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Constrained Marine Resource Management

A dissertation submitted in partial satisfaction of the
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in
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by

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2007

The dissertation of Jason Hastings Murray is approved, and it is acceptable in quality and form for publication on micro-film:

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Chair

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2007

DEDICATION

To my parents

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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This work could not have been written without the guidance and inspiration given by my advisor Richard Carson. Richard's intuition on all manner of economic and policy problems has shaped my work and thoughts and will continue to influence my future research. Dale Squires' expertise and advise both technical and personal was invaluable. I could not have written Chapters 2 or 3 without Ted Groves incisive weekly criticism. The inspiration for Chapter 3 came from several years of involvement with the good people at the Center for Marine Biodiversity at The Scripps Institution of Oceanography. Meeting these passionate ecologists led me to a greater understanding and appreciation for marine systems.

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ABSTRACT OF THE DISSERTATION

Constrained Marine Resource Management

by

Jason Hastings Murray
Doctor of Philosophy in Economics
University of California, San Diego, 2007
Professor Richard T. Carson, Chair

The main theme of this dissertation is a challenge to the traditional paradigm of optimal control for the management of renewable resources. That is not to say that optimization should not be the goal but rather, previous modeling and policy have presumed that managers have greater control and knowledge of marine systems than is the case. All models make simplifying (and false) assumptions but assuming control and knowledge in marine systems is not benign. In a dynamic control problem, one must actually control the variable of interest and know or learn the system's parameters. I discuss reasons why managers may not control harvests and cannot know system parameters and consider possible remedies to the historically sub-optimal management of marine resources.

Marine resources are observed imperfectly and are often held as common property. In this dissertation I explore the feasibility of management plans when natural-capital stock dynamics are unobservable and when political structures constrain the implementation of optimal management. Resource managers are faced with conflicting user groups and limited information. In three chapters I study constrained management. In my first chapter, "Jobs or Resources?" I consider the political economy implications

of technological change under various management scenarios. I show that typical management targets will require the retirement of inputs as technology progresses. This is particularly problematic for fisheries in which labor is involved in management decisions. This can lead to false inference about the health of the stock.

For the second chapter, "Natural Resource Collapse: Technological Change and Biased Estimation", I show that unexpected fisheries collapse may be linked to unobserved technological change. Unexpected collapse of natural resources is of great concern to policy makers. The literature and popular press have attributed collapse to the lack of well-defined property rights and policies that pay inadequate attention to random environmental variability. Both the literature and policy makers have overlooked how unobserved technological change can obscure the depletion of natural capital stocks. The paper shows that even if property rights are well-defined and random fluctuations are small, modest increases in technical efficiency conceal the depletion of stocks. Using the most general model of surplus production in a single-species fishery I show analytically that proportional growth of the fish stock is overestimated when even one period of technological change is ignored. Through simulations, I find that standard statistical tests overestimate the productivity of the fish stock. I show that collapse is inevitable if technology increases without bound and that the path to collapse is not observed until stocks are low and declining rapidly.

In the third chapter, "Marine protected areas as a risk management tool" I consider a potential fix to the inference problems highlighted in the second chapter and in other work such as Carson and Murray (2005). When parameter uncertainty is significant, I show that even in an otherwise deterministic world, expected payoffs can be increased by using simple spatial closures. Though optimal fleet size and reserve size combinations exist, a spatial closure can increase expected payoff even if the fleet-size

is chosen to be too large or too small. The benefit of closures is not limited to hedge against stock collapse but is of value even when stock size is large and steady-state catches are relatively high.

I

Lose Jobs or Resources?

Abstract

Technical progress has long been identified as a factor influencing a fishery but its management implications have not been seriously considered in the literature. This paper considers the implications of disembodied Hicks-neutral technical progress in a static Gordon-Schaeffer fishery model. Implications for ITQ fisheries and other management regimes are considered. While the paper considers fish as the resource, the results are directly applicable to any renewable resource exhibiting compensatory growth.

I.A Introduction

There are many results in the Economic theory literature on fisheries management that have focused on the determination of the optimal TAC (total allowable catch). Causes of randomness have been considered for the biological growth process, stock assessments and fishing quota enforcement. See, for example, Roughgarden and Smith (1996) and Sethi et al. (2005). Randomness in output price has also been considered by Grafton (1993) and Anderson (1982). One potentially crucial source of randomness has been largely overlooked; technical progress. Even a fully rationalized fishery today could, in the face of technical progress, lead to inefficiently high inputs in the future. This is particularly relevant if we expect that inputs to the fishery are not very mobile. Hanneson (2000) shows even in an ITQ fishery with no problems of enforcement, higher than optimal levels of investment can be expected when labor is compensated with a share of vessel rents. In a fishery where total catch limits are difficult to enforce technological change could lead to an over-fishing problem. In a fishery with perfect harvest control, technological change can lead to a sub-optimal allocation of resources. The management implications of this potential include the removal of inputs now (through market based or command/control methods) and discouragement of investment now in order to compensate for future increases in productive capacity due to technical progress.

This paper considers a simple, static Gordon-Schaeffer model of a fishery. While technical progress is not explicitly considered as random, the comparative statics are relevant for deterministic known or realized increases in technical progress or as yet unrealized stochastic ones. Under the assumption that fishing effort is a constant returns to scale aggregator function of labor and capital, it can readily be shown that in either an optimally managed fishery or an open access fishery, the effect of technical

progress on factor demands is ambiguous. The more interesting result is found when the fishery is managed by a given total catch and corresponding level for the resource stock (maximum sustainable yield is a convenient example to consider though the results are similar for any sustainable harvest level.) In this case conditional factor demands can be shown to have negative unit elasticity with respect to a Hicks neutral technical progress parameter. In this simple model, a manager who knows the average rate of technical progress can calculate how exactly how much the inputs should decrease for any given level of harvest. If harvesters manage themselves to minimize costs subject to the given output constraint, then this merely tells the manager the portion of inputs she can expect to see leaving the system. If input decisions are made sub-optimally or if the managers output control is imperfect, this result provides the manager with a target quantity of each input to purchase or remove from the system.

I.A.1 Technical Progress and Inputs in previous literature

There is a great wealth of economic literature measuring and identifying sources of technical progress. These goals, while worthy, are somewhat beyond the scope of this present investigation. Technical Progress of the type to be considered in this paper (disembodied Hicks-neutral) and its potential effects on input demands have been considered theoretically and empirically for both micro and macro applications. For example, Sinclair (1981) considers a very general neoclassical macro model and finds that the effects of technical progress on aggregate employment depend on the reactions of wages, and various elasticities such as that of substitution between labor and capital. Sinclair (1981) also considers some empirical evidence from the U.S. economy and finds that effects of technical progress on number of jobs is still ambiguous and depends on assumptions about the wage rate's flexibility. Empirical micro-level studies

have investigated various types of industries, even as far back as 1930, Baker (1930) investigates the effects of technical progress on job loss in New York printing presses in the 1913-1928 period and finds “less man displacement from technical change than had been anticipated.”

In the micro theory of a fishery, very little work has been done in terms of technical progress. In fact a search of the fisheries economics literature will find no strictly theoretical results but rather many empirical exercises concerned principally with measurement of some proxy for technical change. Two such examples are Kirkley et al. (2004) investigating the Sete trawl fishery in southern France (’85-’99) and Squires (1992) investigating the Pacific coast trawl fishery (’81-’89). Both papers find that total productivity increased on average by approximately 1% per annum over the total period studied.

I.A.2 Why consider technical progress in a fishery?

It is well known that the standard economic optimum of a fishery can be achieved with individual transferable quotas (ITQ’s). An ITQ system is a simple instrument which can solve the inherent ”tragedy of the commons” that characterizes an open access fishery. By establishing a total allowable catch (TAC) for the entire fishery and subdividing this total catch into individual tradeable initial allocations across the individuals involved in the fishery, an ITQ system allows for efficient harvesting of the resource subject to the total catch allowance. That is, since the quotas are tradeable, less efficient vessels will sell their permits to efficient ones and so the TAC will be harvested at minimum cost. The problem of the manager, so the standard story goes, becomes to choose the appropriate TAC. There are real-world success stories for ITQ’s. New Zealand has adopted an ITQ system dubbed the QMS or quota management system.

”New Zealand fishing was on the brink of collapse and now it is not. Fish stocks were finished and now they are being sustained.” Online (2000)

It is also well known that fishermen are frequently resistant to ITQ’s. Their resistance is not surprising. While ITQ’s can lead to a maximization of the aggregate sustainable rents, there are many losers if a fishery’s current harvest levels are sufficiently high that an ITQ (which reduces aggregate harvest) will drive fishers and or vessels out of the fishery. For a discussion of the results of New Zealand’s conversion to an ITQ system directed at the concerns of fishers see Online (2000). The New Zealand fisheries have done well under this new system. Catches and stocks are up and the industry is profitable. There are predictable distributional effects from the ITQ system and these are exemplified by the quote below. It is not surprising that many fishers in current fisheries are reluctant to accept ITQ management schemes given these experiences;

> To begin with, it is the fishing companies and not New Zealand fishermen, which have benefited since 1986. The fishing companies were already running their own fleets of fishing boats, and so they immediately netted a major share of quota. In the 1980’s individual fishermen were more likely to be landing fish to a company than selling the catch on any market. This arrangement had put the companies in a dominant position over the fishermen before anyone had even dreamed of QMS. The fishing companies and fish dealers did then, and still do, represent sole the market for New Zealand fish. In general, an independent fisherman negotiates a price with a company even before going to sea and then fishes at a stable landing price for up to a year. As the major owners of quota and most of the fleet, shore based fishing companies control almost the entire New Zealand fish catching sector....
>
> Once fishermen had sold their quotas, the only assets they had left were boats. As they had no direct access to quota, the boat became virtually redundant. With fishing effort so reduced, there was over-capacity in the fleet. Therefore, even the boats were rendered worthless. An entire generation of owner-operators was pushed out of the industry and the majority of their

boats were either decommissioned or dumped.

The potential for losses to input suppliers have been recognized in the literature by Samuelson (1974) and Karpoff (1989). The latter suggests heterogeneity in fishing captains as the driving force. Alternatively Boyce (2004) finds that the manager's concern with surplus to input suppliers is the main contributor to adoption of suboptimal management tools rather than ITQ's. As the results of this paper demonstrate, in the presence of technical progress even a fishery managed perfectly for some sustainable catch level (or the implied biomass level) will, under some assumptions to be discussed below, experience a percentage decrease in the demand for inputs comparable to the percentage increase in productivity. This result while not surprising, is important to remember for several reasons. In an otherwise well-managed ITQ fishery, we can interpret the decrease in demand for inputs as a cost of continued rational management. It may be important to recognize the need to compensate the losers in such a situation in order to make ITQ's more acceptable to the fishing industry. In fisheries where ITQ's are not an option in the near term, then these results have implications for vessel buy-back programs which seek to reduce capacity or for fisheries with limited entry programs as the principal management tool.

I.B Static Gordon-Schaeffer Model

The model used in this section is based on the work of Gordon Gordon (1954) Schaefer (1957) and Scott Scott (1955) often referred to as the Gordon-Schaeffer model. The model is that of a static single species fishery with parametric output price, P. Harvesting occurs as a deterministic function of total inputs and no distinction is made between vessels or individual harvesters. The treatment below closely follows the summary by Munro in Munro (1982) though some of the notation has been changed to avoid

redundancy. The principal addition to the above mentioned treatments is the specification of the function that converts individual inputs into "fishing effort" discussed below.

Define the biological growth rate of the fish biomass, x;

$$\dot{x} = \rho x(1 - \frac{x}{B}) \tag{I.1}$$

Parameter ρ is sometimes called the natural or intrinsic growth rate and B is the carrying capacity (the maximal biomass level in the absence of harvesting mortality.)

Fishing mortality or harvest, y (measured in the same units as $\dot{x}$, biomass/time) is given by:

$$y = qEx \tag{I.2}$$

The coefficient q is frequently called a catchability coefficient and is assumed constant for now. Fishing effort, E is an aggregator function of various individual inputs. In general we will say that effort, E is a function of n different capital inputs and labor. That is:

$$E = E(K_0, K_1, ..., K_n) = E(\underline{K}) = AF(\underline{K}) \tag{I.3}$$

Input K_0 will be labor in the section 3 and as a matter of expositional convenience may be referred to as L. The Parameter A is a Hicks-neutral technical progress parameter. The effects (comparative statics) of this parameter on conditional factor demands is our main concern in this paper. We do not consider different forms of technical progress for two reasons; firstly, for the Cobb-Douglass function considered in section

3 both Harrod and Solow technological change reduce to Hicks-neutral technological change. Secondly, for most empirical examinations of technical progress, (see Kirkley et al. (2004) and Squires (1992)) the authors consider percentage increases in productivity, a concept naturally modelled by Hicks-neutral technical progress. In section 4 and for the introduction of the model here we generalize to multiple capital inputs and require only that $E(L, K_1, ..., K_n)$ be constant returns to scale, quasiconcave.

As is assumed in Hanneson (1983) and implicitly in most theoretical formulations we presume that the production technology is such that the effort aggregator is weakly separable from the fish stock. This allows us to write equation I.3 independent from the x. Squires (1992) extends the weak separability condition to multi-product fisheries as it is useful for empirical investigations and is required to prevent the crossing of isoquants when switching between target species. As noted in Hanneson (1983) one implication of this assumption is that no technology can become more useful as the stock declines. Because of this, the current model may not be appropriate for fish-finding devices.

Let r_i be the rental rate on input K_i (in section 3 we call $r_0 = w$). Then the single producer's effort constrained cost minimization problem (for some effort level $\widehat{E}$) is given by:

$$\min_{\{K_i\}_{i=0}^n} \sum_{i=0}^{n} r_i K_i \qquad subject\ to;\ E(\underline{K}) = E_{\text{targ}} \tag{I.4}$$

As is well known, the constant returns to scale property gives us that the optimal value function from the above minimization problem (i.e. the total cost function) is linearly increasing in effort, $\widehat{E}$. As in the standard Gordon-Schaeffer model implemented by the authors mentioned above, we will now restrict ourselves to consider only sustainable harvests, i.e. when $y = \dot{x}$. This means that we restrict fishers to steady

states in the biomass where harvest exactly equals growth each period and will not consider the approach paths to these steady states. This allows us to specify each point on the effort expansion path as an implied level for the biomass x. To see this, set equation I.1 equal to equation I.2 and solve for effort to obtain:

$$E(\underline{K}) = \frac{\rho}{q}\left(1 - \frac{x}{B}\right) \tag{I.5}$$

Equation I.5 implies that the total cost curve for sustainable harvest is a decreasing affine function of the biomass achieving zero at $x = B$. If we now multiply equation I.1 by P, the market price of output (taken parametrically) we obtain the total revenue curve for sustainable harvest.

This completes the general model to be used through the rest of the paper. The next section considers the two input Cobb-Douglass specification for effort while section 4 considers a more general formulation. For both sections we will consider cost and input demands as functions of some biomass level. If the reader is confused by the biomass targets as output constraints, recall that sustainability. provides a 1 to 1 and onto correspondence between biomass and effort, the more natural output constraint.

I.C Cobb-Douglass effort with two inputs

In this section the effort production function will be a constant returns to scale Cobb-Douglass function of two inputs; labor and capital. With a specific functional form in hand we can examine the effects of A, our Hicks-neutral technical progress parameter on the factor demands under various conditions. The aggregator function is given as follows:

$$E(L,K) = AL^{\alpha}K^{1-\alpha} \tag{I.6}$$

Therefore we can perform the effort constrained cost minimization problem to obtain the total cost of effort function:

$$\begin{aligned} TC(E,A,\underline{\theta}) &= wK^*(E,A,\underline{\theta}) + rL^*(E,A,\underline{\theta}) \\ &= \frac{E}{A}(w\gamma^{-\alpha} + r\gamma^{1-\alpha}) \end{aligned} \tag{I.7}$$

$$where\ \gamma = \frac{r}{w}\frac{\alpha}{(1-\alpha)} \tag{I.8}$$

$$and\ \underline{\theta} = (w,r,\rho,q) \tag{I.9}$$

When we restrict to sustainable harvest, (setting I.1 equal to I.2) effort choices uniquely imply biomass choices so we can cast I.7 in terms of the implied biomass level;

$$\begin{aligned} TC(x,A,\underline{\theta}) &= wK^*(x,A,\underline{\theta}) + rL^*(x,A,\underline{\theta}) \\ &= \frac{\rho}{qA}\left(1-\frac{x}{B}\right)(w\gamma^{-\alpha} + r\gamma^{1-\alpha}) \end{aligned} \tag{I.10}$$

This then gives us Figure I.1 taught in many undergraduate classes on renewable resource economics. In Figure I.1 there are three points on the biomass curve of interest. The first, x^*, is the biomass level that maximizes sustainable rents (the difference between the sustainable revenue curve and cost of harvest curve.) To the left of x^* is x_{MSY} the biomass level that corresponds to the peak of the sustainable revenue curve and consequently the peak of the sustainable harvest curve (as it is the same as the biomass growth curve.) This maximum has long been identified by biologists as the

maximum sustainable yield or MSY. This point is of particular interest for management and, as will be discussed below, has been the focus of management by legislation in the United States for many decades. The third point of interest is x_{EQ}, the open access equilibrium value for the biomass is the point at which total cost of sustainable harvest equals sustainable revenue. This last point is what we might expect to prevail in an unregulated fishery with many producers (or vessels) and no barriers to entry.

Equation I.10 implies the following sustained biomass constrained input demand equations:

$$L^*(x, A, \underline{\theta}) = \frac{\rho}{qA}\left(1 - \frac{x}{B}\right)\gamma^{-\alpha} \tag{I.11}$$

$$K^*(x, A, \underline{\theta}) = \frac{\rho}{qA}\left(1 - \frac{x}{B}\right)\gamma^{1-\alpha} \tag{I.12}$$

Equation I.10 is the version of the total cost curve shown in Figure I.1 specific to this Cobb-Douglass representation. Using I.11 and I.12 we can obtain formulae for the three focal values for the biomass (highlighted in Figure I.1) and the implications for input demand functions.

I.C.1 Input demands under optimality.

Optimality., here means that we are maximizing sustainable rents. In order to consider the management implications of technical progress we must first determine how technical progress affects input demands conditional on the optimal biomass level x^*. Under optimality., the effects of technical progress on input demands are summarized by the following proposition.

Proposition 1. *Optimal input demands are decreasing in technological changes that are sufficiently small.* $L^*(x^*, A, \underline{\theta})$

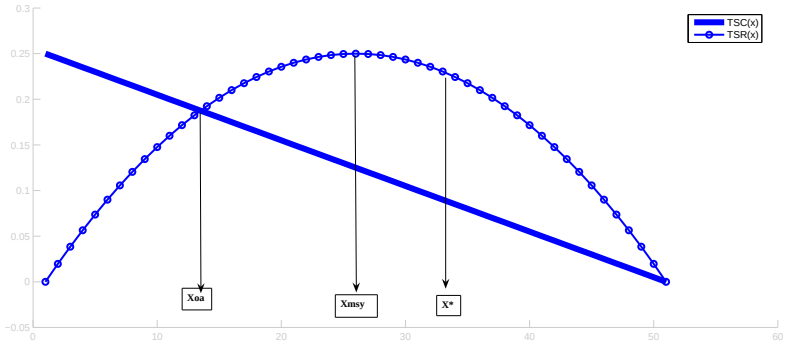

Figure I.1: Sustainable Revenues and Costs in Biomass

and

$K^*(x^*, A, \underline{\theta})$ *are increasing in* A *if and only if*

$A \geq \frac{(w\gamma^{-\alpha}+r\gamma^{1-\alpha})}{\rho q P B}$

Proof. First, note that the optimal biomass level will solve;

$$\max_x P\rho x(1-\frac{x}{B}) - TC(x, w, r, A, \rho, q) \tag{I.13}$$

the solution function to this maximization problem is;

$$x^* = \frac{B}{2} + \frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})}{2qAP} \tag{I.14}$$

substituting this expression into our formula for conditional labor and capital demands we obtain;

$$L^*(x^*, A, \underline{\theta}) = \frac{1}{A}(\frac{\rho\gamma^{-\alpha}}{2q}) - \frac{1}{A^2}\left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})\gamma^{-\alpha}}{2q^2PB}\right) \tag{I.15}$$

$$K^*(x^*, A, \underline{\theta}) = \frac{1}{A}(\frac{\rho\gamma^{1-\alpha}}{2q}) - \frac{1}{A^2}\left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})\gamma^{1-\alpha}}{2q^2PB}\right) \tag{I.16}$$

Both of the above functions are globally convex in A. Respectively they achieve unique minimum values at;

$$A^L_{\min} = \left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})}{\rho q P B}\right) \tag{I.17}$$

$$A^K_{\min} = \left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})}{\rho q P B}\right) \tag{I.18}$$

and the result follows. □

The above proposition gives conditions on the parameters of the model that describe the effects of technical progress on the input demand functions when the production is chosen so as to maximize sustainable rents. For such an optimally managed fishery, the effects of technical progress on labor and capital demands are uncertain. The intuition behind this result is easy to understand. Consider figure I.1 and increase A. This tilts the total cost of sustainable harvest down (by equation I.10) which in turn leads to a decrease in the value of x^* and an increase in the corresponding optimal level of effort. So while we now need less inputs for each level of effort, the optimal amount of effort has increased. Without knowledge of the parameters of the model, we cannot determine which effect will dominate.

I.C.2 Conditional input demands under open access

Under open access all resource rents are driven to zero. The following proposition shows that the open access equilibrium point behaves much in the same way as does the optimal harvest point where input demands and technology are concerned.

Proposition 2. $L^*(x_{EQ}, A, \underline{\theta})$

and

$K^*(x_{EQ}, A, \underline{\theta})$ *are increasing in* A *if and only if*

$A \geq \frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})}{\rho q P B}$

Proof. First, note that the open access biomass level will solve;

$$P\rho x_{EQ}(1-\frac{x_{EQ}}{B}) = TC(x_{EQ}, w, r, A, \rho, q) \tag{I.19}$$

the solution to this equation is;

$$x_{EQ} = \frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})}{qAP} \tag{I.20}$$

substituting this expression into our formula for conditional labor and capital demands we obtain;

$$L^*(x_{EQ}, A, \underline{\theta}) = \frac{1}{A}(\frac{\rho\gamma^{-\alpha}}{q}) - \frac{1}{A^2}\left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})\gamma^{-\alpha}}{q^2PB}\right) \tag{I.21}$$

$$K^*(x_{EQ}, A, \underline{\theta}) = \frac{1}{A}(\frac{\rho\gamma^{1-\alpha}}{q}) - \frac{1}{A^2}\left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})\gamma^{1-\alpha}}{q^2PB}\right) \tag{I.22}$$

These two functions are globally convex in A and achieve minimum values respectively at;

$$A^L_{\min} = \left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})}{\rho qPB}\right) \tag{I.23}$$

$$A^K_{\min} = \left(\frac{(w\gamma^{-\alpha} + r\gamma^{1-\alpha})}{\rho qPB}\right) \tag{I.24}$$

and the result follows. □

Proposition 2 gives a similar result to that of proposition 1. In fact the critical values for A are identical. The intuition is exactly the same. As we increase A, each level of steady state biomass (the biomass which corresponds to some particular harvest level) requires less effort. At the same time, total costs decrease so that the open access biomass value decreases and consequently the required effort increases. Which effect dominates is again an empirical question insofar as we would need to fit this model to data and compare the relative values of the models parameters. This is likely to be a very difficult exercise as to fit this model we would need data on harvest, effort, and

biomass. These are not typically available together for a single fishery. But hope is not lost, as the next section discusses, these past two conditions are unlikely to prevail and we have more concrete results for maximum sustainable yield fisheries.

I.C.3 Input demands under a Maximum Sustainable Yield policy

Most fishery management has historically targeted x_{MSY} by law. For example, the Magnusson Steven's act 94-265 (1996) section 301. National Standards for Fishery 16 U.S.C 1851 states that among other national standards, any fishery management plan must satisfy that "management measures shall prevent overfishing while achieving, on a continuing basis, the optimal yield from each fishery for the United States fishing industry." While this regulation may seem odd to an economist as it leads to economic over-fishing, if our job is to be descriptive we should consider what may happen as well as what should happen. For this reason the proposition below may be more relevant to real management questions as well as more satisfying in the monotonicity of its conclusion.

Proposition 3. *If sustainable harvest is suboptimally constrained to maximum sustainable yield, then the cost minimizing labor and capital demands have a elasticity of negative unity with respect to a Hicks-neutral technical progress parameter,* A.

Proof. First, note that;

$$x_{MSY} = \arg\max \rho x(1 - \frac{x}{B}) = \frac{B}{2} \tag{I.25}$$

Therefore;

$$L^*(x_{MSY}, A, \underline{\theta}) = \frac{1}{A}(\frac{\rho\gamma^{-\alpha}}{2q}) \quad \text{(I.26)}$$

$$K^*(x_{MSY}, A, \underline{\theta}) = \frac{1}{A}(\frac{\rho\gamma^{1-\alpha}}{2q}) \quad \text{(I.27)}$$

and since the elasticity of any function of this form in A is minus one the result follows. □

So it is clear that with such a Cobb-Douglass production function in the stylized Gordon-Schaeffer fishery, the cost minimizing input demands are related to technical progress with a constant elasticity when outputs are constrained to maximum sustainable yield. The next section will considers how robust are these findings.

I.D General CRTS effort function with n inputs

In this section we consider a more general production function and more general biomass targets. The intuitive reason that a target of x_{MSY} leads to concrete predictions about input demand elasticities while x^* and x_{EQ} do not is that the latter two depend on the cost structure and therefore the technology. The x_{MSY} target depends only on the biological growth function. The following proposition summarizes the general finding that the minus unity elasticity result is in fact quite general. Any target biomass level (serving as the constraint on output as does the x_{MSY} target in 3.3) which is independent of the technology will yield a minus unity elasticity for each input demand under fairly general conditions on the aggregator function.

Proposition 4 (General CRTS proposition)**.** *For any constant returns to scale, quasi-concave effort aggregator function $E(\underline{K})$ as in I.3, the elasticity of each sustainable biomass constrained input demand function has elasticity w.r.t. A of minus unity if and*

only if the biomass constraint is independent of A or if the input's demand is independent of the biomass target value.

i.e. for some biomass level x_{targ};

$$\left(\frac{\partial K_i^*(x_{targ}, A, \underline{\theta})/\partial A}{K_i^*(x_{targ}, A, \underline{\theta})/A}\right) = -1 \iff \frac{\partial x_{targ}}{\partial A} = 0 \text{ or } \frac{\partial K_i^*(x_{targ}, 1)}{\partial x_{targ}} = 0 \tag{I.28}$$

Proof. Consider $\widehat{E}(\underline{K}) = \widehat{A}F(\underline{K})$ and $E_1(\underline{K}) = F(\underline{K})$ for some arbitrary $\widehat{A}$. Let $\underline{K}^*(x_{\text{targ}}, A)$ (with all other parameter arguments suppressed for convenience) be the vector of solution functions to the cost minimization problem I.4 where $E_{\text{targ}} = \frac{\rho}{q}(1 - \frac{x_{\text{targ}}}{B})$ as implied by sustainability.

Claim:

$$\frac{\underline{K}^*(x_{\text{targ}}, 1)}{\widehat{A}} = \underline{K}^*(x_{\text{targ}}, \widehat{A}) \tag{I.29}$$

Proof of Claim: since

$$\widehat{E}\left(\frac{\underline{K}^*(x_{\text{targ}}, 1)}{\widehat{A}}\right) = \widehat{A}E_1\left(\frac{\underline{K}^*(x_{\text{targ}}, 1)}{\widehat{A}}\right) = E_1(\underline{K}^*(x_{\text{targ}}, 1)) = E_{\text{targ}} \tag{I.30}$$

we know that $\frac{\underline{K}^*(x_{\text{targ}},1)}{\widehat{A}}$ will produce E_{targ} under aggregator $\widehat{E}(.)$. It remains to check that $\frac{\underline{K}^*(x_{\text{targ}},1)}{\widehat{A}}$ is the cheapest way to produce E_{targ} under aggregator $\widehat{E}(.)$.

Since we know that the first order necessary (and sufficient by quasiconcavity) condition for the optimality. of $\underline{K}^*(x_{\text{targ}}, 1)$ is;

$$\underline{r} \geq \lambda \nabla E(K^*(x_{\text{targ}}, 1)) \tag{I.31}$$

And since $E(.)$ is homogeneous of degree one, each of its partials are homogeneous of degree zero. So $\frac{\underline{K}^*(x_{\text{targ}},1)}{\widehat{A}}$ must satisfy I.31 also. $\square$

With the above claim satisfied, and noting that $\widehat{A}$ was arbitrary we have that each biomass constrained input demand $K_i^*(x_{\text{targ}}, A)$ is of the form; $\frac{K_i^*(x_{\text{targ}},1)}{A}$ We can now calculate the elasticity of each input demand function with respect to A;

$$\begin{aligned}\left(\frac{\partial K_i^*(x_{\text{targ}}, A)/\partial A}{K_i^*(x_{\text{targ}}, A)/A}\right) &= \frac{\frac{K_i^*(x_{\text{targ}},1)}{A^2} + \frac{1}{A}\frac{\partial K_i^*(x_{\text{targ}},1)}{\partial x_{\text{targ}}}\frac{\partial x_{\text{targ}}}{\partial A}}{K_i^*(x_{\text{targ}}, 1)/A^2} \\ &= -1 + \frac{A}{K_i^*(x_{\text{targ}}, 1)}\frac{\partial K_i^*(x_{\text{targ}}, 1)}{\partial x_{\text{targ}}}\frac{\partial x_{\text{targ}}}{\partial A} \\ &= -1 + \epsilon_{K_i, x_{\text{targ}}}\epsilon_{x_{\text{targ}}, A}\end{aligned} \tag{I.32}$$

Equation I.32 proves the result □

Equation I.32 in the proof of the above proposition is suggestive of much more than the result of the proposition itself. As the proposition states the minus unit elasticity result holds only if one of either the elasticity of $K_i^*(x_{\text{targ}}, 1)$ with respect to the target biomass is zero or if the elasticity of the target biomass with respect to technology are zero. Let us consider either of these conditions separately. The biomass elasticity of the demand for an individual input i is unlikely to be zero except in the trivial case of a corner solution where input i is not used or in the case of a rather contrived production function where the marginal product of input i is zero over some finite range. Recall equation I.11 as an example from the Cobb-Douglass aggregator function in section 3; $L^*(x, 1, \underline{\theta}) = \frac{\rho}{q}\left(1 - \frac{x}{B}\right)\gamma^{-\alpha}$. The implied biomass target elasticity is then;

$$\frac{\partial L^*(x, 1, \underline{\theta})/\partial x}{L^*(x, 1, \underline{\theta})/x} = \frac{\frac{\rho}{q}\frac{\gamma^{-\alpha}}{B}}{\frac{\rho}{q}\left(1 - \frac{x}{B}\right)\gamma^{-\alpha}/x} = \frac{-x}{B - x} \tag{I.33}$$

The above expression is clearly zero only when the target biomass is zero, a rather trivial case. This elasticity with respect to the biomass constraint is determined by

the fundamentals of the biology and economics of the system. The technology elasticity of the target biomass level is not and the manager is free to choose a target biomass as a function of A to yield any elasticity she chooses. This suggests a possible management strategy. If a manager wishes to achieve some particular elasticity for an individual input's demand function and is free to choose a particular biomass target, then given knowledge of the elasticity of that input's demand with respect to the biomass constraint, she can choose a biomass target that yields the desired input demand elasticity.

As an example consider the labor demand in the Cobb-Douglass case again. Suppose we have a fishery manager who wishes to ensure that labor demand will be unchanged as technology increases and her only choice is the biomass target. As equation I.33 indicates her desired value for the elasticity of the biomass target with respect to A is then; $\frac{B-x}{-x}$. This condition yields a first order non-homogeneous differential equation with the following solution for x_{targ} as a function of A;

$$x_{\text{targ}}(A) = B + kA \tag{I.34}$$

In the above equation k is any constant. We certainly require that $k < 0$ as x_{targ} would otherwise not be feasible. Unfortunately, if one expects A to continue increasing without bound then for any fixed k this rule for x_{targ} will eventually lead to depletion of the resource. It is not a surprising but is certainly a significant fact that continued increases in technical ability impose either eventual reduction of inputs or eventual depletion of the resource.

I.E Discussion

In this section we discuss the possible implications of the above results in various different types of fisheries. It is worth noting that although the current paper does not explicitly model the innovation process to the technical progress parameter, the comparative statics are relevant for whatever sort of process we expect to govern increases in productivity. We should expect that from the vantage of a manager, innovations to technical progress should at least appear random. This would complicate the analysis but not overly. If managers are risk averse particularly with regards to the potential of stock collapse, we would expect that they would for example wish to remove more inputs than would be indicated by expected values of technical increases. The reader should bear in mind that what follows treats innovations to the parameter A as point values yet the flavor of the analysis should not change drastically were we to complicate it by including complete probability distributions on the innovations. The process by which innovations to A occur should indeed be modelled but not in this static framework. Future work considering the dynamics of the fishery will require specific assumptions on the process of technical change as well as specification of the managers risk preferences.

I.E.1 An ITQ fishery currently at the target biomass

The ”best case scenario” for current fishery management can arguably be highlighted in the current New Zealand ITQ fisheries modulo the distributional effects mentioned in the introduction. A stylized ITQ fishery cast in the context of the model of this paper would consist of a perfectly enforced total allowable catch and an implied x_{targ} value for the biomass. Supposing that such a fishery has achieved a steady state characterized by the chosen harvest (TAC) level and the biomass target. If the manager

expects technical progress in harvesting to occur in the future at say, rate $z\%$ per annum and if the manager is prepared to accept the assumptions of proposition 4 then she can expect to see $\frac{z}{1+z}\%$ of inputs displaced from the fishery each year. As mentioned in the introduction, these inputs are frequently non-mobile and displacement results in substantial loss to the owners. There are at least two possible justifications for the manager to consider compensation for those displaced from the fishery. Fairness considerations may be relevant as the rationalization of the fishery creates a net gain to those still involved in the fishery and a perpetual benefit to the larger economy as the resource is now generating larger sustainable rents. A more compelling reason to be concerned with losses to displaced fishers is that losers can generate political support and attempt to block the managers' quota decisions. To the extent that compensation of the losers in this scenario is a concern for the manager (for either of the aforementioned reasons) this compensation can be viewed as a cost of continued rational management of the fishery. These future costs can be estimated using a simple percentage of the total factor use in the current fishery.

I.E.2 A limited entry fishery

Most of the worlds fisheries have yet to convert to an ITQ system. To the extent that we believe eventual conversion to be inevitable given the potential gains, we may be tempted to say simply that these fisheries will be better off when they switch to ITQ's and restrict the discussion to the possibility of hastening the eventual conversion. However, in the near term, it behooves us to make "second best" recommendations subject to sub-optimality constraints such as imperfect management tools. One such imperfect management tool is limited entry. A common first step in attempting to control recognized over-fishing is limiting the number of licences in the fishery to current

participants and attempting to decrease these numbers as time goes by (examples include Norway see Rettig (1986) and the New England Groundfish fishery). If direct reduction of capacity through either legal mandates or market methods such as vessel retirement programs or so called ”buy-backs” are principal management tools then the results of this paper are salient indeed. In such a case, we can consider a fishery which controls capacity and has reached a steady state in which capacity is at the desired level. The manager should then be aware that further reductions in capacity will be required in the future dependent upon the expected rate of technical progress. The funds necessary for a ”buy-back” program can then be estimated using proposition 4.

I.E.3 Open Access

There remain many unregulated open access fisheries in the world. The U.S. Pacific Albacore longlining fleet is one example as is the Chesapeake Bay Blue Crab. The lesson for these fisheries is slightly beyond the scope of this papers results but the intuition is relatively simple. Section 3 shows that it is uncertain how technical progress will affect labor and capital demands under open access since the point of exhaustion of sustainable rents moves to the left on the biomass axis. This implies more effort is used but less inputs are needed for each level of effort. If we allow ourselves to somewhat informally consider non-sustainable conditions, we can construct a cautionary tale to fishers who might believe that their unregulated fishery is well set for perpetuity of current harvests. Suppose that a fishery has been harvesting at fairly constant levels for several years. Suppose further that the inputs to the fishery have been fairly constant over the same period. It may be tempting to suggest that this fishery is harvesting at sustainable levels. But consider the possibility that technical progress has continually occurred during this time interval. In this case, it seems plausible that as A increases we

increase effort without increasing inputs but this effort increase is paid little attention as the instant that effort increases stocks will begin to decrease. As the stock decreases, if A continues to increase at a more or less comparable rate, looking at equation I.2 we can see that biomass and technological changes might trade off in such a way as to keep harvest values fairly constant as we unwittingly draw down the resource stock.

More formally; revoking the sustainability. condition and substituting I.2 into the labor and capital demands implied by I.7 to get;

$$L^*(y, x, A, \underline{\theta}) = \frac{y}{qx}\frac{\gamma^{-\alpha}}{A} \tag{I.35}$$

$$K^*(y, x, A, \underline{\theta}) = \frac{y}{qx}\frac{\gamma^{1-\alpha}}{A} \tag{I.36}$$

Clearly from the above equations, there exists a path for A such that for whatever value x takes at each instant, both labor and capital demands are unchanged even though harvest, y is constant. For the above story to occur we need only have the path of A through time be ”close” to that which keeps labor and capital demands constant. The likelihood of such ”closeness” is beyond the scope of this discussion.

A similar story to that above was employed by Hanneson (1983) to explain the sudden near collapse of Atlanto-Scandian herring and Southwest pilchard stocks. Hanneson’s argument focuses on the parameter q, the catchability or availability coefficient in I.2. While the two parameters q and A are empirically indistinguishable the causal interpretation of his argument is quite different. In Hanneson’s story as fish stocks are drawn down, the stock ”maintains its density by occupying a smaller and smaller area” so that the catch per unit effort remains high. Both stories lead to sudden collapse of the stock after apparent sustainable catch rates. It may be somewhat more general to consider the increase in technical ability as the driving factor rather than a particular

behavior of the fish. The technical progress story could produce similar results even in a fishery where the species became more sparse and difficult to find as the abundance decreased.

I.F Conclusions

The results of this paper provide a first look at the relationship between fishery management and technological progress. The general result is that, with constant returns to scale production, technology affects input demands with a constant elasticity of minus unity except when biomass targets depend on costs (and consequently technology.) Future work should consider non-neutral varieties of technical progress such as changes in the marginal rates of technical substitution between inputs.

The manager's problem in this paper is one of enforcing a target biomass. This is a bit of a departure from previous literature. Frequently, the manager is treated as the social planner in dynamic fisheries models. While the social planner's problem must be solved for these models, it is perhaps unrealistic to interpret the fishery manager as the social planner. Fishery managers are real individuals with complicated mandates from government who must work with the tools they are given and be wary of the demands and desires of various lobby groups such as fishers and environmentalist. Future work should take the target biomass as exogenous to the manager and she will minimize a distance function between actual biomass levels and this target. The managers choice set must include a range of different available instruments. As an example, one political constraint to the manager can be the maintenance of some level of surplus to input suppliers who may block one or more of the manager's instruments if the constraint is violated.

As mentioned, future work will need to specify the dynamics of the system.

Optimal control theory has been used for decades to investigate various economic concepts pertaining to fishery management (see Clark (1976) and Clark and Munro (1975).) Preliminary inspections have found results for the simplest optimal control problems similar to proposition 1. This is not surprising as optimal control maximizes present discounted value of future rents which must depend on the cost structure. Another possibility is over-lapping generation models as applied in macroeconomic models which can make separate the roles of manager and social planner. Sources of randomness in biological growth should be considered as well as the random process driving technical progress. Should technical progress be disembodied? It is likely that changes in technology are driven by investment which may be highly correlated with fish stocks. When stocks are declining, we should expect more investment in fish catching technologies. This feature may reinforce many results in the current paper, particularly the cautionary tale for open access.

II

Natural Resource Collapse: Technological Change and Biased Estimation

Abstract

Unexpected collapse of natural resources is of great concern to policy makers. The literature and popular press have attributed collapse to the lack of well-defined property rights and policies which pay inadequate attention to random environmental variability. Both the literature and policy makers have ignored how unobserved technological change can obscure the depletion of natural capital stocks. The paper considers the example of the fishery. In a simple but general model of a single species fishery, technological change can readily generate unexpected collapse after a long period of apparent stability. The paper shows that even if property rights are well-defined and random fluctuations are small, modest changes in technology conceal the depletion of stocks. When technological change is ignored, biological productivity of the fish stock is

overestimated and as a result sustainable catches are overestimated and collapse results.

II.A Introduction

Collapse of natural resources is a costly phenomenon. It has been shown in the literature that under certain conditions on uncertainty and discount rates, it may indeed be optimal to fully deplete a natural capital stock (see for example Clark (1976) and more recently Amundsen and Bjørndal (1999).) The current research is concerned with unexpected collapse. Unexpected collapse can cause serious political economy problems when non-malleable human and physical capital is rendered valueless by the shutdown of an industry.

In this paper, I show that the manager of a renewable natural resource needs to be aware of technological change. If the manager ignores technological change, she overestimates the productivity of her natural capital stock. Analytically, I show that an increase in the state of technology over one period leads to an overestimation of the proportional rate of growth for that period. Through simulations I find that standard statistical tests overestimate policy variables. I show that collapse is inevitable if technology increases without bound. In simulations, the path to collapse is not observed until stocks are low and declining rapidly.

As natural resources go, fisheries have proven to be particularly difficult to manage. Fisheries collapse has received much attention in recent years, particularly after the costly closures of cod and other groundfish fisheries in Newfoundland and the Georges Bank. With a few exceptions, economists have been uncharacteristically silent on this topic.

Biologists have tried to identify the causes of collapse and suggest remedies. Notably, Ludwig et al. (1993), Roughgarden and Smith (1996) and Walters and Maguire (1996) point to the importance of uncertainty, and the lack of political will to enforce appropriate input or output limits. To be sure, uncertainty is an important consideration

for marine resource management. What has been missing is a thorough discussion of the lack of observability. Even if random variability is not great in magnitude, the fact that neither stocks nor technology are observed means that the production function is not identified. This fact combined with technological progress can lead to unexpected collapse.

Technological change is discussed widely in the resource economics literature but seldom in the context of resource management and conservation. Often it is invoked to rescue consumption streams from the pressures of population growth and resource depletion. I show that unobserved technological change can be quite problematic for a renewable resource manager who does not observe the resource stock. Even in the case of a single-owner, inference about stock growth and therefore appropriate harvest is confounded with technological change. In the case of sub-optimal management, the predicted outcome is sudden collapse following a period of apparent stability. The example considered is that of the fishery but the cautionary tale applies whenever a natural capital stock is observed imperfectly and when the production function unknown and dynamic.

Technological change has received surprisingly little attention in the fisheries economics literature, largely limited to empirical measurements of changes in total factor productivity (for example, Squires (1992), Squires (1994) Jin et al. (2002), Kirkley et al. (2004)). Squires (1992) showed that if one ignores stock effects one tends to under-estimate technological improvements. The converse here is shown, that ignoring changes in technology leads to over-estimation of surplus-production, current stock size, and appropriate catches. Ignoring technological change in input-managed systems leads to collapse. A fishery manager must invest in either fishery independent signals of changes in resource stock or accept costly precaution in setting catch limits.

The next section reviews the relevant economic and fishery literature. Section II.C introduces the modeling framework. The results are organized by assumptions about management. Section II.D shows that even when property rights are assigned and perfectly enforced, the productivity of the fishery is overestimated. Many of the worlds fisheries are either un-managed or managed via a suite of input controls; the dynamics of collapse in these fisheries are described in section II.E. Section II.F concludes.

II.B Relevant Literature

Fishery collapse is not a rare phenomenon. In addition to the well known collapses of Northern Cod, Peruvian Anchoveta, Virgina Oyster and California Sardine, Mullon et al. (2005) have identified collpases in nearly one quarter of the world's fish stocks. Using FAO data the authors find that 366 fisheries have collapsed. Collapse is defined as four consecutive periods of catch below 10% of the 50 year high.

The limited economic literature considering fishery collapse has considered exogenous sources of uncertainty and finds optimal rules to respond to these forces. (c.f. Amundsen and Bjørndal (1999) and Johnston and Sutinen (1996).) In some cases it is found to be optimal to allow the stock to collapse. Generally, collapse is considered to be the result of critical depensation, regime shifts, or allee effects. In another paper, Ruitenbeek (1996) studied the Newfoundland cod collapse and concluded that quota management, removal of subsidies, and greater attention to ecological uncertainty might have helped avoid costly collapse.

The biology literature is more concerned with this last topic; the goal is to explain collapse and offer lessons for management so that future collapse may be avoided. Ludwig et al. (1993) describe a 'ratchet' process by which uncertain variability is treated inappropriately. In years where the stock is subject to positive shocks, we invest but this

physical capital stock is fully utilized in years of negative shocks. A political result of this line of thinking has been the somewhat arbitrary notion of precaution. The precautionary principle or some similar concept is generally found in management plans in most OECD countries.

A notable contribution to the theory of fishery collapse is Roughgarden and Smith (1996). The authors use a logistic growth function to criticize the standard economic paradigm of fishery management. The proposition is that fisheries collapse because management attempts to balance the underlying fish stock at an unstable equilibrium (less than one half of the carrying capacity). The dynamic optimum of Clark (1976) involves so called bang-bang control of harvests; harvest nothing when the stock is below the target stock and harvest at the maximum rate whenever the stock is above the target. Random variability makes the stability of the target equilibrium relevant and the authors claim stock crash is unavoidable. This is because mangers do not (or cannot) in practice cut harvests to zero when the stock is believed to be below the target.

The solution offered by Roughgarden and Smith (1996) is to purchase 'natural insurance.' By this the authors mean the manager should forgo revenue by maintaining a stock greater than the economically optimal target. They suggest a target stock of three-quarters of the carrying capacity, K for the logistic model. An equilibrium to the right of the maximum of the logistic growth curve is a stable equilibrium and therefore risk of stock collapse is minimized.

Economists recognized fishery uncertainty some time ago, beginning with Reed (1979). Reed assumes that randomness enters the growth function as a multiplicative $i.i.d.$ random variable and derives a constant-escapement rule to maximize expected discounted rents.

The first reply from economists to Roughgarden and Smith (1996) is Sethi

et al. (2005). These authors use Reed's model and explicitly model two other sources of uncertainty cited by Roughgarden and Smith (1996), stock measurement error and quota enforcement uncertainty. Through simulations the authors find that while constant escapement is no longer optimal, a dynamic escapement rule can be derived to avoid stock collapse and extract higher discounted resource rents than would be gained by using the $3/4K$ rule of Roughgarden and Smith (1996).

Reed (1979), Roughgarden and Smith (1996), and Sethi et al. (2005) all assume that growth functions are known. Optimal or recommended policies are defined using key parameters such as carrying capacity. The current research considers the more realistic situation in which these parameters are not known and shows that fishery collapse is no surprise.

A final line of literature to mention is the empirical literature which establishes technological change in fisheries. The measurement of changes in total factor productivity is the primary focus of fisheries economics literature relating to technological change (see Squires (1992), Squires (1994) Jin et al. (2002) Kirkley et al. (2004), Squires et al. (2005)). These articles use economic indexes to estimate changes in total factor productivity various fishery independent measures of changes in biomass. These articles are relevant to the current research as a verification that technological change does occur in fisheries and rather small annual percentage increases tend to be found. As seen below, ignoring this dynamic parameter causes a particular kind of faulty inference and increases the likelihood of collapse.

II.C Model

The model here is a single fish species, governed by dynamics similar to Reed (1979) and Sethi et al. (2005).

$$B_{t+1} = B_t + \epsilon_t G(B_t) - C_t \tag{II.1}$$

The natural capital stock, fish biomass, at time t is given by B_t. The function $G(\cdot)$ represents natural growth. When $G(\cdot)$ has a maximum it will be referred to as maximum sustainable yield, MSY, and the corresponding biomass level, B_{MSY}. Growth equation II.1 differs from those in Reed (1979) and Sethi et al. (2005) in that growth occurs here over period t biomass rather than escapement. The harvest or catch C_t is given by the standard Schaefer production function;

$$C_t = q_t E_t B_t \tag{II.2}$$

The variable E_t is fishing effort, an aggregator function of physical capital and labor inputs to the fishery. For this investigation I ignore potential problems associated with measurement and even existence of such an aggregator function (see Squires (1987).) The potentially dynamic parameter, q_t, is referred to as catchability or fishing power and represents technological and environmental effects as well as non-linearities and even errors in the measurement of E_t. Note that by stating nothing about the determinants and dynamics of q_t equation II.2 is not restrictive and permits any general specification of harvest function for there always exists a q_t such that II.2 holds. This form is convenient as it is consistent with most standard empirical specifications and it allows the simple specification of technical change below.

When making statements about technological change it is convenient to specify the following;

$$q_t = q_0 \prod_{i=1}^{t} (1 + a_i) \tag{II.3}$$

Note, as with the production function specification, this is not restrictive until statements about a_i are made. When this specification is invoked, assume that a_i are weakly positive, implying that technological change is sufficient to insure that efficiency of harvest does not decrease over time. This still allows that other unobserved dynamics affect catchability but assumes that the dominant trend is an increase in catchability.

The general model is complete but for computer simulations further specifications are required. Sections II.D and II.E contain computer simulations which use specific forms of equation II.1 and equation II.2. Technology is modeled by constant percentage Hicks neutral improvements in efficiency each period. This amounts to constant a_i's for a given simulation.

The growth function $G(\cdot)$ is specified as the logistic in spite of criticisms of this Schaefer model as in Maunder (2003). It is certainly the case that this simple functional form may be inappropriate for many fishery data. This is not a concern here. For computer generated data we are free to choose the specification and since the final result is that inference is limited even when our model is correctly specified, it is not troublesome that the simplest model is used. Adding more parameters is not going to provide better inference here. The familiar logistic specification follows in two forms. The first has multiplicative noise as in equation II.1. The second has additive noise and is used only for the simulations and regressions in section II.D in order to provide more well-behaved estimators:

$$B_{t+1} = B_t + \epsilon_t r B_t (1 - \frac{B_t}{K}) - C_t \tag{II.4}$$

$$B_{t+1} = B_t + r B_t (1 - \frac{B_t}{K}) - C_t + \omega_t \tag{II.5}$$

Note also that for this specification, the peak of the growth curve is given by:

$$MSY = \frac{rK}{4} \tag{II.6}$$

II.D Single Owner

This section shows that even in an optimally managed fishery, ignoring unobserved technological change can lead to overestimation of growth.

There is much work on the optimal harvest of stocks subject to random disturbances. If B_t is observed and $G(\cdot)$ is known then we are in the framework of Reed (1979); optimal catch can be calculated and, provided that collapse is not optimal, the risk of unexpected collapse is zero. The optimal constant escapement policy insures that the natural capital stock never drops below a certain level, chosen to maximize discounted rents. If stock is observed imperfectly but growth functions and parameters are still known then we are in the framework of Sethi et al. (2005) and though the constant escapement of Reed (1979) is no longer optimal, more complicated rules allow for the quasi-maximization of discounted rents. But these rules require knowledge of parameters such as carrying capacity, K.

The reality is that stocks are not observed, growth and production functions are not known and therefore a manager in a fully rational fishery faces a statistical challenge; determine appropriate catch limits. It is often the case that catch limits must be estimated solely based on catch and effort data. In this section I show first analytically and then through simulations that ignoring technological progress in estimation leads to faulty inference of a specific kind, growth is over-estimated; catch limits are overestimated. The following establishes the general result that ignoring technological change period-by-period implies overestimation of last period's natural growth or surplus production.

Proposition 5. *Given catch and effort data for periods t and $t+1$ and known technology for period t an estimate of period t proportional surplus production, $\epsilon_t(\frac{G(B_t)}{B_t})$ which does not account for technological change between periods has strictly positive bias.*

The proof is in the appendix. This intuitive result shows that as long as technical efficiency increases over one period and is ignored the manager attributes a greater proportion of the catch per unit effort to the natural growth than is warranted. The econometrician does not observe decreases in the natural capital stock.

The period-by-period result of proposition 5 demonstrates the most general inference problem with unobserved technological change. Even if the manager knows today's technology she overestimates the productivity of the resource if she ignores just one period of technical change. Technological increases disguise the decrease in the natural capital stock. This fact is explored further in simulations below.

In order to relate this result more realistically to stock assessments made in a rationally managed fishery, we must consider statistical techniques which make use of some finite sample of data. It is necessary to pass to specific functional forms and parallel stock assessment techniques. If we specify $G(\cdot)$ to be the logistic growth function, then we can derive the standard catch-effort regression taught in introductory resource economics courses. As noted by Hilborn and Walters (1992) these equilibrium methods frequently lead to over-estimation of surplus production in small samples and will therefore not be discussed further. One of the simplest dynamic catch-effort relationships was derived by Walters and Hilborne (1976) for the Schaefer model;

$$\frac{U_{t+1}}{U_t} - 1 = r - \frac{r}{qk}(U_t) - qE_t + \omega_t \tag{II.7}$$

Here, the observable variable, U_t, catch-per-unit-effort is defined; $U_t = \frac{C_t}{E_t}$. Using this definition and equation II.4 one obtains equation II.7. It is straightforward to

show that the classical regression assumptions are violated when q is dynamic.

Proposition 6. *Under positive technological change the residuals from a regression of the form in equation II.7 have strictly positive mean.*

Proposition 6 (the proof is in the appendix), shows that ignoring technical change of the form in equation II.3 over the sample period implies the residuals of the regression are positive, implying that at least the intercept, r, is biased. And this occurs even if the growth and harvest functions are correctly specified. At first glance, proposition 6 suggests that we overestimate the intrinsic growth rate, r, and that we have a result of the same flavor as proposition 5.

Furthermore, the final statistic(s) of interest are nonlinear function(s) of the regression coefficients. If the manager is like most real managers, the statistic of interest is maximum sustainable yield or a multiple thereof. Though MSY is rarely the harvest target, the target is often a multiple of MSY and assessments often attempt to determine if MSY has been exceeded. The following definition of MSY applies to the logistic model and the regression II.7.

Definition 1. *The estimate obtained for MSY from the regression II.7 is:*

$$\widehat{MSY} = \frac{\hat{r}^2\hat{q}}{4\widehat{(\frac{r}{qk})}} \tag{II.8}$$

This nonlinear function of several estimates is not necessarily unbiased even if each individual coefficient is. There are several sources of bias, (for example, the convex function of $\widehat{(\frac{r}{qk})}$ introduces an upward bias by Jensen's inequality but potential covariance between estimators may counteract this and the unbiasedness of all estimators further confounds this). To explore the net implications of these estimation problems, computer simulations are useful.

Using the logistic model with a unit carrying capacity, a computer simulated 50 periods of a fishery 10,000 times for each pair of r and a values. The intrinsic growth rate, r, ranged from .1 to .5. The increase in efficiency multiplier, a, varied from 0 to .03. Growth noise was additive and $i.i.d.$ drawn from a normal distribution having mean zero and variance .0001. Effort values were randomly generated with a mean of $r/2$, the effort required to harvest MSY when the stock is at B_{MSY}. The multiplicative noise factor perturbing this effort target had mean one and variance .03. All trials began with initial stock value B_{MSY}.

For r values between .1 and .3 and technological increases of 0% to about 3% per period, the results are clearly an increasing positive bias in estimates of MSY. The results are less clear for very small r values or those larger than .3. When technological change becomes too fast (more than about two percent per year) results are also difficult to interpret (the results for the full range are displayed in tabular form in the appendix.). But for the range in figure II.1 below there is a clear increase in the overestimation of MSY as a function of the magnitude of technological progress. As a increases, moving to the right and back of the figure, the percentage error in estimation of MSY rises. Increases in the rate of technological change cause more and more dramatic upward bias in our estimate of sustainable yield. The range in figure II.1 contains most of the annual percentage changes estimated in the literature and the range for r is quite relevant as well. For example Hutchings (1999) found r values for Newfoundland Cod to be between .135 and .164.

In the best real-world fish-stock assessments, the potential for change in 'fishing power' is not ignored. In their review of techniques for standardizing catch and effort data Maunder et al. (2006) describe a 'year effect' which should summarize the concerns raised in this section and other parameter dynamics. In order to calculate this

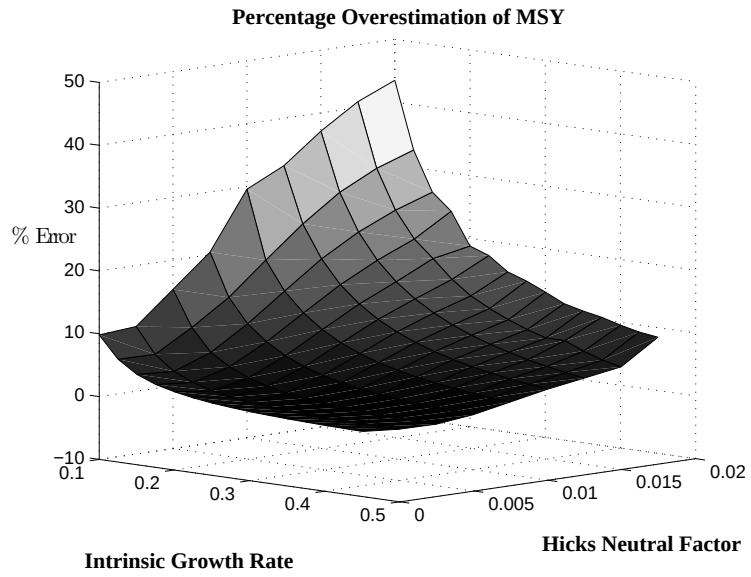

Figure II.1: Estimation Error

year effect data beyond catch-and-effort data are required. Fishery independent data are necessary to identify the system.

II.D.1 A Note on MEY

The reader may worry that the previous results apply to MSY which is not necessarily the optimal harvest policy. While this author is not aware of many fish stock assessments which actually attempt to estimate the economic optima of Gordon (1954) or Clark (1976) this section shows that the results from the last section imply that overestimation is still a problem if economically optimal harvest targets are the statistics of interest.

The seminal article by Gordon (1954) showed that with constant marginal costs of effort, the static optimal harvest target is less than MSY. Given P, the mar-

ket price of output and C, the marginal cost of fishing effort, the harvest target which corresponds to the static maximum of Gordon (1954) is given as follows.

$$MEY = MSY - \frac{rC^2}{K(2qP)^2} \tag{II.9}$$

Equation (II.9) is readily re-written in terms of the regression coefficients from equation (II.7) and our estimate of MSY from equation (II.8);

$$\widehat{MEY} = \widehat{MSY} - (\widehat{\frac{r}{qK}})\frac{C^2}{4p^2\hat{q}} \tag{II.10}$$

From the previous section, we know that MSY is over-estimated. In the simulations, $(\widehat{\frac{r}{qK}})$ is decreasing in magnitude with the rate of technological change. Whenever there is technological change an estimate of q is some average of the q_t over the period and so increasing in the rate of technological change. In particular this is true in simulations. These facts taken together show that MEY is also overestimated when technological change is ignored.

II.E Dynamics of Collapse

This section looks at the actual dynamics of collapse and avoids recalculation of quota estimates each period. Consider a suboptimal management regime which fixes inputs based on a target catch and biomass level. While output (harvest) management is often superior both in theory and in practice to input controls, many of the world's fisheries are still effort-managed or un-managed and so the implications of technical change are salient.

The policy is one of fixed effort based on a stock target. Even without technological progress this policy is clearly suboptimal as shown by proposition 7 below but proposition 8 shows that it is not terribly bad for this model. First some notation.

Suppose management has a stock target of B_0.

Definition 2. *Management's effort target is E_0 and satisfies:*

$$E_0 = \frac{G(B_0)}{q_0 B_0} \tag{II.11}$$

If q does not change this is the effort required to harvest the expected growth at target stock B_0. For the specifications of the current model, this management strategy amounts to taking a constant proportion of the stock provided that technology does not change. Note that there is literature supporting this type of harvesting rule in the face of some types of natural variability such as climate change (Walters and Parma (1996)) and cyclical variability (Carson et al. (2005)).

The analytical results in this section assume the general forms of equation II.1 and II.2 with the restriction that $G(\cdot)$ be strictly positive and concave. Simulations use the logistic form with multiplicative errors.

II.E.1 Effort management without Technological Progress

When management prescribes Effort each period as E_0 the following propositions are satisfied (proofs in the appendix).

Proposition 7. *If $B_0 \leq B_{MSY}$, then*

$$\boldsymbol{E}(B_t|B_0) \leq B_0 \forall t \tag{II.12}$$

Proposition 8. *Whenever $B_t \leq B_0$, B_t is a submartingale;*

$$\boldsymbol{E}(B_{t+1}|B_t \leq B_0) \geq B_t \tag{II.13}$$

These results establish that a constant effort policy for this model is not a bad policy so long as technological change is not present. While constant effort does not achieve an average stock size equal to the stock target the stock tends to increase whenever the stock is below the target.

Simulations agree with these analytical results. Fisheries generated similarly to section II.D do not crash when effort levels are fixed. A typical such simulation is given below in figure II.2.

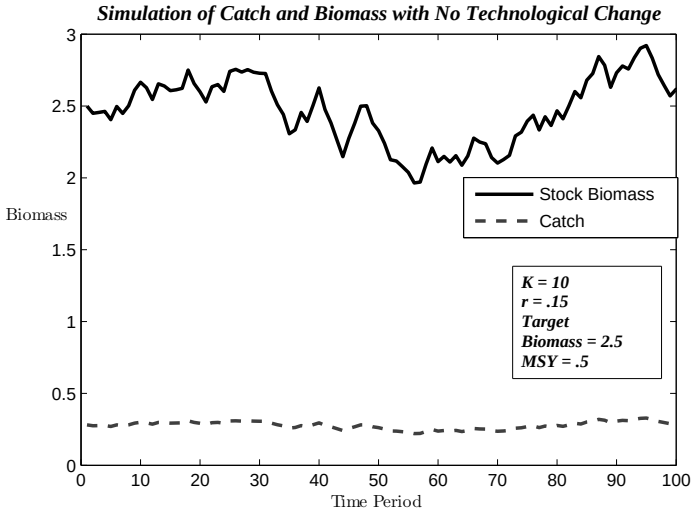

Figure II.2: Fixed effort with constant technology

II.E.2 Dynamics with Technological Progress Under Effort Management

Proposition 9 below establishes that under the assumption that technology increases weakly each period according to equation II.3, constant effort guarantees that a stock tends toward zero. While the stock does not go extinct using this constant effort harvest strategy, it eventually drops below any arbitrary level, δ;

Proposition 9. *When technology increases without bound, given any $\delta > 0$ there exists a time, τ, for which the unconditional expectation of B_τ is less than δ.*

Stocks shrink to arbitrarily low levels. Simulations agree with this result and provide more information. A typical simulation is shown below in figure II.3 and it is notable that the catch levels do not begin to decline until the 60th period when the stock level is less than half of its target. This graph was generated by a typical simulation described in the previous section but run for 100 periods. Observable variables, catch and effort, are not changing much but the capital stock is drawn down as technology changes.

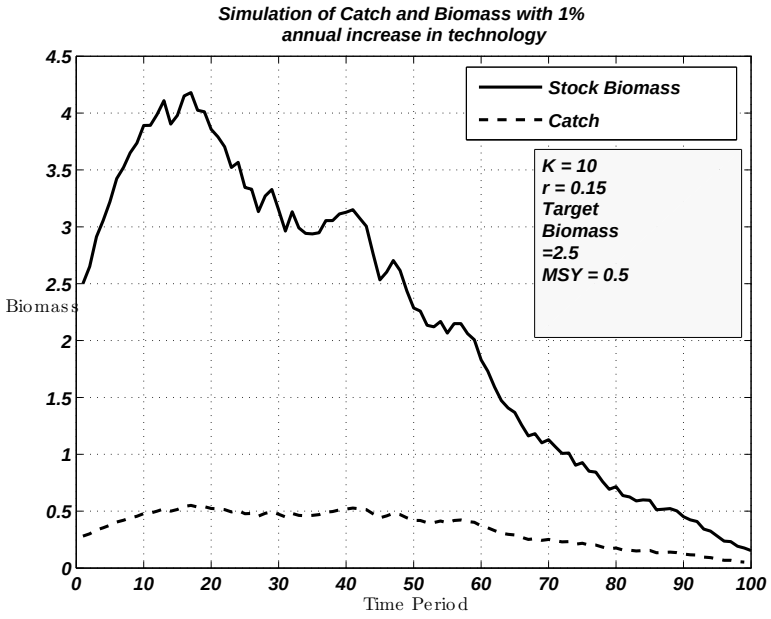

Figure II.3: Technology Driven Collapse

Generating 10000 of these simulations for each r and a pair allows estimation of the expected time to collapse. I define collapse loosely following Mullon et al. (2005)

as the first period when expected catch is less than 10% of MSY. In the appendix these times to collapse are given in tabular form along with biomass levels and rates of change at collapse. Biomass at collapse tends to decrease with a but does not vary much with r. The magnitude of the rate of change of the biomass is increasing in both a and r.

II.F Conclusion

Technological progress is potentially problematic to managers of unobserved natural capital stocks. In particular, the likelihood of unexpected collapse is higher when productivity creep is present. The problem is one of inference. Statistical techniques and simple observations are confounded by an unidentified system. As the stock is drawn-down, the catch-per-unit-effort increases so that total catches increase or remain constant.

There are many potential causes for unobserved collapse. Environmental variability, the tragedy of the commons and high discount rates are among the proximate causes of collapse. Technological change is present in industries which depend upon natural resources and this alone can lead to sudden collapse. It behooves mangers to consider this possibility and invest in methods to detect and correct for faulty inference.

On the one hand, this paper presents a plausible explanation of natural resource collapse. On the other hand this paper is a call for fishery independent data and for greater attention to technological change. It is common to invest in expensive fishery independent biological surveys. These efforts are costly but necessary to identify the system. The economic literature generally ignores these estimation problems but unobserved and therefore unidentified systems are fundamental features of fishery management. Where fishery independent signals of stock change are not feasible managers should seek signals of technological change and attempt to incorporate these directly

into management decisions.

A last resort is the arbitrary notion of precaution. This paper gives yet another reason for precaution in setting harvest targets. Conservationists have long argued that catch limits should be reduced because of uncertainty. Though I can say no more on the quantity of precaution that is appropriate, I make explicit the direction of bias in harvest targets; harvest targets are biased up when technological change is ignored.

Table II.1: Average Percentage Overestimation of MSY

Table 1: Average Percentage Overestimation of MSY

	r						
a	**0.1**	**0.125**	**0.15**	**0.175**	**0.2**	**0.225**	**0.25**
0	9.8%	6.4%	4.4%	3.2%	2.4%	1.9%	1.5%
0.0025	10.3%	6.3%	4.0%	2.7%	1.8%	1.2%	0.7%
0.005	15.3%	9.7%	6.2%	4.3%	3.0%	2.1%	1.4%
0.0075	20.4%	13.6%	9.9%	7.4%	5.6%	4.3%	3.4%
0.01	29.6%	18.7%	14.2%	11.1%	8.9%	7.2%	5.9%
0.0125	32.5%	23.6%	18.5%	14.8%	12.1%	10.1%	8.5%
0.015	37.1%	27.8%	21.9%	17.8%	14.8%	12.5%	10.7%
0.0175	40.9%	30.8%	24.5%	20.3%	17.6%	14.8%	12.5%
0.02	43.5%	32.8%	26.5%	23.9%	18.8%	17.7%	15.5%
0.0225	45.0%	34.3%	28.0%	27.8%	24.4%	45.0%	29.1%
0.025	102.3%	37.9%	37.2%	34.6%	67.4%	89.9%	63.0%
0.0275	46.6%	49.9%	50.6%	110.4%	80.5%	126.3%	146.5%
0.03	48.6%	50.3%	117.3%	97.9%	140.7%	206.0%	262.5%

II.G Appendix: Tables

II.G.1 Section II.D

II.G.2 Section II.E

II.H Appendix: Proofs

Proof of Proposition 5. Suppose the resource owner observes C_t and E_t and knows period t technology, q_t. Define $U_t = C_t/E_t = q_t B_t$ and assume that $q_{t+1} = q_t$ and substitute into equation II.1 to obtain;

$$\frac{U_{t+1}}{U_t} - 1 = \epsilon_t \frac{G(B_t)}{B_t} - q_t E_t \tag{II.14}$$

Now since U_{t+1}, U_t and E_t are observed and q_t is assumed known, our manager may calculate the realized proportional surplus production for period t, $\epsilon_t \frac{G(B_t)}{B_t}$ by rearrang-

Table II.2: Time periods to collapse

Table 4: Time periods to collapse

	r								
a	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
0	300	300	300	300	300	300	300	300	300
0.005	260	217	198	187	179	174	170	166	164
0.01	161	131	117	109	103	99	96	94	92
0.015	123	99	87	81	76	73	70	68	67
0.02	102	81	72	66	62	59	57	55	54
0.025	88	70	62	57	53	50	48	47	45
0.03	78	62	55	50	47	44	43	41	40
0.035	70	56	49	45	42	40	38	37	36
0.04	64	52	45	41	39	36	35	34	32
0.045	60	48	42	38	36	34	32	31	30
0.05	56	45	39	36	33	31	30	29	28

Table II.3: Biomass at Collapse

Table 5: Biomass at collapse

	r								
a	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
0	0.499	0.498	0.498	0.497	0.496	0.496	0.495	0.494	0.493
0.005	0.013	0.016	0.018	0.019	0.021	0.021	0.021	0.022	0.021
0.01	0.010	0.013	0.015	0.016	0.018	0.019	0.019	0.018	0.019
0.015	0.008	0.011	0.014	0.014	0.016	0.016	0.017	0.018	0.016
0.02	0.006	0.010	0.011	0.013	0.014	0.015	0.015	0.016	0.014
0.025	0.005	0.008	0.010	0.011	0.013	0.015	0.015	0.014	0.017
0.03	0.005	0.008	0.008	0.011	0.011	0.014	0.011	0.014	0.013
0.035	0.005	0.007	0.009	0.010	0.011	0.011	0.013	0.012	0.012
0.04	0.004	0.005	0.008	0.010	0.008	0.013	0.011	0.010	0.015
0.045	0.003	0.005	0.007	0.009	0.008	0.009	0.012	0.011	0.012
0.05	0.003	0.004	0.007	0.007	0.010	0.011	0.010	0.010	0.011

Table II.4: Rate of Change of Biomass at Collapse

Table 6: Rate of Change of Biomass at Collapse

	r							
a	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.005	-0.044	-0.051	-0.056	-0.057	-0.063	-0.066	-0.066	-0.074
0.01	-0.078	-0.088	-0.096	-0.106	-0.105	-0.115	-0.117	-0.124
0.015	-0.114	-0.128	-0.133	-0.146	-0.158	-0.155	-0.167	-0.171
0.02	-0.150	-0.163	-0.179	-0.191	-0.201	-0.207	-0.211	-0.205
0.025	-0.190	-0.204	-0.225	-0.234	-0.248	-0.238	-0.251	-0.277
0.03	-0.229	-0.245	-0.262	-0.271	-0.293	-0.290	-0.320	-0.312
0.035	-0.266	-0.285	-0.300	-0.314	-0.324	-0.348	-0.360	-0.382
0.04	-0.307	-0.342	-0.342	-0.356	-0.397	-0.378	-0.411	-0.440
0.045	-0.374	-0.386	-0.400	-0.414	-0.451	-0.462	-0.450	-0.499
0.05	-0.426	-0.443	-0.441	-0.486	-0.474	-0.490	-0.523	-0.546

ing equation II.14. But this is based on the assumption that technology does not change. In fact if technology evolves according to II.3 our estimate of t, $\epsilon_t \frac{G(B_t)}{B_t}$ is actually given as follows;

$$\begin{aligned} [\frac{U_{t+1}}{U_t} - 1] + q_t E_t &= [(1 + a_{t+1})\frac{B_{t+1}}{B_t} - 1] + q_t E_t \\ &= (1 + a_{t+1})\epsilon_t \frac{G(B_t)}{B_t} + (1 - \frac{C_t}{B_t})a_{t+1} \end{aligned} \tag{II.15}$$

Now since $\frac{C_t}{B_t}$ must be less than one (otherwise the stock would be extinct and $U_{t+1} = 0$ the final expression in II.15 is strictly greater than the true realized proportional surplus production and this concludes the proof. □

Proof of Proposition 6. If we assumed that $q_t = q$ for all t then Walters and Hilborne (1976) showed that if we define $U_t = C_t/E_t = q_t B_t$ we can rewrite II.4 as in II.7.

If technological change evolves according to equation II.3. In this case, the residuals from II.7 are actually given by;

$$\begin{aligned}
\omega_t &= [\frac{U_{t+1}}{U_t} - 1] - [r - \frac{r}{q_t k}(U_t) - qE_t] \\
&= [\frac{B_{t+1}}{B_t}\frac{q_{t+1}}{q_t} - 1] - [r - \frac{r}{k}(B_t) - qE_t] \\
&= [\frac{B_{t+1}}{B_t}(1 + a_{t+1}) - 1] - [\frac{B_{t+1}}{B_t} - 1] \\
&= \frac{B_{t+1}}{B_t}(a_{t+1}) \qquad \text{(II.16)}
\end{aligned}$$

□

Proof of Proposition 7. Proceed by induction and first note that:

$$\mathbf{E}(B_1|B_0) = B_0 + G(B_0) - G(B_0) = B_0$$

Now, show that if the proposition is true for t it must be for $t+1$; by the Law of Iterated Expectations:

$$\begin{aligned}
\mathbf{E}(B_{t+1}|B_0) &= \mathbf{E}(\mathbf{E}(B_{t+1}|B_t, ..., B_0)|B_0) \\
&= \mathbf{E}((1 - qE_0)B_t + \epsilon_t G(B_t)|B_0) \\
&\leq (1 - qE_0)B_0 + \mathbf{E}(G(B_t)|B_0) \quad \text{by assumption} \\
&\leq B_0 - G(B_0) + G(\mathbf{E}(B_t|B_0)) \quad \text{by Jensen's inequality} \\
&\leq B_0 - G(B_0) + G(B_0) \quad \text{by assumption and since } X_0 \leq X_{MSY} \\
&= B_0
\end{aligned}$$

□

Proof of Proposition 8. Assume $B_t < B_0$. Then $\mathbf{E}(B_{t+1}|B_t) = B_t + G(B_t) - qE_0B_t$. Now by concavity of $G(\cdot)$ and the definition of $E_0, G(B_t) > qE_0B_t$. Therefore $\mathbf{E}(B_{t+1}|B_t) > B_t$. □

Proof of Proposition 9. For any δ let τ be such that $q_\tau > \frac{G(\delta)}{\delta E_0}$. Apply proposition 7 with B_0 replaced with δ and the result follows. □

III

Marine protected areas as a risk management tool

Abstract

There is considerable debate in the literature about the usefulness of Marine Protected Areas as fishery management tools. While most economists have found that it is unlikely that marine reserves will improve steady-state yields, some biologists have shown that protected areas have the potential to reduce uncertainty. Most of the work on uncertainty has focused on exogenous environmental variability; the probability of collapse can be reduced with protected areas, but this comes at the cost of lower yields. Here I consider single-owner management with spatial closures under growth and production-function parameter uncertainty. There are many reasons to suspect that estimates of fishery growth parameters are highly uncertain: intrinsic variability, lack of data, weak identification, and technological change to name a few. If a single owner does not know growth parameters very well then it is difficult to determine optimal extraction paths. Traditional optimal management utilizes a single control variable, catch. When growth

and production parameters are uncertain I consider the expected benefits of utilizing a second control variable: fraction of area harvested. I show that even in a deterministic dynamical system, if parameters are unknown, expected harvests can be improved with protected areas.

III.A Introduction

Marine protected areas, marine reserves or spatial closures (or perhaps space-time closures) to exploitation are often heralded as the answer to the troubled history of marine resource management. Uncertainty in the marine environment is one strong justification for a simplified, spatial (or perhaps space-time) form of management. In the following I will use reserves and protected areas interchangeably to mean some form of closure to extraction.

Suppose we have the rosy scenario of a single-owner managed fishery. Ultimately, when growth-parameters of a fishery are unknown, the goal of the manager making catch decisions is really a stochastic control problem under parameter uncertainty, or an 'adaptive control' problem as in Bagchi (1993) and Walters (1986). In the case of the fishery we have a control variable, catch, with an underlying stock variable subject to random fluctuations. Maximizing expected discounted payoff is well understood for such problems under some forms of uncertainty, for example, Reed (1979) or even Sethi et al. (2005) for multiple-uncertainty. In these cases the parameters of the dynamical system are assumed known. In reality, the manager must estimate these parameters using past decisions and outcomes. In turn the updated estimate each period should inform the next period's control decision. This leads us to the adaptive control paradigm in Walters (1986). The text lays out the most thorough treatment of what a renewable resource managers strategy should be. This strategy involves seeking some "optimum, or at least reasonable, balance between learning and short-term performance." But even Walters admits that real managers are more likely to "act so as to filter out the informative variation in favor of more conservative, incremental policies." This is fairly intuitive; if management seeks to maintain catch or stock levels, we learn only locally about the dynamical system.

For reasons cited by Walters it may be quite difficult to implement the adaptive rule that maximizes the infinite horizon expected payoff. Additionally, there may be confounding factors in marine fisheries which lead to a certain 'irreducible uncertainty' (see Ludwig (1989)). For marine fisheries, we might imagine several reasons that parameter uncertainty will not be reduced as more observations are collected: poor observability and measurement in marine systems; under identification of growth functions, Carson and Murray (2005); technological change can lead to overestimation of natural growth, Murray (2006), unstable parameter due to natural fluctuations, Carson et al. (2005) or due to increasing variability as a function of exploitation, Hsieh (2006).

Here, I explore the potential for a management strategy requiring far less information than an adaptive control policy: marine protected areas. Some authors such as Lauck (1996), Lauck et al. (1998) and Murray et al. (1999) find that MPA's can reduce or eliminate management uncertainty, Hastings and Botsford (1999) finds that in the absence of uncertainty maximum sustainable yield can be achieved by spatial closure and harvesting fully outside the closure. Neubert (2003) uses a spatially explicit Fisher equation and finds that all optimal harvesting policies include at least one reserve. This last result while very intriguing is in no small part driven by the assumption that fish flow out of the fishery at the boundaries and cannot be recovered for harvest or reproduction. This implies that it is always optimal to harvest maximally near the boundaries and so no spatially homogeneous harvest policy could be optimal.

Economists such as Sanchirico (2000) are skeptical of the hedging potential for MPA's. Also Hannesson (1998), Sanchirico and Wilen (2001) and Smith and Wilen (2003) are skeptical of the ability of reserves to improve yields. With the exception of Lauck (1996) and Lauck et al. (1998) none of these papers consider uncertainty. A few articles do address ecological uncertainty and harvesting payoff. Grafton et al.

(2005) show that expolited populations recover from environmental shocks faster when marine reserves are in place and show that reserves can be economically optimal. Also, Grafton and Kompass (2005) develop a procedure for designing marine protected areas in response to environmental fluctuations. The crucial difference in this paper is that uncertainty is not based on external ecological variability in time. The only uncertainty is parameter uncertainty and I find that reserves can increase expected harvests when marine systems are imperfectly understood even if they are dynamically deterministic.

Let me note that there are many justifications for marine protected areas aside from fishery yields. Many environmental amenities and ecosystem services may require large marine regions which are relatively less disturbed. These are not the topic of this research. These benefits are certainly relevant to policy makers but the case is rather easily made. For fishery yield benefits, there remain serious doubts and many open questions as to the utility of protected areas. There is also a significant potential fishery benefit, I will not explore. Walters (1986) notes that the only way to avoid serious biases in parameter estimation for heavily exploited stocks is to "stop harvesting for a long period." Protected areas allow for long periods of ceased harvesting without a complete shut-down of the industry. The current research is limited to finding improvements to expected catches under some form of irreducible uncertainty.

The goal here is to model parameter uncertainty in a single-species extracted resource. There is both stock and growth-parameter uncertainty. Ultimately I want to determine if heuristic methods of management can improve on a strictly catch-decision management strategy. The next section describes some previous models of protected area management. Section III.C describes my model of a simple diffusion rate as a function of the density differential at the imposed boundary. Section III.D describes some initial steady-state results.

III.B Fisheries Models

It is worth reviewing the models that some authors have used to describe the potential gains from spatial management. While this is not exhaustive, the two papers below are the most convincing theoretical papers I have found making a case for the usefulness of protected areas. Interestingly, for all of the popularity of patchy ecosystem models amongst conservation oriented ecologists, neither of these models is spatially explicit.

III.B.1 Lauck's Model

Following Lauck (1996), use the following notation:

X_t : biomass at time t.

N : Natural growth multiplier.

H_t : Fraction harvested, a random variable.

h_t : Target harvest fraction.

a : Fraction of the stock protected by marine reserve.

This yields the dynamics of the stock given by:

$$X_{t+1} = X_t N(a + (1-a)(1-H)) \tag{III.1}$$

Given and initial value, X_0, these dynamics can be written:

$$X_t = X_0 \prod_{i=1}^{t-1} N_i(a + ((1-a)(1-H_i))) \tag{III.2}$$

Lauck claims that by choosing $H_i = 1$ and making the reserve large enough, i.e., $a = 1 - h$, we reduce uncertainty to zero. What is missing here is the optimization

of catch. Lauck is only looking at reducing variance. This is also the case in Lauck et al. (1998) a similar paper that uses simulations to show that reserves can reduce the probability of stock crash.

III.B.2 Hasting's Model

In Hastings and Botsford (1999), the authors construct another model of spawning populations protected in a reserve area to show an equivalence in yield for spatial management and traditional management. The main contribution here is that an age-structured model shows that a reserve can yield equivalent yields with a larger standing stock. This is based simply on the fact that older individuals continue to reproduce.

Notation:

- m number of juvenile recruits per adult
- j age of sexual maturity
- a annual adult survivorship
- c fraction of area in reserve
- H fraction harvested
- n_t^r density inside reserve
- cmn_t^r number of juveniles generated by reserve

Note immediately that homogeneous mixing is assumed. First, the authors calculate the MSY for traditional management (when H is the choice variable):

$$Y_h = maxH[f(mn) + an] \tag{III.3}$$

In the case of reserves, c is the choice variable (chosen to maximize the and MSY is given by:

$$Y_r = max[(1-c)f(cmn_t^r)] \tag{III.4}$$

The authors show that both MSY's are equivalent and that the optimal c is given by:

$$c = (1-H) - H[\frac{an}{f(mn)}] \tag{III.5}$$

The density, n is the density at the optimal level of harvest. "Thus the optimal fraction of the coastline to put in reserves is always less than the fraction of adults allowed to escape harvest under traditional management techniques ... This makes sense because the adults in reserves can reproduce until they die, so if the population is iteroparous, the fraction of the adult population set aside can be lower than that under traditional management."

III.B.3 Economic Models

Most economic work has focused on reserves as the only management tool. This means that the analysis focuses on an open-access steady-state. One advantage these papers have over the biological papers mentioned above is the explicit modeling of fishermen's behavior and response to reserve creation.

Hannesson (1998) uses a non-spatially-explicit model but shows that a protected area is unlikely to improve catches in open-access equilibrium. More interesting is the result in discrete time that the reserve will generate over-capacity in the fishing fleet. The main insight gained by the spatially explicit models in Sanchirico and Wilen (2001) and Smith and Wilen (2003) is that spatial behavior by the harvesters is important. Their models are also open-access in nature and focus solely on improving net

yields in cases when spill-over is sufficient to compensate fishers for lost harvests from reserve areas. This unsurprising result is that it is unlikely that reserves will increase aggregate catches in an open-access fishery. Sanchirico and Wilen (2001) do also find some results which will be relevant to designing marine reserves; relative dispersal rates in a patchy system are important in choosing which patches to close.

The only economic work finding value for reserves as a hedging strategy is Grafton et al. (2005) and Grafton and Kompass (2005). These articles model uncertainty as ecological shocks and reserves manage this risk by keeping a population more resilient.

None of this literature considers parameter uncertainty. The next section begins to model the use of protected areas as a supplemental management tool to the single-owner harvest decision under parameter and stock uncertainty.

III.C Model

Notation:

- $B \sim$ biomass
- $F \sim$ Harvest
- $E \sim$ Fishing effort
- $r \sim$ intrinsic growth rate
- $K \sim$ carrying capacity
- $z \sim$ intrinsic migration rate

- $q \sim$ catchability coefficient
- $\alpha \sim$ fraction of area closed

In order to generalize the logistic growth function to spatially differential harvesting, we must specify the rate of diffusion from the higher density region. Specifically, if we have an entire fishery (area normalized to 1) satisfying a simple logistic equation so that the law of motion of the biomass, B is:

$$\dot{B} = rB(1 - \frac{B}{K}) - F \tag{III.6}$$

Fishing harvest, F is given by the standard Schaeffer production function:

$$F = qEB \tag{III.7}$$

If we choose to harvest differentially in space, let's first consider two regions. For the region of size α we have:

$$\dot{B}_\alpha = B_\alpha \left[r(1 - \frac{B_\alpha}{\alpha K}) + M(B_\alpha, B_{1-\alpha}; \alpha, K) \right] - F_\alpha \tag{III.8}$$

The equation of motion for the remaining region of size $1 - \alpha$ is then:

$$\dot{B}_{1-\alpha} = B_{1-\alpha} \left[r(1 - \frac{B_{1-\alpha}}{(1-\alpha)K}) - M(B_\alpha, B_{1-\alpha}; \alpha, K) \right] - F_{1-\alpha} \tag{III.9}$$

One good candidate for the per-capita migration rate is:

$$M(\cdot) = m(\alpha) \left(\frac{B_{1-\alpha}}{(1-\alpha)K} - \frac{B_\alpha}{\alpha K} \right) \tag{III.10}$$

That is, the migration rate is some intrinsic rate, $m(\alpha)$, multiplied by the density differential. At this point I insist only that $m(\alpha)$ satisfy the boundary conditions $m(0) =$

$m(1) = 0$. This is the form used for the results in the following section. As an aside we might also consider:

$$M(\cdot) = n\left(1 - \frac{B_\alpha}{B_{1-\alpha}}\right) \tag{III.11}$$

for some constant n.

III.D One-time effort choice

Choosing catches under parameter uncertainty is certainly the most realistic adaptive control problem but involves dynamics and learning. For tractability I focus on the plausible approximation of a single owner making a one-time fleet-size decision and look at the expected long run steady state. For both reserves and without reserves I will look at expected steady-state catches (ignoring price and cost) and I will compute the relevant payoff variables as functions of the effort (or fleet size) choice and reserve size choice.

III.D.1 No reserve

Steady-state biomass as a function of effort choice:

$$B^{SS}(E) = K - \frac{qK}{r}E \tag{III.12}$$

Steady-state yield as a function of effort choice:

$$F^{SS}(E) = qKE(1 - \frac{q}{r}E) \tag{III.13}$$

To round out this section we begin to consider uncertainty. Suppose we have prior beliefs on the three parameters: q,r, and K. If we want to maximize the expected steady-state yield $\mathbb{E}(F^{SS}(E))$. The effort value maximizing this maximand is given by:

$$E^* = \frac{\mathbb{E}(qK)}{\mathbb{E}(\frac{2q^2K}{r})} \tag{III.14}$$

Even in the unlikely event that these these three random variables are mutually independent under our prior beliefs, we are left with the following:

$$E^* = \frac{\mathbb{E}(q)}{2\mathbb{E}(q^2)\mathbb{E}(\frac{1}{r})} \tag{III.15}$$

By Jensen's inequality and the definition of variance it is easy to show that in the above formulation $E^* \leq \frac{\mathbb{E}(r)}{2\mathbb{E}(q)}$, the effort level that harvests the maximum sustainable yield under our prior beliefs. One interpretation of this result is that parameter uncertainty alone necessitates a certain level of precaution even under risk neutrality.

III.D.2 With reserves

With two regions and fishing effort restricted to a region of size $(1-\alpha)$, denoted $E_{1-\alpha}$, the steady state density differential between the regions is:

$$\left(\frac{B_{1-\alpha}}{(1-\alpha)K} - \frac{B_\alpha}{\alpha K}\right) = \frac{-qE_{1-\alpha}}{r + 2m(\alpha)} \tag{III.16}$$

This equation III.16 shows that the steady-state fish density in the reserve is higher than that in the fished region; this is not a surprising result but a comforting one.

The biomass levels in the two regions are:

$$B_\alpha^{SS}(E_{1-\alpha}) = \alpha K - \frac{q\alpha K}{r}E_{1-\alpha}\left(\frac{m(\alpha)}{r + 2m(\alpha)}\right) \tag{III.17}$$

$$B_{1-\alpha}^{SS}(E_{1-\alpha}) = (1-\alpha)K - \frac{q(1-\alpha)K}{r}E_{1-\alpha}\left(1 - \frac{m(\alpha)}{r+2m(\alpha)}\right) \tag{III.18}$$

The steady-state harvest in this context is given by:

$$F_{1-\alpha}^{SS}(E_{1-\alpha}) = q(1-\alpha)KE_{1-\alpha}\left(1 - \frac{q}{r}E_{1-\alpha}\left(1 - \frac{m(\alpha)}{r+2m(\alpha)}\right)\right) \tag{III.19}$$

Also note that the sum of the two biomass values is given by:

$$B_{Total}^{SS} = K - \frac{qK}{r}E_{1-\alpha}\left(\frac{(2\alpha-1)m(\alpha)}{r+2m(\alpha)} + (1-\alpha)\right) \tag{III.20}$$

Note that because $m(0) = 0$ equation III.20 reduces to equation III.12 when there is no reserve.

III.E Optimal Steady-State

If our manager wishes to maximize expected yield under prior beliefs then the optimization problem is given by:

$$\underset{\alpha,E_{1-\alpha}}{max}\,(1-\alpha)\mathbb{E}\left[qKE_{1-\alpha} - \frac{q^2K}{r}E_{1-\alpha}^2\left(1 - \frac{m(\alpha)}{r+2m(\alpha)}\right)\right] \tag{III.21}$$

The first order conditions for this maximum are:

$$\frac{\partial}{\partial E_{1-\alpha}} = 0 = \mathbb{E}\left[qK - 2E_{1-\alpha}\left(\frac{q^2K}{r}\left(1 - \frac{m(\alpha)}{r+2m(\alpha)}\right)\right)\right] \tag{III.22}$$

and

$$\frac{\partial}{\partial\alpha} = 0 = (1-\alpha)\mathbb{E}\left(\frac{-q^2K}{r}E_{1-\alpha}^2\Psi'_\alpha\right) - \mathbb{E}\left(qKE_{1-\alpha} - \frac{q^2K}{r}E_{1-\alpha}^2\Psi_\alpha\right) \quad \text{(III.23)}$$

where

$$\Psi_\alpha = 1 - \frac{m(\alpha)}{r + 2m(\alpha)} \quad \text{(III.24)}$$

and therefore

$$\Psi'_\alpha = -\frac{rm'(\alpha)}{(r + 2m(\alpha))^2} \quad \text{(III.25)}$$

It is important to first note that the derivative of the expected value with respect to α can be both positive and negative. Suggesting there may be an optimal reserve and fleet size. The exact analytical solutions to these first order conditions are not easily solved so it is necessary to pass to numerical methods as in the next section.

III.F Numerical solutions

In order to numerically optimize equation III.21 I normalize $K = 1$ and specify $m(\alpha) = z\alpha(1-\alpha)$. Call z the intrinsic migration rate. I consider values for r and q ranging from .01 to 2. The result is that reserves do indeed increase expected payoff. For each parametrization, the optimal steady-state is achieved with a positive value for α, that is reserves are optimal when fleet size and reserve size are the only management tools. Not only does a reserve decrease the probability of a stock crash to zero but it also increases the payoff in very low catch steady-states when too little or when too much effort has been applied. In fact, even when distributions are such that the probability of a stock crash is zero reserves still improve expected payoffs.

III.1 displays a typical three dimensional graph of the expected payoff function III.21. This particular graph was generated with independent and identical discrete uniform distributions on r and q (mean = .1050 and variance = .0035) and an intrinsic migration rate of 1. In this case the optimal reserve size was approximately one-third of the region. All other parameter distribution revealed qualitatively similar results with unique optima but no clear patterns emerged. Changes in the variance appear to have little effect on optimal reserve size except when variance is zero, optimal reserve size is zero.

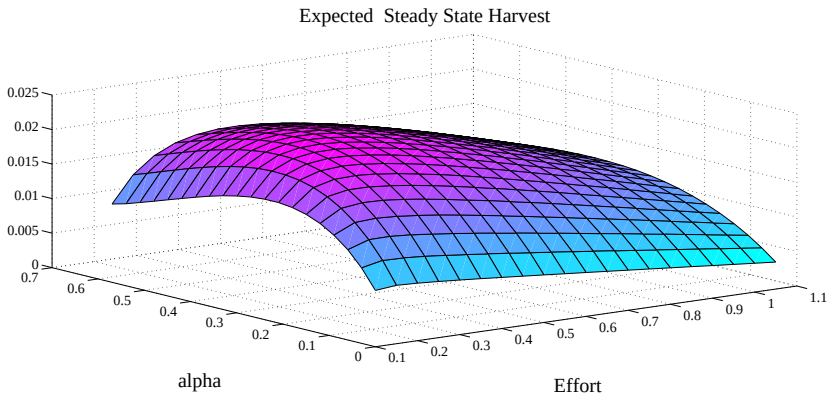

Figure III.1: Expected steady-state harvest

Perhaps more interesting than the existence of a unique optimum is the ex-post value of reserves given a particular fleet size. For an r and q both with mean of .1 the maximum likelihood choice for fleet size for harvesting maximum sustainable yield is $E_{mle} = \frac{\mathbb{E}(r)}{2\mathbb{E}(q)} = .5$. Recall that equation III.15 is less than or equal to this effort level. Implying that the best the manager can do without a reserve is to choose a fleet size lower than this maximum likelihood fleet. Here, I can show (for these and other parameterizations) that certain reserve sizes can improve, not just expected payoff but

can actually dominate the choice without reserves except in the case when fleets were far too small. That is, ex-post payoff is higher for every realization of r and q whether our maximum likelihood fleet size was too high or too low. For much larger reserves, the result is that we still do better if our fleet size is too large but we significantly underperform if our fleet size was too small.

To see this, fix the fleet size at .5. Then compare different realized payoffs for different reserve sizes for all pairs of r and q realizations in the support. Here, I find that with a small reserve of 10% we do better or equal to no reserve for almost every realization pair $\{r, q\}$. The only exception is when $r > 2q$ so that our fleet choice was far too small. But for a larger reserve (70%) our payoff is higher only in the region where our fleet size was too large ($r < \frac{1}{2}q$). These results are represented graphically in Figure III.2. There is an intriguing political economy implication of this result; when fleet sizes are too large, yields can be uniformly improved by protected areas. More generally, protected areas that are 'small enough' can improve steady-state yields no matter the size of the fleet. To the extent that protected areas provide numerous other benefits they may be far more politically achievable than attempts to reduce fleet sizes, such as the notoriously troublesome vessel buy-back programs.

III.G Conclusion

Reserves in this model do help improve expected payoffs when parameters are uncertain. The exact size of the optimal reserve is determined by the particular parametrization. In particular the optimal size depends on the prior probabilities and the intrinsic rate of migration. This improvement is not a feature of any directional spatial dynamics and disappears without uncertainty. Reserves can be too large; in every trial, expected payoffs are eventually decreasing in α. Small reserves, over the large center of

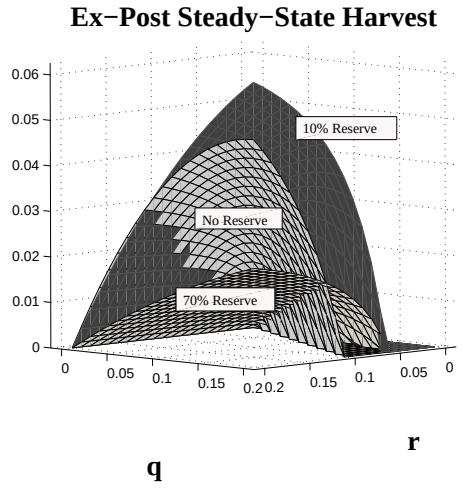

Figure III.2: Ex-post steady-state harvest

the belief support, yield large benefits over no-reserve policies and large reserve policies. Large reserves only dominate small ones in the extremes where fleets are far too large. No-reserve policies are only marginally better when fleets are far too small.

The actual design of marine protected areas will involve models far more complicated than the present investigation, taking into account idiosyncratic features of the region and non-fishery values as well. This paper suggests that reserves of the right size are not strictly a loss to fishing industry. To the extent that managers and the public wish to create reserves in nurseries or in regions serving other values such as existence values, the fishing industry may benefit in the long run as well, provided the reserves are not too large. This paper establishes the qualitative result that many ecologist's intuition is sound; marine protected areas can help manage the risk associated with our uncertain knowledge of marine systems.

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