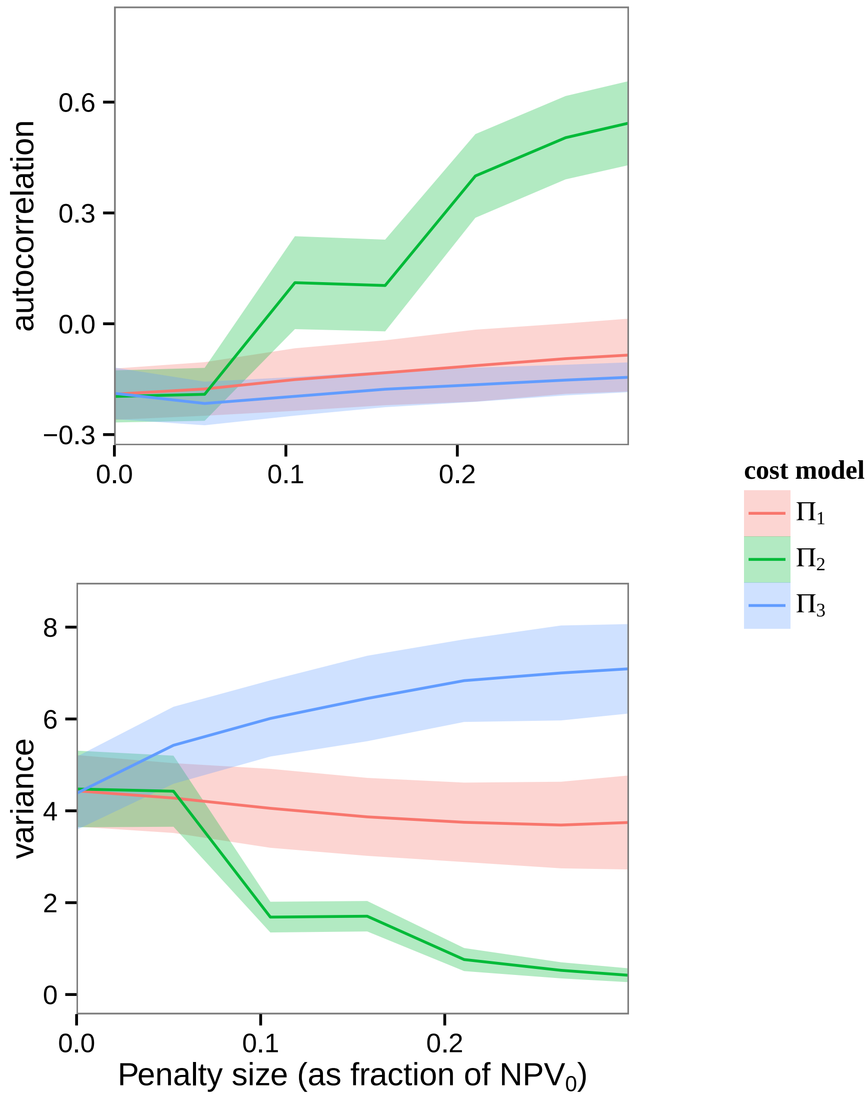

Figure 4: Variance and autocorrelation of harvest dynamics, as a function of the penalty coefficient. Adjustment penalty is calculated as percentage of the maximum expected NPV in the basic case with no policy adjustment costs.

the differences is greatest when the penalty is larger. Note that the supplementary material provide further evidence that these patterns are independent of the exact reduction shown by providing results analogous to Figure 3 (S8, S9) and Figure 5 (S10, S11), and Figure 6 (S6).

While still not common for the particular parameter combinations we examine, we find that positive unaltered quotas through time are much more likely to occur when optimizing against Π_1 where policy adjustment costs scale linearly with the size of proposed policy changes: over the 100 replicates time series the harvest policy is strictly positive and identical in consecutive intervals only 9.88% of the time for quadratic costs Π_2, compared with 20.78% with linear costs Π_1 and 0.37% for fixed costs Π_3. Moreover, these occurrences increase in frequency as the severity of these costs (c_i) increases. Note that the restriction of only positive quotas lets us distinguish between cases that are constant due purely to adjustment costs from cases that are constant purely due to boundary effects.

Consequences of policy adjustment costs

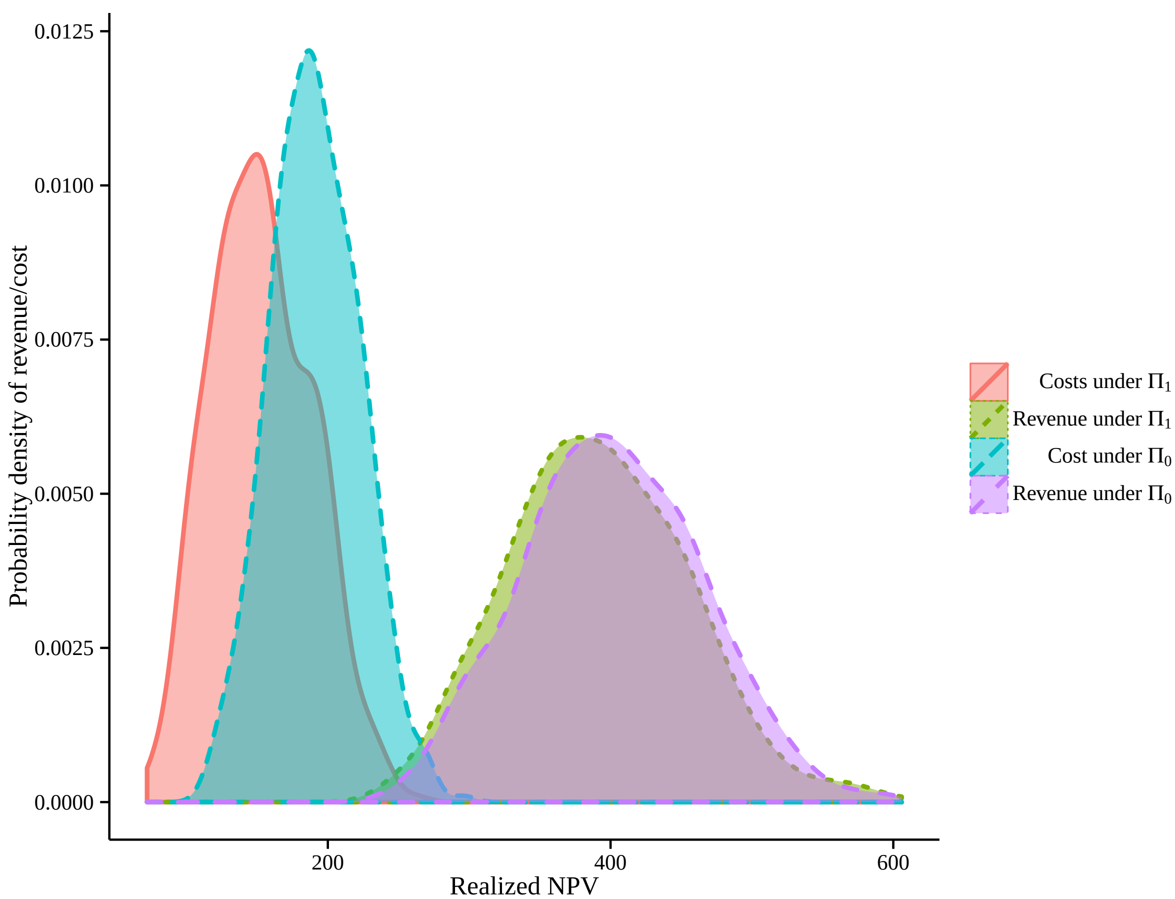

Figure 5: Distribution of revenues from fishing and costs paid to adjustment. Plot shows distributions for the linear costs structure (Π_1) only, alternate penalties can be found in the supplementary materials. Dockside revenues are always higher than adjustment costs. When those costs are not accounted for in the policy ('no adjustment costs'), it is possible to obtain only marginally higher revenues, but pay higher adjustment costs.

Next we examine the consequences either of ignoring policy adjustment costs when they are present or assuming they are present when they are not.

To do so, we will simulate managing a fish stock when adjustments are costly. We will perform 500 replicate simulations of this for each of the three cost structures, Π_1, Π_2, & Π_3. For each replicate, we will use two different management policies: one which ignores the adjustment costs, (that is, the Reed optimum policy, Π_0), and a second which accounts for the adjustment cost in place.

By comparing the NPV of this second scenario against the first, we can quantify the impact of ignoring costs when they are present.

Figure 5 shows that the difference in dockside revenue (labeled "profits" in the figure) between these two scenarios (green vs purple distributions) is very small, while a larger difference exists between the costs paid for making policy adjustments (red vs blue). This is predicted by the optimization: the first scenario must outperform (or at least equal) the NPV of the second scenario in aggregate, and as it cannot do so through higher profits (these having already been maximized by the cost-free strategy), it must do so through lower costs. Interestingly, for this set of parameters very little is lost in revenue. This suggests that the impact of assuming costs are present when they are not is rather small, as the revenue is nonetheless near optimal. This also suggests that the converse error – ignoring costs when they are present – is more severe.

We illustrate the differences between these two errors directly in Figure 6. Subtracting revenue from adjustment costs and considering only the mean across the replicates, we can derive the expected NPV in each case. To standardize against a common baseline, we will express this value as a fraction of the cost free optimum, NPV_0. Note that we have calibrated the optimal solutions to anticipate that 25% of their NPV would go into adjustment costs. When these adjustment costs are not actually present (blue bars, Fig 6), we thus expect a NPV higher than the anticipated 75% but not quite as high as the optimal policy for that scenario (100%). When adjustment costs are present but the policy assumes that they are not (red bars), we would expect the NPV to be less than 75% of NPV_0 (since that's as good as the optimal solution for this scenario can do).

Figure 6 shows that across each penalty form Π_1, Π_2 & Π_3, the economic impact of ignoring adjustment costs when they are present is higher than accounting for them when they are absent. This holds even after accounting for effect described above: the red bars are consistently well below the 75% of NPV_0, while the blue bars are barely below NPV_0 (a value of 1 on the vertical axis). We also see that the impacts on net present value of the fishery of incorrectly assuming or ignoring policy adjustment costs are most severe when these costs are assumed to scale quadratically with the size of the policy change being implemented (Π_2). In the Supplementary Materials we show that pattern holds across different severity of adjustment costs (robust to choice of c_i), though the larger the adjustment cost, the greater the difference between these two errors.

Note that this analysis does not consider the possibility that an adjustment cost is present, but of a different functional form than the policy assumes. The consequences of managing under the wrong functional form can be as or more severe than simply ignoring adjustment

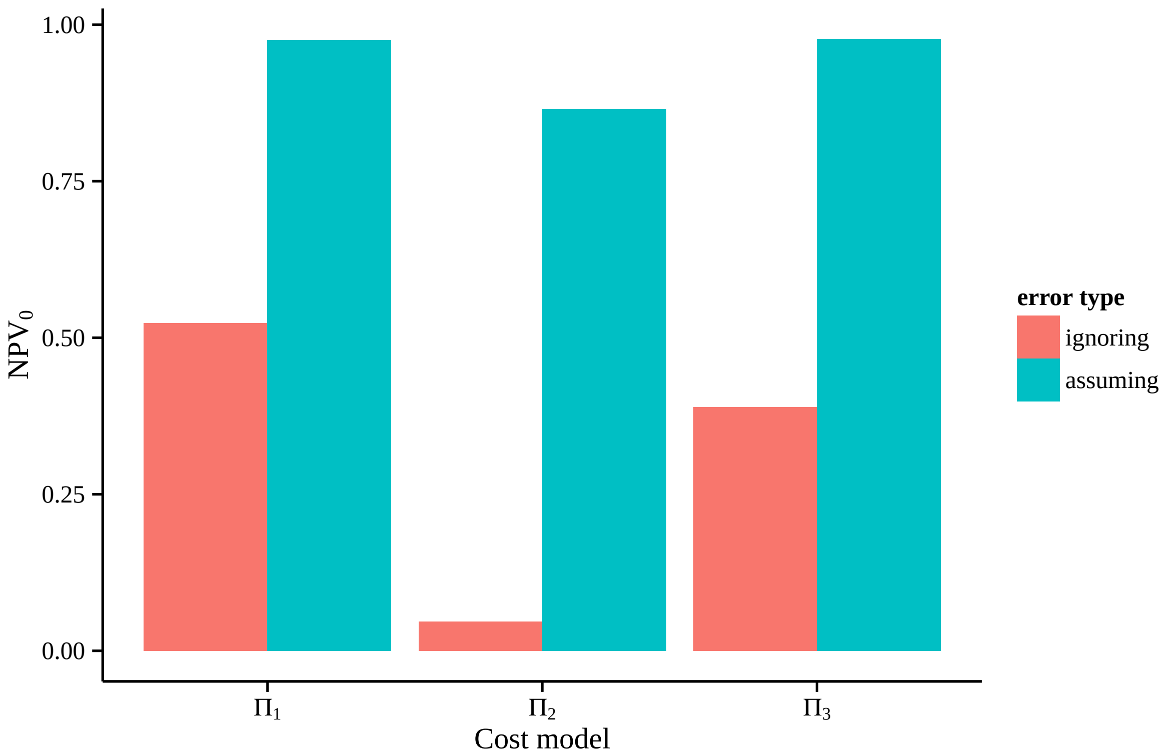

Figure 6: Relative cost of ignoring adjustment costs when they are present ('ignoring', red) vs assuming the adjustment costs when they are absent ('assuming', blue). All values are relative to the cost free adjustment optimum, NPV_0. In each case, it is less costly to assume adjustment costs are present when they are not than it is to ignore them when they are present.Supplementary Figure S6 shows how the magnitude of this effect changes with the size of the reduction to NPV.

costs in the optimization altogether. We illustrate several of these mismatch errors in the Supplementary Material.

Discussion

Policymakers managing ecological systems that vary in space and time must evaluate how much of that variation to reflect in management recommendations. Finer tuning a policy to respond to frequent variations in ecological dynamics may incur increased transaction costs associated with constantly revisiting past policy decisions. A more pragmatic approach would be one that balances benefits from responding to frequent variations in ecological conditions with the increased transaction costs involved. As a first step towards exploring these ideas, we revisited a classic problem from bioeconomics concerning the optimal management of a fish stock subject to stochastically varying recruitment (Reed 1979, Clark 2010). We examined how optimal policy recommendations – here annual catch quotas – changed when accounting for costs associated with policy adjustment and what the implications of following these policy recommendations would be for the exploited population. We also compared how the value of the fishery is affected by managers either under- or overestimating the importance of policy adjustment costs of this type.

Estimating policy adjustment costs and how they respond to the size of proposed policy changes would be empirically challenging. Recognizing this fact, we compared different plausible forms that these costs might take. We compared two cost structures where we assumed the magnitude of policy adjustment costs increased with the magnitude of the change in policy being proposed with an alternative formulation in which we assumed there was a fixed cost associated with making any change to current policy. While each formulation provides only very phenomenological representations of the policy-setting environment, we believe that each enables us to explore meaningful differences in how policy adjustment costs might operate. That being said, in the real world we might expect the different types of adjustment cost to operate in combination.

The biggest differences between the representations of policy adjustment cost that we consider are between those that have a smoothing effect on annual quotas and those that do not. The few past studies that incorporate policy adjustment costs in models of fisheries or other environmental management contexts (Feichtinger et al. 1994, Wirl 1999) have assumed costs of policy adjustment increased as a quadratic function of the magnitude of the policy change being proposed (analogous to Π_2 formulation). In effect, this means that small changes to annual quotas incur little extra cost, but large changes to annual quotas become disproportionately expensive to make. Including costs of this form smooths inter-annual variation in the recommended catch quotas. Also, the catches and remaining stock sizes corresponding to optimal management become more autocorrelated in time, because it takes the fishery multiple timesteps to harvest down peaks in abundance that follow large recruitment pulses. The effects of smoothing here are similar to those predicted when assuming the cost per unit effort is increasing in the amount of effort expended (Brown 1974, Lewis 1981, McGough et al. 2009); (see Supporting Information for a summary of the relevant results) as opposed to associating extra costs with changes to policy *per se*.

Smoothing effects of this type are what one might have expected when including policy adjustment costs.

Standing in sharp contrast to these smoothing predictions is our finding that including policy adjustment costs can actually *increase* the variability of quotas through time if there is a fixed cost associated with making any changes to current policy (e.g. costs of running relevant stakeholder meetings and public consultations on proposed policy changes, Π_3). With this formulation, as stock sizes vary in response to recruitment, the fishery manager must balance the cost of brokering a policy change with the cost in forgone fisheries revenue from not responding to favorable recruitment pulses. The optimal policy involves ignoring small variations in recruitment, but then assigns a larger quota when particularly strong recruitment years arise than would have been the case in the absence of policy adjustment costs. The other functional form we consider, in which the costs of policy adjustment scale linearly with the size of the adjustment (Π_1), has less obvious effects on optimal policies. Interestingly, it is this structure that most frequently produces stretches of strictly positive but unchanging quotas of the type most commonly encountered in real world applications.

That the different representations of policy adjustment costs result in such different dynamics suggests that researchers constructing fisheries economics models should proceed cautiously when choosing how to represent these costs. However, in our own experience, we have found that while modeling studies sometimes mention policy adjustment costs when motivating model assumptions (Brown 1974, Lewis 1981, Feichtinger et al. 1994, Wirl 1999, McGough et al. 2009), they rarely provide much justification for the choice of functional form used or test the sensitivity of any conclusions drawn to alternative specifications. Indeed, we were surprised to find such clear differences between the functional forms, because we anticipated that the limiting case of increasing policy adjustment costs within each functional form should be the same, namely a constant annual quota that does not change through time.

We also compared the efficiency costs that would result from failing to account for policy adjustment costs, if they are present, with those involved in assuming them when in fact they are absent. The results of this comparison were not sensitive to the particular form of policy adjustment costs assumed. Instead, we always found the efficiency costs of ignoring policy adjustment costs when they were present to be much larger than the efficiency costs of assuming policy adjustment costs applied when they were in fact absent. Policy adjustment costs affect the overall value of the fishery in two ways here. First, there is the direct cost associated with each quota change. Second there is a cost in foregone revenue from missed catches when not following what would be the optimal policy if quotas were free to track recruitment variability. Our finding that it is more costly to ignore policy adjustment costs when they are present arises because the first, more direct, cost contribution here is the larger.

Assuming an adjustment cost exists when in fact it is absent is not the same as using the wrong functional form when it is present. In the supplement we show that choice of the functional form makes a significant difference. We show it can be better to ignore policy costs than to derive a policy based on assuming the wrong functional form. This result further underscores the importance of modelers using caution when seeking to account for these costs. Assuming an arbitrary form in order to capture the influence of adjustment costs is thus unlikely to be instructive.

As with any modeling analysis, our formulation makes many assumptions. For example, we assume that the fishery in question is being optimally managed by a policymaker who acts as the "sole owner" of the stock. This approach is different to models that assume fisheries are not well managed, e.g. by assuming regulated open access conditions (Homans and Wilen 1997), or models that derive policy recommendations endogenously by modeling strategic interactions between different stakeholders (Kaitala 1993, Laukkanen 2003). As such, we anticipate that our approach will be more relevant to some fisheries, particularly domestic fisheries in developed countries that are subject to relatively strong regulatory regimes, than to others (e.g., artisanal fisheries that are subject to weaker regulation). To focus on the effects of policy adjustment costs, we focused narrowly on the basic model specification of Reed (1979) and examined how the predictions of this classic problem were changed by introducing policy adjustment costs of different forms. However, there have been many elaborations on Reed's basic approach that increase the realism of the optimization models involved by relaxing other assumptions (see for example Sethi et al. (2005); Singh et al. (2006); McGough et al. (2009)).

One obvious research avenue suggested by our models is that of empirically estimating costs of policy adjustment. A direct estimation approach could quantify some sources of policy adjustment costs, e.g. costs to processing plants that arise from having more variable catches. However, other more intangible sources of policy adjustment costs, e.g. preferences of policymakers or different stakeholders for less variable quotas, might be missed. An alternative, more holistic, approach would be to apply revealed preference methods to fisheries management agencies themselves, in the tradition of (McFadden 1975, 1976). Such an analysis would involve comparing quotas that were set relative to stock sizes as they were estimated at the time each management decision was taken to try to infer what objective managers were maximizing.

A worthwhile modeling extension suggested by our results would be to examine the implications of policy adjustment costs for risks of stock collapse. This includes models with larger stochasticity as well as model formulations that can permit alternative stable states. Examining risks of stock collapse is not possible with the Reed model formulation that we followed here (both cases are inconsistent with the assumptions of Reed (1974)) but would be worthwhile in light of our finding that the variance and autocorrelation in stock sizes through time can be affected when accounting for costs of policy adjustment. Both are properties known in other modeling settings to be associated with changes to the risk of extinction or of transitions between alternative stable states (Scheffer et al. 2009). This highlights the risk that changes in management policies can either mimic or mask such possible early warning signs of sudden transitions, and points to another way in which more context is needed before such approaches can be useful to management (Boettiger et al. 2013).

When facing highly variable ecological systems, how often should natural resource managers respond? A highly interventionist strategy would track ecosystem variation very closely. Alternatively, a manager might choose only to take action or change policy only when conditions look very different to those previously experienced. We took a modeling approach to begin to explore these ideas. Specifically, we focused on a well-known problem from fisheries management and examined how optimal management recommendations changed when we accounted for costs associated with frequently changing management decisions. While we focused on a fisheries context, our findings would be relevant to many other settings where natural resource managers revisit management decisions through time in light of ecological variability, including game management, management of instream flow rates, fire management, habitat restoration, and managing for endangered species. The analyses that we present can also be thought of as providing a temporal counterpart to discussions about the spatial scale over which ecosystem management.

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References

Armsworth, P. R., and J. E. Roughgarden. 2003. The economic value of ecological stability. Proceedings of the National Academy of Sciences of the United States of America 100:7147–51.

Armsworth, P. R., B. A. Block, J. Eagle, and J. E. Roughgarden. 2010. The role of discounting and dynamics in determining the economic efficiency of time-area closures for managing fishery bycatch. Theoretical Ecology.

Biais, G. 1995. An evaluation of the policy of fishery resources management by TACs in European Community waters from 1983 to 1992. Aquatic Living Resources 8:241–251.

Boettiger, C. 2015. An introduction to Docker for reproducible research, with examples from the R environment. ACM SIGOPS Operating Systems Review 49:71–79.

Boettiger, C., M. Bode, J. N. Sanchirico, J. LaRiviere, A. Hastings, and P. Armsworth. 2015, July. Repository for: Optimal management of a stochastically varying population when policy adjustment is costly.

Boettiger, C., N. Ross, and A. Hastings. 2013. Early warning signals: the charted and uncharted territories. Theoretical Ecology.

Brown, G. 1974. An optimal program for managing common property resources with congestion externalities. Journal of Political Economy.

Clark, C. W. 2010. Mathematical Bioeconomics: The Mathematics of Conservation. Third editions. Wiley; Sons, Hoboken, NJ, USA.

Clark, C. W., and M. Mangel. 2000. Dynamic state variable models in ecology. Oxford University Press, Oxford.

Durrett, R., and S. A. Levin. 1994. The importance of being discrete (and spatial). Theoretical Population Biology 46:363–394.

Feichtinger, G., A. Novak, and F. Wirl. 1994. Limit cycles in intertemporal adjustment models. Journal of Economic Dynamics and Control 18:353–380.

Halpern, B. S., C. White, S. E. Lester, C. Costello, and S. D. Gaines. 2011. Using portfolio theory to assess tradeoffs between return from natural capital and social equity across space. Biological Conservation 144:1499–1507.

Homans, F. R., and J. Wilen. 1997. A model of regulated open access resource use. JEEM 32:1–21.

International Commission for the Conservation of Atlantic Tunas (ICCAT). 2009. Report of the 2008 ICCAT bluefin stock assessment session. ICCAT Collective Volume of Scientific Papers 64:1–352.

Kaitala, V. 1993. Equilibria in a stochastic resource management game under imperfect information. European Journal of Operational Research 71:439–453.

Laukkanen, M. 2003. Cooperative and non-cooperative harvesting in a stochastic sequential fishery. Journal of Environmental Economics and Management 45:454–473.

Lewis, T. R. 1981. Exploitation of a renewable resource under uncertainty. The Canadian Journal of Economics 14:422.

Ludwig, D. 1980. Harvesting strategies for a randomly fluctuating population. Journal du Conseil 39:168–174.

Mangel, M., and C. W. Clark. 1988. Dynamic modeling in behavioral ecology. (J. Krebs and T. Clutton-Brock, Eds.). Princeton University Press, Princeton.

McFadden, D. 1975. The revealed preferences of a government bureaucracy: Theory. The Bell Journal of Economics 6:401.

McFadden, D. 1976. The revealed preferences of a government bureaucracy: Empirical evidence. The Bell Journal of Economics 7:55.

McGough, B., P. A. J., and C. Costello. 2009. Optimally managing a stochastic renewable resource under general economic conditions. The B.E. Journal of Economic Analysis & Policy 9:1–31.

Neubert, M. G. 2003. Marine reserves and optimal harvesting. Ecology Letters 6:843–849.

Patterson, K. 2007. Social resistance to the obvious good: A review of responses to a proposal for regulation of european fisheries. American Fisheries Society Symposium:587–596.

Patterson, K., and M. Resimont. 2007. Change and stability in landings: the responses of fisheries to scientific advice and TACs. ICES Journal of Marine Science 64:714–717.

Porch, C. E. 2005. The sustainability of western Atlantic bluefin tuna: a warm-blooded fish in a hot-blooded fishery. Bulletin of Marine Science 76:363–384.

Reed, W. J. 1974. A stochastic model for the economic management of a renewable animal resource. Mathematical Biosciences 22:313–337.

Reed, W. J. 1979. Optimal escapement levels in stochastic and deterministic harvesting models. Journal of Environmental Economics and Management 6:350–363.

Safina, C. 1998. Song for the blue ocean: Encounters along the world's coasts. Henry Holt, New York.

Sanchirico, J. N., M. D. Smith, and D. W. Lipton. 2008. An empirical approach to ecosystem-based fishery management. Ecological Economics 64:586–596.

Scheffer, M., J. Bascompte, W. A. Brock, V. Brovkin, S. R. Carpenter, V. Dakos, H. Held, E. H. van Nes, M. Rietkerk, and G. Sugihara. 2009. Early-warning signals for critical transitions. Nature 461:53–9.

SEDAR. 2013. SEDAR 36 stock assessment report: south Atlantic snowy grouper. Page 146. SEDAR, North Charleston SC.

Sethi, G., C. Costello, A. Fisher, M. Hanemann, and L. Karp. 2005. Fishery management under multiple uncertainty. Journal of Environmental Economics and Management 50:300–318.

Singh, R., Q. Weninger, and M. Doyle. 2006. Fisheries management with stock growth uncertainty and costly capital adjustment. Journal of Environmental Economics and Management 52:582–599.

Sissenwine, M. P., P. M. Mace, J. E. Powers, and G. P. Scott. 1998. A Commentary on western Atlantic bluefin tuna assessments. Transactions of the American Fisheries Society 127:838–855.

Spulber, D. F. 1982. Adaptive harvesting of a renewable resource and stable equilibrium. Pages 117–139 *in* L. Mirman and D. Spulber, editors. Essays in the economics of renewable resources. North-Holland Publishing, Amsterdam.

Walters, C. J. 1978. Some dynamic programming applications in fisheries management. *in* J. Petkau, editor. Dynamic programming and its applications. Academic Press.

Wirl, F. 1999. Complex, dynamic environmental policies. Resource and Energy Economics 21:19–41.