# Benefits of Spatial Regulation in a Multispecies System

GUILLERMO E. HERRERA
Bowdoin College

**Abstract** *Spatial heterogeneity in multispecies systems affects both ecological interactions and the composition of harvest. A bioeconomic model is used to analyze the nonselective harvest of two stocks with generalized ecological interaction and different persistent distributions across two spatial strata. Harvester response to aggregate effort controls is shown to partially dissipate rents relative to the case where the spatial distribution of effort can be specified. Numerical solutions for time paths of spatial (first-best) and aggregate (second-best) input constraints indicate factors affecting their relative efficiency. In the scenarios studied, benefits of spatial specificity range from 0 to 15% of total net present value (NPV), depending upon the spatial correlation of stocks, their relative growth rates and prices, and the cost gradient across space. The benefits of spatial regulation are also heightened by the presence of ecological interaction, especially predator-prey dynamics.*

**Key words** Bycatch, multispecies system, second-best regulation, spatial bioeconomic model.

JEL Classification Codes Q20, Q22, Q28.

## Introduction

Bioeconomic models of single, spatially homogeneous stocks (Clark 1990, chs. 2–3) serve as the point of departure for more realistic and complex analyses. The canonical (and indeed, almost definitional) prescription for dynamic efficiency is that each marginal unit of stock should be extracted if resulting current profits exceed its *in situ* (or shadow) value; *i.e.*, its discounted marginal contribution to the flow of future rents. Those who actually make decisions about exploitation often fail to fully internalize the forgone shadow value of the resource. Harvesters, therefore, extract some units of biomass that should be left *in situ*, eroding dynamic rents along various dimensions and—in the extreme of open-access—dissipating them altogether. Regulations either explicitly constrain extractive inputs or outputs, or otherwise alter incentives of harvesters (*e.g.*, through output taxes or a market for harvest rights) to better align them with those of society.

Dynamically efficient harvest of multiple stock resource systems can be complicated by predator-prey relationships (Mesterton-Gibbons 1988; Chaudhuri and Saha

Ray 1996; Mesterton-Gibbons 1996; Supriatna and Possingham 1999), transitions between age classes (Anderson 1989), competition (Clark 1990, sec. 10.2), or cannibalism (Armstrong and Sumaila 2001). These "ecological externalities" imposed by one stock on the other(s) alter *in situ* values relative to those emerging from partial equilibrium optimization. Decentralized management of individual stocks that ignores such interactions achieves a lower level of dynamic rents in aggregate than a "central planner" who optimizes subject to ecological interactions. For example, a predator imposes a negative externality on its prey while the prey benefits the predator. *Ceteris paribus*, this increases the shadow value of prey biomass and decreases that of predators; dynamically optimal harvest involves maintaining lower predator biomass and more prey than under ecological independence.

When stocks interact, traversing one stock's partial equilibrium optimal time path causes other stocks to deviate from theirs (Mesterton-Gibbons 1988; Chaudhuri and Saha Ray 1996; Mesterton-Gibbons 1996). The jointly efficient path may even involve movement *away* from the steady-state optimum, relative to the starting stock levels, en route to the final equilibrium (Ragozin and Brown 1985). Clark (1990, sec. 10.2) characterizes optimal harvest of interdependent species; Mesterton-Gibbons (1988, 1996) solves for the singular control and describes the approach to equilibrium for a generalized ecological interaction; Hoagland and Jin (1997) partially solve the same generalized interacting-species case when one species has extractive value and the other existence value.

Even when stocks are ecologically independent, nonselective effort links the dynamics of others through incidental harvest ("bycatch"). Analogous to ecological relationships, technological linkages give rise to different optimal harvest policies than those arising under perfect selectivity (Chaudhuri 1986, 1987; Mesterton-Gibbons 1987; Clark 1990).

When organisms are heterogeneously distributed in space, the location of harvest activity, as well as its overall intensity, influences efficiency. Biological productivity may vary across space, causing *in situ* value to vary as well. Harvesters have been shown empirically to respond to differences in expected rents when deciding where and how intensively to operate (Eales and Wilen 1986; Hilborn and Kennedy 1992). Ignoring this response of harvesters to profit gradients, for example in the establishment of marine protected areas, leads to suboptimal results (Smith and Wilen 2003).

Numerous studies consider the exploitation of metapopulations comprising two or more sub-populations, or patches, in discrete space. These models take into account the dynamics of sub-populations as well as the transfer of organisms between patches when describing, or optimizing with respect to, the spatial distribution of harvest activity. An emergent rule of thumb is that, *ceteris paribus*,[1] areas with relatively high intrinsic growth rates (*i.e.*, net *sources* of biomass) should be harvested less aggressively than net *sinks* (Tuck and Possingham 1994). Source-sink relationships may be due to biological factors; *e.g.*, differential fecundity or mortality rates, or physical ones; *e.g.*, advective dispersal or space limitations (Brown and Roughgarden 1997).

Sanchirico and Wilen (1999) develop a dynamic model of effort and stock levels in a metapopulation in which effort evolves in response to profit gradients. They assume rent dissipation at equilibrium, and therefore do not consider efficient spatial

––––

[1] In particular, assuming homogeneous harvest costs across space. When there is a cost gradient that runs counter to the flow of biomass in a system, it is not unequivocal that one should protect the net sources of biomass and focus exploitation on the net sinks of biomass. Political or management costs of closing productive areas may also be high, which should be factored into policy design (Sanchirico and Wilen 2005).

policy *per se*. Their subsequent analysis solves for dynamically efficient spatial management, which entails a spatial tax on harvest equal to the shadow value at each point in space (Sanchirico and Wilen 2005). Spatial management necessarily outperforms that which ignores spatial structure.

Though the interplay between ecological interaction and spatial structure has not been well studied, these two characteristics are likely to coexist in many actual systems. In Supriatna and Possingham (1999), optimal harvest of a two-patch, predator-prey metapopulation consists of a constant escapement policy that depends upon dispersal rates and the strength of ecological interactions. Their model assumes perfect selectivity; *i.e.*, the ability to choose escapement of each species in each patch independently.

The model presented here combines spatial structure and ecological interaction in the context of *nonselective* effort. The analysis includes the impact of spatial distribution of effort on the catch composition, and therefore on evolution of the stocks and dynamic efficiency. First-best regulation,[2] with an optimal level of effort chosen at each point in space and time, is compared to the second-best case, in which the regulator is unable to directly control spatial effort allocation but does so indirectly by optimizing subject to the expected response of harvesters.

## Bioeconomic Model

The system in question consists of two technologically and ecologically linked stocks. Biomass of each stock $i = 1,2$ at time $t$ is denoted by the scalar $X_{it}$. The spatial distribution of stock $i$ across discrete spatial strata 1 and 2 is captured by the row vector[3] $\boldsymbol{X_{it}} = (x_{i1t}, x_{i2t})$. The binomial distribution of each stock $i$ is represented by the vector $\boldsymbol{C_i} = (c_{i1}, c_{i2})$ satisfying $c_{i1} = 1 - c_{i2}$, so that $\boldsymbol{X_{it}} = X_{it}\boldsymbol{C_i}$. Spatial distributions are assumed constant, regardless of the biomass of the stocks, which redistribute themselves at the beginning of each time period $t$ so as to restore the spatial proportions $\boldsymbol{C_i}$.[4] The sign of spatial stock correlation is that of $(0.5 - c_{11})(0.5 - c_{21})$. If stocks are perfectly correlated across space; *i.e.*, if $\boldsymbol{C_i} = \boldsymbol{C_j}$, spatial distribution of effort has no impact on its selectivity, catch composition is then determined entirely by the relative catchability coefficients of the two stocks and their total abundance.

The harvest industry consists of a large number of agents who act according to the tenets of regulated open access (Homans and Wilen 1997). Harvesters act in a decentralized fashion to maximize current private profits without regard for their

---

[2] This scenario gives a "first-best" outcome subject to the nonselective harvest technology; presumably an even more efficient approach path could be achieved if effort were perfectly selective.

[3] Vector notation is used where possible. Boldface characters represent row vectors (and their transpose column vectors); parameters defined across space (strata), such as a particular stock's spatial distribution or space-specific wage levels, are given in row format, and those indexed by stock, such as prices or catchability coefficients, are given in column format. Plain-text uppercase variables or parameters apply to both species or to both strata; and lower-case variables are specific to one species in a single location.

[4] Constant proportionality arises if the organisms assort according to habitat quality, and the habitat qualities (with respect to a particular stock $i$) in the two strata have the same intercept, but different slopes. That is, suppose the habitat quality inhabited by the marginal unit of stock $i$ in each stratum $m$ declines according to $q_{im} = a_i - b_{im}x_{im}$ as biomass increases. Organisms will settle in two strata $m$ and $n$ so as to equalize habitat quality on the margin. This gives rise to the condition $x_{im} = (b_{in}/b_{in})x_{in}$, which, in turn, implies a constant fraction $c_{im} = b_{in}/b_{im}$ of stock $i$ in stratum $m$. This assumption simplifies the dynamics of this system (necessitating two state variables rather than four). Implications of the constant proportionality assumption, and the potential effect of relaxing it, are discussed in the conclusions.

impact on future stock levels. This is tantamount to assuming an infinite discount rate on the part of harvesters.[5]

Harvesters exert nonselective extractive effort $F_t = (f_{1t}, f_{2t})$ across space at time $t$, with catchability coefficients $Q = (q_1, q_2)^T$ constant across strata. Marginal cost of effort varies over space according to wage vector $W = (w_1, w_2)$. Marginal harvest is linear in effort and stock as in the standard Schaefer model; *i.e.*, $dh = qx(df)$. Correspondingly, as in Homans and Wilen (1997), harvest depletes stocks within a time period: $dx_{imt}/df_{mt} = -q_i x_{imt}$, with a corresponding decline in the marginal productivity of effort.[6] Starting with biomass $x_{imt}$ in stratum $i$ before time $t$ harvest, the escapement subsequent to exertion of effort $f_{mt}$ is:

$$s_{imt}(x_{imt}, f_{mt}) = x_{imt}e^{-q_i f_{mt}}, \tag{1}$$

and harvest is:

$$h_{imt}(x_{imt}, f_{mt}) = x_{imt} - s_{imt}(x_{imt}, f_{mt}) = x_{imt}(1 - e^{-q_i f_{mt}}). \tag{2}$$

$H_{it}$ is the spatial harvest vector of stock $i$ and $S_{it}$ the corresponding escapement: $S_{it} = X_{it} - H_{it}$. Aggregate escapement of stock $i$ is the scalar $S_{it}$.

Harvested biomass of both stocks sells in perfectly competitive markets, with price vector $P = (p_1, p_2)^T$ constant across time. Current-period rents associated with effort vector $F_t$ are:

$$(\mathbf{X}_{1t,}\mathbf{X}_{2t}, \mathbf{F}_t) = TR(\mathbf{X}_{1t,}\mathbf{X}_{2t}, \mathbf{F}_t) - TC(\mathbf{F}_t) = \sum_i \sum_m p_i h_{imt}(x_{imt}, f_{mt}) - \mathbf{W} \bullet \mathbf{F}_t, \tag{3}$$

where the '•' operator is the inner (dot) product of the two vectors.

Subject to harvest, each stock evolves in discrete time according to a logistic growth function modified by local ecological interaction:

$$\mathbf{X}_{i(t+1)} = \mathbf{S}_{it} + \mathbf{C}_i \bullet \mathbf{G}_i(\mathbf{S}_{it}, \mathbf{S}_{jt}), \tag{4}$$

$$G_i(\mathbf{S}_{it}, \mathbf{S}_{jt}) = r_i S_{it} + \sum_{m=1,2} {}_{ji}s_{imt}s_{jmt} \left(1 - \frac{S_{it}}{K_i}\right); \quad i \quad j. \tag{5}$$

Intrinsic growth rate of species $i$ is $r_i$, and $K_i$ are carrying capacities vis-à-vis total biomass. Parameters ${}_{ji}$ denote the nature and magnitude of ecological impact of stock $j$ on stock $i$. For example, ${}_{ji} > 0$, ${}_{ij} < 0$ depicts a predator-prey relationship (stocks $i$ and $j$, respectively), and ${}_{ji} < 0$, ${}_{ij} < 0$ competition.

Figure 1 shows a schematic of the system, including depletion of stock (from its

---

[5] Admittedly, this is not always an accurate characterization of the harvest industry. If an individual harvester constitutes a significant portion of the fleet, and if their tenure in the industry is likely to last into the future (due to legal entitlements or large capital investments which give them a competitive edge over other potential entrants), the harvester will internalize at least some portion of their dynamic impact on the stock; *i.e.*, they will act as though they have a finite discount rate. The assumption of harvesters acting entirely in the present is appropriate for cases where a highly elastic labor force participates in an industry whose costs are mostly variable.
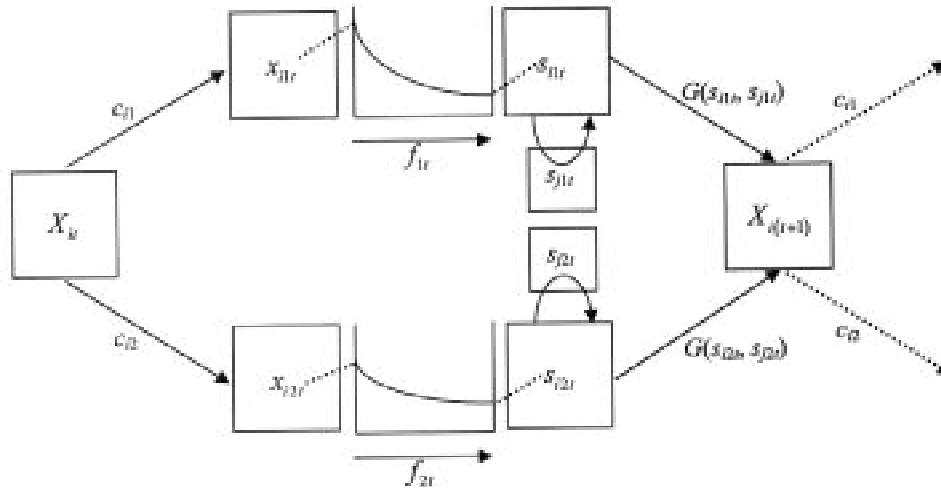[6] or, equivalently, a rising marginal cost of output within a season.

**Figure 1.** Schematic of the Dynamics of a Representative Species

initial level to escapement) as a result of harvest. In each time period, escapement of each stock in each stratum gives rise to a gross productivity[7]—the first component of the first term on the RHS of equation (5)—and then stocks interact within strata (the second component of this term). The net productivity is converted into adult biomass in the subsequent period via a density-dependent process, with density expressed as the ratio between total escapement (across both strata) and the stock's total carrying capacity. After recruitment into the aggregate biomass, stocks re-assort themselves spatially according to their respective distribution vectors $C_i$ to give rise to the spatial stock vectors in the subsequent period.[8]

## Dynamic Optimization with Spatially Structured Control

In the "first-best" case, the regulator specifies both elements of the spatial effort vector $F_t$ at each time $t$ so as to maximize the present value of rents[9] arising from the system. The Bellman equation for the associated dynamic programming problem over an infinite time horizon is:

$$V(\mathbf{X}_{1t}, \mathbf{X}_{2t}, \mathbf{F}_t) = \max \quad (\mathbf{X}_{1t}, \mathbf{X}_{2t}, \mathbf{F}_t)$$
$$+ \quad V[\mathbf{X}_{1(t+1)}(\mathbf{X}_{1t}, \mathbf{X}_{2t}, \mathbf{F}_t), \mathbf{X}_{2(t+1)}(\mathbf{X}_{1t}, \mathbf{X}_{2t}, \mathbf{F}_t)], \tag{6}$$

---

[7] Separate ecological interactions take place within each stratum as a function of the respective portions of the two stocks present.

[8] A further clarification of the stock dynamics: Ecological interaction takes place within strata, following harvest (*i.e.*, it is a function of escapements). Stocks from both strata then "pool" in some location (*e.g.*, a breeding ground) at the start of each season. Reproduction takes place subsequent to density-dependent effects (*e.g.*, from limited food or substrate on the breeding grounds). Biomass then redistributes itself, in time-invariant proportions, to the fishing grounds. Biomass does not flow between strata (fishing grounds) during the harvest season. While this depiction of stock dynamics is adopted, in part, as a simplifying assumption, it is also a reasonable representation of reality for stocks which migrate each year to a remote location to reproduce.

[9] Future rents are discounted by the factor $= 1/(1 + )$, where is the discount rate.

subject to the equations of motion (4), the initial conditions:

$$\mathbf{X}_{1,0} = \mathbf{X}_1^0; \ \mathbf{X}_{2,0} = \mathbf{X}_2^0, \tag{7}$$

element-by-element non-negativity constraints on the state and control vectors:

$$\mathbf{X}_{it} \geq 0; \tag{8}$$

$$\mathbf{F}_{it} \geq 0; \ i = 1,2, \tag{9}$$

and the aggregate harvest capacity constraint:

$$\sum_m f_{mt} \leq F_{\max}. \tag{10}$$

In theory, this problem can be solved by substituting equations (4) into the RHS of equation (6). First-order conditions would then set the derivatives of the RHS of equation (6) with respect to the two effort levels to zero. The Benveniste-Scheinkman condition (Sargent 1987) would result from differentiating equation (6) with respect to the state variables. This latter condition, together with the first-order condition, would give rise to a time-consistent harvest policy dependent only upon the state variables, assuming the value function converges[10] (Lucas, Stokey, and Prescott 1989). By inspection, however, it seems this protocol is unlikely to yield analytical results, given the nonlinearity in the growth function and the ecological and technical linkages between the stocks. Instead, this problem is solved using numerical methods, as discussed below.

*Aggregate Effort Control*

Complete specification of the spatial effort distribution requires both fixed (*e.g.*, an initial investment in technology) and variable (*e.g.*, monitoring) costs and therefore may not be feasible or cost effective. If spatial effort control is prohibitively costly or unenforceable, the regulator must resort to a "blunt" regulatory instrument. Though there are other possibilities, the blunt control considered here is an aggregate effort constraint; *i.e.*, a limit on the total effort exerted across all strata. Optimal aggregate effort control takes place as a two-stage game.[11] To characterize the solution to this game, it is necessary to first describe the outcome of the second stage; *i.e.*, the response of harvesters to an aggregate effort constraint. Incorporating this response as a constraint, the regulator then chooses a time path of aggregate effort so as to achieve the highest possible NPV. Inability to choose effort levels separately renders this approach second-best relative to spatially specific regulation.

———

[10] In fact, in the numerical solution to this problem, the value function converges for a sufficiently long time horizon, yielding a time-invariant, state-dependent numerical policy function.

[11] Spatially structured and aggregate effort controls are not the only instruments regulators are likely to have at their disposal. A number of other regulatory instruments, such as trip limits and size limits, are commonly employed to elicit changes in catch compositions. Quotas (transferable or otherwise) or taxes on landed biomass could also be used. The analysis here could be carried out with a focus on quotas or prices rather than input restrictions.

## The Harvesters' Problem

The marginal net benefit of effort applied to stratum $m$ depends upon the starting stocks in that stratum, the amount of effort already applied, and economic parameters:

$$MNB(x_{1mt}, x_{2mt}, f_{mt}) = \sum_i p_i q_i c_{im} x_{it} e^{-q_i f_{mt}} - w_m. \tag{11}$$

Harvesters respond to an aggregate effort allotment $\overline{F}_t$ at time $t$ by allocating marginal effort quanta[12] to the more lucrative stratum until the constraint binds. An interior outcome, with positive effort in both strata, consists of a vector of effort levels $\tilde{F}_t(\overline{F}_t) = \{f(\overline{F}_t), f(\overline{F}_t)\}$ satisfying an equimarginal net benefit condition:

$$MNB(x_{11t}, x_{21t}, f_{1t}) = MNB(x_{12t}, x_{22t}, f_{2t}), \tag{12}$$

and the regulatory constraint:[13]

$$\sum_m f_{mt} \leq \overline{F}_t. \tag{13}$$

A corner solution with all effort focused in stratum $m$ (*i.e.*, $\tilde{f}_{mt} = \overline{F}_t$) arises if the marginal net benefit of effort in stratum $m$, after all allowed effort $\overline{F}_t$ has been exerted there, exceeds that of effort in stratum $n$ before *any* effort has been exerted; *i.e.*, if:

$$MNB(x_{1mt}, x_{2mt}, \overline{F}_t) \geq MNB(x_{1nt}, x_{2nt}, 0). \tag{14}$$

## The Regulator's Second-best Problem

Limited to an aggregate control, the regulator incorporates the reaction of the harvesters into a problem analogous to equation (6), but with a single scalar control variable, $\overline{F}_t$:

$$V(\mathbf{X}_{1t}, \mathbf{X}_{2t}) = \max_{\overline{F}_t} \left[ \mathbf{X}_{1t}, \mathbf{X}_{2t}, \tilde{F}_t(\overline{F}_t) \right] \tag{15}$$

$$+ V\Big\{ \mathbf{X}_{1(t+1)}\big[\mathbf{X}_{1t}, \mathbf{X}_{2t}, \tilde{F}_t(\overline{F}_t)\big], \mathbf{X}_{2(t+1)}\big[\mathbf{X}_{1t}, \mathbf{X}_{2t}, \tilde{F}_t(\overline{F}_t)\big] \Big\}.$$

Figure 2 illustrates the relationship between the first-best and second-best solutions in a given time period using isoprofit curves for the principal and agent. The principal's (regulator's) isoprofit[14] lines are drawn as concentric ellipses surround-

---

[12] Note that the outcome of the harvesters is not a coordinated optimization *per se* over the total effort levels in the two strata. Rather, it is the aggregate result of the successive allocation of effort quanta across space, where each quantum is allocated to the location where it yields the highest profits.

[13] The regulatory constraint is nonbinding only if $MNB(x_{11t}, x_{21t}, \tilde{f}_{1t}) = MNB(x_{12t}, x_{22t}, \tilde{f}_{2t}) = 0$ with equation (13) satisfied as an inequality. There is, however, no reason for the regulator to issue a nonbinding aggregate effort constraint.

[14] These are really better described as "iso-*dynamic*-profit," or "iso-NPV" curves, as they take into account all future rents emerging from the system rather than just the current payoff.
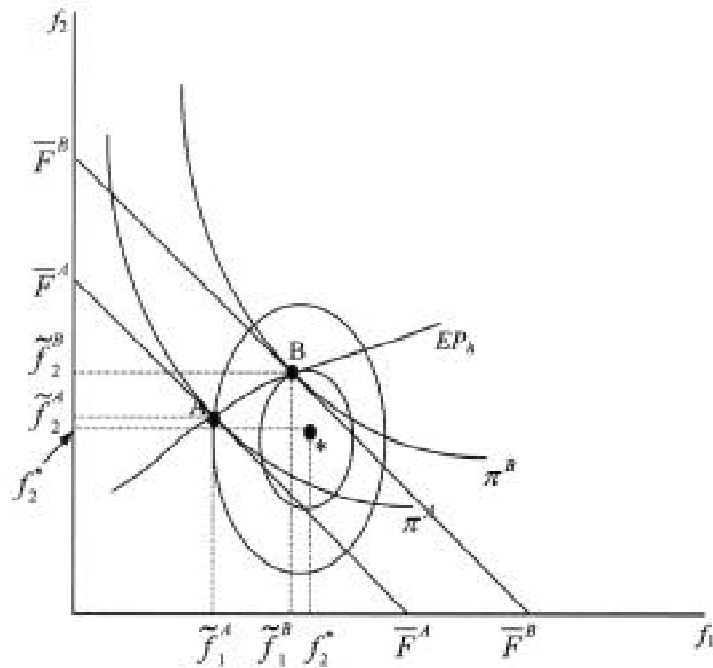
**Figure 2.** Comparison of First-best and Second-best Solutions
Note: Points A and B, harvester responses to aggregate effort constraints $\bar{F}^A$ and $\bar{F}^B$,
are on the second-best expansion path $EP_h$, and '*' is the first-best outcome.

ing the point '*'. This first-best effort pairing $\{f_1^*, f_2^*\}$ corresponds to the spatially structured controls that maximize dynamic rents; *i.e.*, the solution to equations (6)–(10) where the future value function is known. Social NPV declines moving radially outward in any direction from the optimum.

In the second-best solution, the regulator specifies the aggregate effort constraint $\bar{F}$, which corresponds to a linear regulatory frontier with a slope of $-1$. Barring corner solutions, harvesters divide the aggregate effort allowance among the strata so that the marginal profitability of effort is equal. This corresponds to a point of tangency between an isoprofit curves $_h$ and the regulatory constraint, such as points A and B in figure 2. The expansion path $EP^h$ traces out the response of harvesters to varying aggregate effort constraints. The regulator then chooses the aggregate effort constraint with the harvester response that yields the highest level of dynamic *social rents*.

In the scenario pictured in figure 2, the highest dynamic social rents attainable in the second-best solution emerge with aggregate effort $\bar{F}^B$, which gives rise to harvester response $\{\tilde{f}_1^B, \tilde{f}_2^B\}$. This second-best solution involves too little effort in stratum 1 and too much in stratum 2, relative to the first-best solution.

## Numerical Results

A numerical dynamic programming routine was used to solve for the rent-maximizing effort and stock paths over a finite time horizon, using backward induction.[15] Such paths were derived both for the case of spatially structured effort, solving equations (6)–(10), and aggregate effort control; *i.e.*, solving equation (15).

*Comparative Statics*

The "base parameter set" (BPS) of table 1 was chosen, fairly arbitrarily, for purposes of comparison. It depicts two ecologically independent stocks with moderate negative spatial correlation: 30% of stock 1 and 70% of stock 2 is in stratum 1. Stock 1 has a higher intrinsic growth rate and a lower *ex-vessel* price than stock 2. Carrying capacities are equal. The marginal cost of effort in stratum 2 is higher than that in stratum 1.

 The first-best steady-state stocks and controls, emerging from the solution to equations (6)–(10), are given in table 2. The first row (Scenario 1) corresponds to the BPS; subsequent rows give results for the indicated parameter changes. Comparisons of equilibrium stock and effort levels for this collection of parameter changes largely corroborate economic intuition.

 Increasing the discount rate from = 0.03 to = 0.06 (Scenario 2) leads to higher steady-state effort levels in both strata, as well as a decrease in both stock

**Table 1**
Base Parameter Set (BPS)

| Parameter | Stock $i = 1$ | Stock $i = 2$ |
|---|---|---|
| $r_i$ | 0.35 | 0.25 |
| $K_i$ | 100 | 100 |
| $c_{i1}$ | 0.3 | 0.7 |
| $q_i$ | 0.1 | 0.1 |
| $p_i$ | 10 | 20 |
| $_{ji}$ | 0 | 0 |
| | Stratum $m = 1$ | Stratum $m = 2$ |
| $w_m$ | | |
| | 4 | 6 |
| | System-wide | |
| | 0.03 | |

————

[15] A terminal condition of zero salvage value was used in the computations here. This could be replaced with a positive salvage value function, such as a linear salvage function (*i.e.*, constant value per unit stock remaining in the terminal period), some concave function, *etc.* Some exploratory solutions to the model with non-zero salvage value were used to determine that, while the behavior toward the end of the time horizon is affected by the salvage value assumption, the steady-state levels of biomass and controls are *not* affected for sufficiently long time horizons. Because the numerical solution is an approximation to an infinite-horizon problem in which the system would remain at this steady-state in perpetuity, the salvage value assumption does not seem to be of much consequence.

**Table 2**
Comparative Statics with Respect to First-best (Spatially Specific) Regulation

| Scenario | Parameter(s) (%Δ) from BPS | Steady-State Stocks and Controls (%Δ from BPS Results) | | | |
|---|---|---|---|---|---|
| | | $X_1$ | $X_2$ | $t_1$ | $t_2$ |
| 1 | — — | 58.74 | 50.51 | 1.08 | 1.85 |
| 2 | δ: 0.03 → 0.06 (+100) | 55.12 (–6.2) | 44.65 (–11.6) | 1.21 (+12) | 1.94 (+4.9) |
| 3 | $r_1$ 0.35 → 0.40 (+14)<br>$r_2$: 0.25 → 0.20 (–20) | 60.17 (+1.4) | 49.40 (–2.2) | 0.52 (–51.9) | 2.43 (+31.4) |
| 4 | $w_1$: 4 → 6 (+50)<br>$w_2$: 6 → 8 (+33) | 59.91 (+1.5) | 51.01 (+0.1) | 1.08 (0) | 1.80 (–2.7) |
| 5 | $w_1$: 4 → 5 (+25)<br>$w_2$: 6 → 5 (–17) | 57.31 (–2.4) | 51.38 (+1.7) | 1.01 (–6.5) | 1.94 (+4.9) |
| 6 | $p_1$: 10 → 20 (+100)<br>$p_2$: 20 → 10 (–50) | 56.06 (–4.6) | 52.23 (+3.4) | 0.96 (–11.1) | 2.02 (+9.2) |
| 7 | $\alpha_{21}$ ‡ 0.0025<br>$\alpha_{12}$ ‡ –0.0025 | 53.84 (–8.3) | 42.10 (–16.7) | 0.24 (–77.8) | 3.09 (+67.0) |
| 8 | $\alpha_{21}$ ‡ –0.0025<br>$\alpha_{12}$ ‡ –0.0025 | 40.25 (–31.5) | 40.45 (–19.9) | 0.73 (–32.4) | 2.19 (+18.4) |

Note: Scenarios are deviations from the Base Parameter Set (BPS) of table 1.

levels. A higher rate of return elsewhere makes it efficient to substitute out of biomass and into other forms of capital. This change is analogous to the standard single-stock optimal control results in which steady-state stock decreases and effort increases with the discount rate.[16]

Scenario 3 examines the effects of an increase in the intrinsic growth rate of stock 1 and a decrease in that of stock 2. Because stock 1 is concentrated in stratum 2 and vice-versa, this shift in reproductive rates leads to increased effort in stratum 2 and decreased effort in stratum 1. Steady-state biomass levels move in the same direction as the growth rates.

In Scenario 4, both wage rates increase, but at different rates. Effort shifts away from stratum 1, which becomes relatively more expensive to exploit. The effects on effort and steady-state biomass in stratum 2 are ambiguous. In Scenario 5, there is no such ambiguity: Stratum 2 becomes less expensive to harvest in both an absolute and a relative sense. Changing relative output prices (Scenario 6) has an effect similar (but opposite in direction) to that of changing wages.

Ecological interactions also alter the first-best steady-state. The regulator takes into account the effect of interspecific dynamics on the shadow values of stocks and the variation in these effects over space according to the spatial distributions of the species. Relative to the ecologically independent case, the presence of a predator-prey relationship (Scenario 7) makes it efficient to harvest more intensively where the predator is concentrated and less so in the stratum preferred by the prey. Ecological competition (Scenario 8), on the other hand, acts as a sort of depreciation. Much like a discount rate, it prompts substitution out of both stocks into other forms of capital; effort is increased and standing stocks decreased in both strata.

## Comparative Dynamics and NPV Comparisons

Numerical solution of the first- and second-best dynamic programming problems allows for comparative dynamic analysis, as well as computation of differences in NPV over the entire time horizon. Given the dimensionality of the parameter space, it is not feasible to exhaustively describe the impacts of different parameter combinations on dynamic behavior. Rather, a few representative scenarios of interest are discussed. The focus is on cases where spatial regulation is likely to be most important; *i.e.*, where the incentives of harvesters seeking current profits conflict most strongly with the social objective of maximizing dynamic rents.

## Inversely Related Growth Rates and Prices

Suboptimal use of resources often results when a stock has a low growth rate but a high *ex vessel* price. Like non-renewable resources, slow-growing, high-priced stocks give rise to high marginal *in situ* rents when managed optimally, and are hence prone to over-exploitation under open access. Examples of such stocks are the Pacific grenadier (*Coryphaenoides acrolepis*); Patagonian toothfish (*Dissostichus eleginoides*), marketed as "Chilean sea bass; and orange roughy (*Hoplostethus atlanticus*).

The dynamic efficiency of spatial and non-spatial regulation was compared for various combinations of growth rates ($r_2$) and prices ($p_2$) for stock 2. Table 3 shows

---

[16] Specifically, from the canonical Gordon-Schaefer model solved with optimal control, $x^* = (K/2)(r - \ )/r$ and $E^* = (r + \ )/2q$.

**Table 3**

NPV Gains (%) from Spatial Regulation for Different Growth Rates and Prices of Stock 2

|       |      | $p_2$ | | | | |
|-------|------|-------|------|------|------|-------|
|       |      | 10    | 15   | 20   | 25   | 30    |
|       | 0.10 | 0.51  | 2.29 | 4.38 | 7.07 | 9.37  |
|       | 0.15 | 0.78  | 3.18 | 6.50 | 9.76 | 12.73 |
| $r_2$ | 0.20 | 0.73  | 3.23 | 6.38 | 9.59 | 11.61 |
|       | 0.25 | 0.56  | 2.84 | 5.67 | 7.75 | 9.32  |
|       | 0.30 | 0.43  | 2.27 | 4.60 | 6.12 | 7.33  |

Note: Other parameters are as in the base parameter set of table 1.

relative NPV gains from spatial control, in percentage terms, associated with these parameter combinations.[17] Benefits of spatial control increase for all growth rates as $p_2$ increases. In general, NPV gain also increases as the growth rate of $X_2$ declines, though at very low levels (*e.g.*, $r_2 = 0.10$) NPV gain declines slightly due to the diminished contribution of $X_2$, in percentage terms, to overall NPV.

Figure 3 shows stock and effort trajectories for spatial and aggregate control in the scenario $r_2 = 0.15$, $p_2 = 30$; *i.e.*, for an $X_2$ that is slow-growing and high-priced relative to the BPS. Aggregate control leads to depletion of $X_2$ below the level emerging from the first-best solution; the second-best solution involves more effort in stratum 1, where $X_2$ is concentrated, than in stratum 2. In the first-best solution, more effort is exerted in stratum 2 than in stratum 1 at all points in time.

### Interaction of Ecological Linkages and Spatial Correlation

When stocks are heterogeneously distributed in space, ecological interactions can amplify the divergence between the performance of spatial and aggregate controls. For example, consider the case of a predator-prey interaction, where $X_1$ is the predator and $X_2$ the prey. Under spatial control, the social planner will account for the negative externality imposed by $X_1$ on $X_2$ by increasing the amount of effort exerted in the location(s) where $X_1$ is concentrated and decreasing effort where $X_2$ is concentrated. Under aggregate control, no such direct adjustment is possible. Therefore, dissipation of rents due to suboptimal spatial effort allocation is exacerbated by the presence of the interaction.

Table 4 reports NPV gains from spatial control as a function of both the strength of ecological interaction and the degree of negative spatial correlation of the stocks. Assuming (as in the BPS) $X_1$ is concentrated in stratum 2 and $X_2$ in stratum 1, a range of negative spatial correlations is represented by the single

---

[17] The gains from spatial control vary depending on the starting stock levels; *i.e.*, NPV = $f(x_1^0, x_2^0)$. For example, spatial control is more beneficial when the stock of a slow-growing, valuable stock is initially depleted. The numbers presented in this and subsequent tables are the *maximum* NPV gains across all possible starting stock levels.
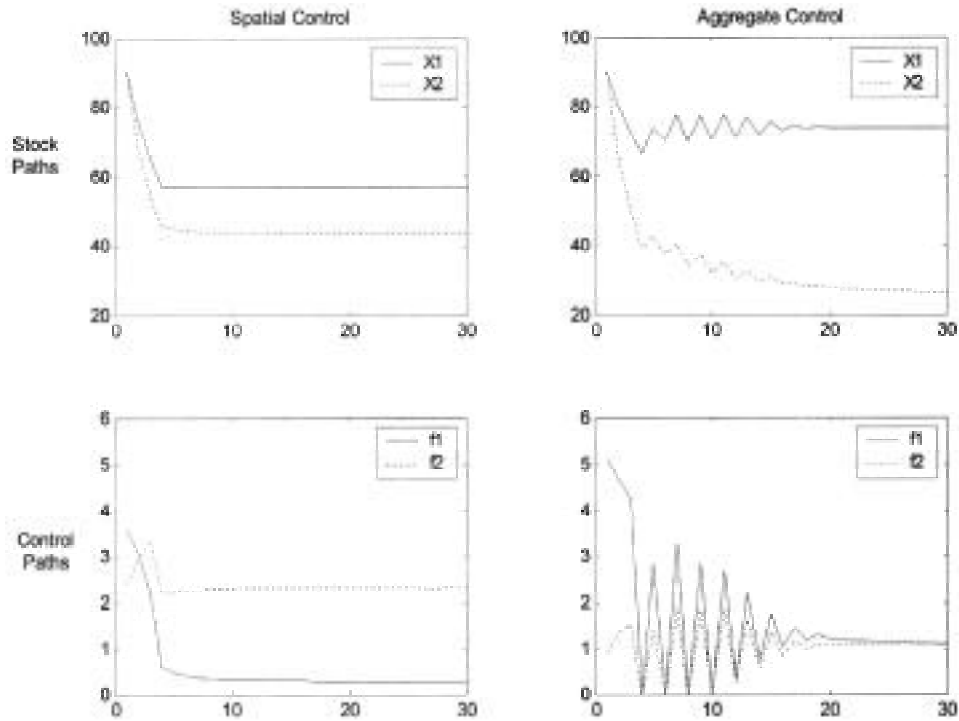
**Figure 3.** Stock and Effort Trajectories, under Spatial and Aggregate Control, for a High-priced, Slow-growing Stock 2 ($r_2 = 0.15$, $p_2 = 30$)

parameter $c$ {0.1, 0.2, 0.3}. Spatial distribution vectors $C_1 = (0.5 - c, 0.5 + c)$, $C_2 = (0.5 + c, 0.5 - c)$ are considered for each of the $c$. Panel (a) reports the results for a predator-prey relationship (stock 1 the predator, stock 2 the prey), and (b) a competitive relationship (both interaction coefficients negative).

Under both predator-prey and competitive ecological interactions, the importance of spatial control generally increases with the strength of the ecological interaction and with the degree of negative spatial correlation. There is some concavity in the benefits of spatial control; *i.e.*, a differential of 12.75% for a predator-prey relationship of ± 0.0035 and $c = 0.2$, and only 10.57% when $c = 0.3$.

The benefits of spatial control are larger in the case of predator-prey relationships than in the case of competition, *ceteris paribus*. Competing stocks impose reciprocal negative externalities, so it is efficient to increase harvest intensity in general. The decline in NPV under aggregate effort control comes from not fully adjusting intensity of harvest to emphasize areas where the interaction is greatest. In a predator-prey scenario, the prey imposes a *positive* externality on the predator, while the predator's effect on the prey is negative. Myopic incentives, which cause harvesters to harvest too much prey and not enough predators are, therefore, doubly detrimental to NPV in the predator-prey case.

**Table 4**

NPV Gains (%) from Spatial Control as a Function of Ecological Interaction and Spatial Correlation

(a)

| $\alpha$ | $\Delta c$ | | |
|---|---|---|---|
| | 0.1 | 0.2 | 0.3 |
| ±0.0005 | 5.63 | 7.14 | 7.46 |
| ±0.0015 | 8.75 | 9.53 | 8.68 |
| ±0.0025 | 9.73 | 11.69 | 9.84 |
| ±0.0035 | 8.61 | 12.75 | 10.57 |

(b)

| $\alpha$ | $\Delta c$ | | |
|---|---|---|---|
| | 0.1 | 0.2 | 0.3 |
| −0.0005 | 1.43 | 2.49 | 4.13 |
| −0.0015 | 2.63 | 3.82 | 5.02 |
| −0.0025 | 4.56 | 5.48 | 5.84 |
| −0.0035 | 6.86 | 7.39 | 6.94 |

Note: Panel (a) reports results for predator-prey interactions ($X_1$ predator, with $\alpha > 0$: $X_2$ prey, with $\alpha < 0$), and panel (b) captures competitive relationships ($\alpha < 0$ for both stocks).

## Conclusions

The importance of curtailing the intensity of extractive effort in common-pool resources is well understood. The existing literature emphasizes the tendency of harvesters, under open access, to ignore some or all of the *in situ* value of standing biomass. Therefore, they exert *too much* effort, partially or fully dissipating social rents. The current analysis demonstrates that in resources with heterogeneous spatial distributions, space can provide an additional dimension along which harvesters dissipate rents. Technology that improves the regulator's ability to dictate the *location* of effort as well as its intensity can, therefore, increase dynamic rents. Aggregate, or blunt, constraints on the quantity of harvest effort[18] are suboptimal (second-best), because harvesters perceive homogeneous market value while the shadow value of extracted stock is in fact heterogeneous. It is impossible to compel harvesters to fully internalize spatial variations in shadow values with an instrument that does not itself have spatial resolution.

Regulation that incorporates spatial structure, like any instrument that reduces the information deficit of the regulator, can significantly increase the efficiency of resource use. Scientific understanding of the spatial dimension of biological and economic processes is improving, and technology for spatial monitoring of agent behavior at high resolution is increasingly available (Wilen 2004). Indeed, if large fishes (sharks) *themselves* can be tracked accurately through space and time (Klimley *et al.* 2001), it should be feasible to track the spatial deployment of fishing vessels and gear. Such technologies are, however, costly; the decision whether to incorporate a spatial dimension into a regulatory instrument depends upon the magnitude of these costs relative to efficiency gains. Without considering the costs of spatial monitoring and enforcement, the current analysis provides a framework in which to assess the magnitude of efficiency gains associated with adding a spatial dimension to regulations. General qualitative results emerge regarding the attributes of a multispecies system that make spatial regulation more or less beneficial. For example, spatially structured effort regulations are less likely to justify costs of implementation when stocks are well correlated over space or when the rate of discount is high.

The analysis revolves around a multispecies bioeconomic model with generalized ecological interactions. Each stock has a unique binomial distribution across space; the fractions of a given stock in each of the strata are constant in time. The same nonselective harvest technology is employed in both strata. The spatial distribution of effort, therefore, interacts with stock distributions to determine the catch composition; *i.e.*, the ratio of different species in the overall harvest.

The second-best scenario, in which only aggregate effort can be controlled, constitutes a dynamic principal-agent problem: In each period, a subgame perfect Nash equilibrium is obtained by deriving the harvesters' response (consisting of a spatial distribution of effort levels). This response is then incorporated into the social planner's optimization problem.

The model presented here employs a fairly stringent assumption regarding the spatial dynamics of the stock; *i.e.*, that the stocks are distributed in time-invariant proportions across the spatial strata at the start of each period. Even though harvest differentially depletes the stocks locally, stock dynamics presume stocks pool and are subsequently redistributed each period so as to maintain these spatial proportions. This assumption is arguably less realistic than metapopulation models, such as those employed by Sanchirico and Wilen (1999, 2005), in which substocks evolve separately. In a two-species, two-patch metapopulation model, however, there are

---

[18] In the context of a spatially structured effort, this quantity dimension of harvest effort refers to the sum of the elements of the spatial harvest vector.

four state variables rather than two over which to optimize, making computation of optimal control paths more difficult. Aside from expedience in this sense, the formulation presented here has another advantage; it allows for an assessment of the effect of differential spatial correlation *per se* on the benefits of spatial control, without the need to consider dynamic changes in such spatial correlation.

Numerical analysis was used to explore the relationship between biological and economic parameters and the gains from implementing depth-specific regulation. Some substantial gains from spatial management—as high as a 15% increase in NPV—were found in the scenarios examined, and the sample of parameter sets explored was not exhaustive. It is likely there are other parameter sets for which the gains are larger than those reported here.

Spatial regulation is found to be particularly beneficial when one of the stocks is slow growing and high priced. When such stocks are optimally managed, they are maintained at a level where their *in situ* value is high relative to faster-growing stocks. Because aggregate (non-spatial) effort constraints give harvesters an opportunity to partially disregard this high shadow value of such stocks, the efficiency losses associated with a blunt instrument are especially high.

A key result of this paper is the effect of ecological interactions, in particular predator-prey and competitive relationships, on the benefits of spatially structured regulation. These interactions take place within the strata, after the harvest process, as a modification of pre-recruitment larval production. Because such interactions are proportional to local stock abundances, the spatial pattern of harvest affects the interspecific dynamics and, in turn, the *in situ* value of stocks.

For example, from a social standpoint it is optimal to harvest more intensively in areas of high density of both stocks when there are strong competitive interactions, or in areas with relatively high concentrations of a predator in the case of a predator-prey interaction. If harvesters act myopically in pursuit of current profits, they do not account for such interactions in their decisions about where or how much to harvest. Ecological interaction is, therefore, another locus of rent dissipation. Numerical results presented here suggest that both predator-prey and competitive interactions magnify the benefits of spatially structured controls, though asymmetry of the externality in the predator-prey case makes spatial regulation even more important.

The dynamic programming technique used to determine optimal time path of effort could be modified to include stochastic growth or spatial dynamics or spatial distributions that follow a density-dependent process. Most existing literature dealing with joint harvest of multiple species assumes stocks are evenly and deterministically mixed at each point in time; it would be more realistic to model the degree of mixing as a stochastic variable. The methods above could be used to determine when and whether this extension to stochastic harvest composition is likely to matter for either single-pool or spatially structured resources.

Spatially structured multispecies resources provide a new set of theoretical challenges. When the regulator is able to specify only the magnitude of extractive inputs, but not their spatial allocation, spatial structure introduces asymmetries of information not present in single-pool resources. Spatially structured regulations provide a means of improving the selectivity of harvest and mitigating the partial dissipation of social rents resulting from this informational asymmetry. This paper provides a methodology for assessing the benefits associated with such regulations.

## References

Anderson, L.G. 1989. Optimal Intra- and Interseasonal Harvesting when Price Varies with Individual Size. *Marine Resource Economics* 6:145–62.

Armstrong, C., and U.R. Sumaila, 2001. Optimal Allocation of TAC and the Implications of Implementing an ITQ Management System for the North-East Arctic Cod. *Land Economics* 77(3):350–59.

Brown, G., and J. Roughgarden. 1997. A Metapopulation Model with Private Property and a Common Pool. *Ecological Economics* 22(1):65–71.

Chaudhuri, K.S. 1986. A Bioeconomic Model of Harvesting a Multispecies Fishery. *Ecological Modelling* 32:267–79.

―――. 1987. Dynamic Optimization of Combined Harvesting of a Two-species Fishery. *Ecological Modelling* 41:17–25.

Chaudhuri, K.S., and S. Saha Ray. 1996. On the Combined Harvesting of a Predator-prey System. *Journal of Biology and Systematics* 4:373–89.

Clark, C.W. 1990. *Mathematical Bioeconomics: The Optimal Management of Renewable Resources*. New York, NY: Wiley & Sons.

Eales, J., and J. Wilen. 1986. An Examination of Fishing Location Choice in the Pink Shrimp Fishery. *Marine Resource Economics* 2(4):331–51.

Hilborn, R., and R.B. Kennedy. 1992. Spatial Patterns in Catch Rates: A Test of Economic Theory. *Bulletin of Mathematical Biology* 54(2/3):263–73.

Hoagland, P., and D. Jin. 1997. A Model of Bycatch Involving a Passive Use Stock. *Marine Resource Economics* 12:11–28.

Homans, F.R., and J. Wilen, 1997. A Theory of Regulated Open Access Resource Use. *Journal of Environmental Economics and Management* 32(1):1–21.

Klimley, A.P., B.J. Le Beouf, K.M. Cantara, J.E. Richert, S.F. Davis, and S. Van Sommeran. 2001. Radio-acoustic Positioning as a Tool for Studying Site-specific Behavior of the White Shark and Other Large Marine Species. *Marine Biology* 138(2):429–46.

Lucas, R., N. Stokey, and E. Prescott, 1989. *Recursive Methods in Economic Dynamics*. Cambridge, MA: Harvard University Press.

Mesterton-Gibbons, M. 1987. On the Optimal Policy for Combined Harvesting of Independent Species. *Natural Resource Modeling* 2(1):109–34.

―――. 1988. On the Optimal Policy for Combined Harvesting of Predator and Prey. *Natural Resource Modeling* 3:63–90.

―――. 1996. A Technique for Finding Optimal Two-species Harvesting Policies. *Ecological Modeling* 92(2-3):235–44.

Ragozin, D.L., and G. Brown. 1985. Harvest Policies and Nonmarket Valuation in a Predator-prey System. *Journal of Environmental Economics and Management* 12:155–68.

Sanchirico, J.N., and J. Wilen. 1999. Bioeconomics of Spatial Exploitation in a Patchy Environment. *Journal of Environmental Economics and Management* 37(2):129–50.

―――. 2005. Optimal Spatial Management of Renewable Resources: Matching Policy Scope to Ecosystem Scale. *Journal of Environmental Economics & Management* 50(1):23–46.

Sargent, T.J. 1987. *Dynamic Macroeconomic Theory*. Cambridge, MA: Harvard University Press.

Smith, M.D., and J. Wilen. 2003. Economic Impacts of Marine Reserves: The Importance of Spatial Behavior. *Journal of Environmental Economics and Management* 46(2):183–206.

Supriatna, A.K., and H.P. Possingham. 1999. Harvesting a Two-patch Predator-prey Metapopulation. *Natural Resource Modeling* 12(4):481–97.

Tuck, G.N., and H.P. Possingham. 1994. Optimal Harvesting Strategies for a Metapopulation. *Bulletin of Mathematical Biology* 56(1):107–27.

Wilen, J. 2004. Spatial Management of Fisheries. *Marine Resource Economics* 19(1):7–19.