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Optimal spatial management of renewable resources: matching policy scope to ecosystem scale

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Abstract

We investigate the characteristics of an optimally managed spatially explicit renewable resource system. The bioeconomic system is depicted with a metapopulation model where the subpopulations are connected by dispersal processes and are affected by the spatial distribution of harvesting effort. We characterize the optimal way to distribute harvesting effort over space and time in order to optimize returns from this spatial/dynamic system. We also investigate how the optimal spatial allocation of effort, harvesting, and biomass compare with second-best allocations that ignore spatial processes in this system. We find that optimal instruments reflect the interplay between the spatial gradient of rents and the spatial gradient of biological dispersal. Using a simple parameterization to explore qualitative properties in several specific examples, we find that second-best solutions blend or average results of the differentiated case and differ in intuitive ways from first-best optima.

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1. Introduction

The management of *terrestrial* renewable resources has evolved in ways that are strikingly different from the management of renewable *marine* resources. For example, it is common to observe states managing game hunting by a complex system of zones, each of which may have different bag limits, gear regulations, and season openings. The use of spatially differentiated policies makes it possible to manage harvesting in ways that match exploitation to differences in biological productivity, population levels, and socioeconomic payoffs. Areas near population centers, where the value of a recreation day is large, may be managed to permit high total effort but at reduced individual exploitation rates (e.g. with low bag limits), whereas distant areas may be managed to actually attract effort away from congested population centers. Importantly, matching the policy scope more closely with the scale and characteristics of ecosystem functions enables fine-tuning that achieves higher levels of biological and socioeconomic objectives.

Management of marine resources, on the other hand, has historically been characterized by relative uniformity of regulatory actions over space. It is common, for example, in commercial fisheries for gear and season restrictions to be imposed over large spatial units that span the range of the population. Spatial differentiation of policy, when present, more often reflects different political jurisdictions than conscious attempts to tailor policy instruments to ecosystem heterogeneity. The fundamental difference between terrestrial and marine ecosystem management reflects the difficulty of monitoring and measuring fish populations. As one seasoned fishery scientist summed it up, “managing fish populations is just like managing forests, except that fish move and you can’t see them.”

Despite the historical state of affairs in fisheries management, the characterization of homogeneously distributed marine populations is gradually giving way to a so-called metapopulation paradigm that depicts biological populations as heterogeneously distributed in space, linked by oceanographic processes and trophic interaction.¹ This shift has been spurred on by recent technological innovations that have increased our understanding about the spatial distribution of population abundances, how oceanographic processes can generate this patchiness, and how ecological interactions in multispecies assemblages are driven by a spectrum of forces with hourly, daily, interannual and interdecadal time spectrums.²

In an important sense, therefore, we are on the cusp of a knowledge revolution in managing marine resources, where future management systems are likely to involve zones delineated by spatially and inter-temporally differentiated policy instruments. For example, instead of limited entry or transferable quota systems granting access to fish species over their whole ranges, fishermen in the future will hold portfolios of licenses and quotas that permit individual access to some species, with some gear, in particular areas, at certain periods in the season. In addition, there will be areas that are set aside permanently as reserves protected from any exploitation, other areas set aside to protect rare and special ecosystem assemblages, and areas that temporarily close on a rotating basis. All of this is likely to be monitored and enforced with satellite tracking systems that either allow or lock out certain activities by various individuals at various times and

¹See, for example, Levin [13,14], Roughgarden [18], Hastings [8], Pulliam [17], and Hanski [7].

²For example, we now know much more about how large-scale oceanographic events like El Niños and La Niñas affect ocean temperature gradients, wind velocity and direction, sea surface height, and upwelling indices, in some cases in three-dimensional space. This has led, in turn, to a new understanding of the manner in which populations are distributed in space and the mechanisms that link subpopulations.

places. An under appreciated fact is that technology currently exists to “fence the ocean” electronically, if not literally.

Zoning the oceans will require radical changes in the science supporting marine resource management. Whereas natural scientists have been incorporating new spatially explicit details into their depictions of renewable resource systems for several decades, economists have only recently begun to incorporate space into renewable resource models [19]. We know little, for example, about how to design optimal spatial policy instruments that account for biological and economic interconnections (and externalities) in spatially linked systems. What does the optimal spatial pattern of effort, harvest, and abundance look like, and how does it reflect oceanographic processes, patch-specific productivity, and unit rents in a linked biological system? What are the qualitative differences between optimally managed systems with spatially differentiated instruments and systems that ignore spatial processes and spatial bioeconomic heterogeneity? These are some of the questions we address in the modeling that follows.³

We develop in the next section a simple bioeconomic model that marries a patchy description of the biology with a regulated open access depiction of the harvesting industry. The model is used in the third section to identify and describe the policies that a rent-maximizing regulator would choose if the spatial character of the resource were well understood and if it were feasible to implement spatially explicit measures. We then compare this first-best optimal system with policy systems that homogenize or ignore spatial heterogeneity, for example because of high transactions costs or inadequate enforcement.

Although our focus is on renewable resources and particularly marine resources, the question of how to design fiscal instruments to account for spatial and intertemporal externalities is of broader interest and applicable to optimal design of policies for biodiversity conservation, air and water pollution, and urban/rural land use.⁴ In addition, in an age in which Geographic Information Systems (GIS) and remote sensing are providing policymakers with finer spatial resolution data and information, an understanding of the costs of not matching the policy scope and ecosystem scale is critical for policy analysis. Our analysis thus fits into a broader quest to understand spatial processes and the policy consequences of fine tuning human activities on a spatial as well as intertemporal scale.

2. A spatial model of a fishery

In this section, we develop a model to explore the issue of *optimal* management of a patchy system and show how one might choose economic instruments to guide this system toward a rent-maximizing equilibrium. The institutional setting we have in mind is one in which property rights have not been established so that, without additional incentive-changing instruments, the system will simply converge to the spatial rent-dissipated bioeconomic open access equilibrium as

³An important “empirical” question that we do not address is the effect of implementing spatially explicit policies on management and transactions costs, which will depend on the system and policy instruments being considered. For example, designing individual fishing quota markets will need to balance the appropriate size of the market (number of participants, trading region) against the ecological scale of the system.

⁴Within the literature on pollution regulation and the use of incentive-based market mechanisms, a sizable and growing collection of papers investigates both theoretically and empirically the impacts of uniform policies and the “design” of trading rules in the presence of various dimensions of heterogeneity such as firm size, location, and pollution agents. See, for example, [1,2,9,15,16,22,23].

depicted in Sanchirico and Wilen [19]. To this end, consider a *regulated open access* system, by which we mean that entry is open but subject to control by policy instruments such as landings taxes or effort taxes chosen by the regulator. For example, suppose that the regulator has two kinds of instruments at his/her disposal, patch-specific landings tax equal to τ_i per unit of harvest landed, and patch-specific effort taxes π_i per unit effort. Then we could depict the objective of the regulator as determining the optimal tax policy that maximizes the present discounted value of rents in the fishery. This choice would be subject to a spatially explicit biological system in which there are n -discrete patches of biomass linked by a biological dispersal process and by movements of the fishing fleet across the patches in response to differentials in net rents.⁵

The problem of *optimal regulated open access* can be formally represented as

$$\begin{aligned} \max_{\tau_i(t), \pi_i(t)} \quad & J = \int_0^{\infty} e^{-\delta t} \sum_{i=1}^n R_i(E_i, x_i) dt \\ \text{s.t.} \quad & \dot{x}_i = f_i(x_i)x_i + ND_i(x_1, x_2, \dots, x_n) - h_i(E_i, x_i), \end{aligned} \quad (1)$$

$$\dot{E}_i = s_i R_i(E_i, x_i, \tau_i, \pi_i) + \sum_{\substack{j=1 \\ j \neq i}}^n s_{ij} [R_i(E_i, x_i, \tau_i, \pi_i) - R_j(E_j, x_j, \tau_j, \pi_j)], \quad (2)$$

where rents in each patch i ($R_i(E_i, x_i, \tau_i, \pi_i)$) are a function of a one-dimensional measure of fishing effort (E_i), biomass (x_i), and tax levels, and δ is the discount rate. Note that although taxes are instruments in the state equations for effort, they do not appear in the objective function, since they are properly considered transfer payments.

Eq. (1) represents the biological system for which the instantaneous rates of change of biomass in each patch depend on three factors. First, growth in each patch depends upon the “own” per capita growth rate in patch i , or $f_i(x_i)$, generally assumed to be a density-dependent process. A typical assumption is that per capita growth is linearly related to the level of current biomass relative to a carrying capacity biomass, or $f_i(x_i) = r_i[1 - (x_i/k_i)]$, where k_i is the carrying capacity biomass level and r_i is the intrinsic growth rate. Second, biomass change depends on net dispersal, ND_i , of biomass into and out of patch i , which may depend upon own biomass as well as biomass in any or all of the other patches. Finally, net biomass change depends upon the harvest $h_i(x_i, E_i)$ in each patch, itself a function of the levels of effort and biomass levels in the patch.

As will be demonstrated, the optimal solution depends importantly on the net dispersal function. The explicit form taken by the net dispersal function can vary widely depending upon the type of population and the mechanisms that drive spatial dispersal and determine spatial connectivity. Dispersal flows could be based on relative densities, whereby patches with high densities disperse to patches with lower densities, everything else being equal, or based on unidirectional flows. We refer to the former system as relative density-dependence dispersal and the latter is commonly referred to as a

⁵It is important to note that because space is treated in a discrete (patchy) way, the model is well suited to illustrate characteristics of spatial policies and the implications of heterogeneity in biological and economic parameters. This model is a variant of a metapopulation model, where we are interested in population levels and the nature of the linkages, and not simply whether a patch is occupied—the traditional structure [7]. Brock and Xepapadeas [3] use the traditional structure, which is a reduced-form model of an ecosystem, to investigate the optimal economic management of an ecosystem when species are competing for a limiting resource.

sink–source system.⁶ Finally, we might have a closed system that is spatial in the sense that the population consists of multiple patches located over space, but the patches are assumed biologically independent and driven solely by their own growth processes.⁷ There are other possible permutations [19], but in this paper we focus on these three systems.

The second set of Eq. (2) depicts a behavioral model of a harvesting industry operating over a heterogeneous environment in a manner symmetrical with biological spatial movements. Following Sanchirico and Wilen [19], we hypothesize a simple adjustment process in which the effort level in patch i changes in response to the level of “own” rents net of the taxes vis-à-vis outside opportunities (captured in first term), where s_i is the entry/exit adjustment rate. In the system, fishing effort also responds to arbitrage spatial rent differences by moving sluggishly to patches with higher rents, where s_{ij} is the spatial adjustment rate between patches i and j . This process is captured in the second term consisting of a sum of pairwise spatial dispersal rates each proportional to rent differentials across space between the patch in question and alternative patches. Without any interventions, fishing effort will be misallocated spatially, and there will also be too much effort drawn into the whole system since effort will be responding to average and not marginal rents.

This multi-patch regulated open access model is a generalization of the dynamic reaction model first introduced by Clark [5].⁸ In this formulation, fishing fleets are depicted as responding competitively but myopically across space and time to changes in rents due to biological, market, or policy effects, and the regulator uses taxes to indirectly and sluggishly move the industry toward the optimal equilibrium. This stands in contrast to traditional optimal harvesting models that assume direct and instantaneous control over fishing effort.⁹ While the equilibrium results are qualitatively identical between the two formulations, the optimal paths differ due to the ability (or

⁶While it is not uncommon to characterize marine systems as sink–source systems, there is some debate about whether the notion applies directly [17]. The notion of a sink was originally developed to depict more closed terrestrial systems in which local reproduction needed augmentation from outside sources to offset mortality. Marine systems are typically more open so that local populations are almost always replenished via transport mechanisms from parent populations located elsewhere. For many populations of marine organisms, the offspring of parental populations located at a particular place replenish other locations, and the extent to which they do so relative to recruitment supplied to their own parental population determines the relative role of the location as a sink.

⁷It is important to point out that although our analysis is focused on renewable resources that mix directly due to biological dispersal and indirectly due to fleet dispersal, our model could also depict other economic metapopulation systems, such as regional population centers where pollution and human populations are moving between centers. The analog to the closed biological case would be when there is no mixing of pollutants, the source–sink analog would be when the pollution is following wind currents from the source to sink, as is the case with the SO_2 and NO_x pollution generated in the Ohio River Valley and depositing in the Northeast. Restrictions on effort movements, which are not considered here, would be analogous to emigration and immigration laws.

⁸The model as presented in Eq. (3) is rather general and can be used to depict different biological and economic institutions falling into the broad class of regulated open/closed access systems. These include limited entry licensing, landings quotas, and landings and effort taxes, at both patch-specific and system-wide levels of specificity.

⁹See Clark [5,6] for a two-patch model of optimal spatial exploitation where harvests can be instantaneously adjusted in the case of relative density-dependent dispersal systems. Using the Clark [6] formulation, Tuck and Possingham [24] investigate optimal management in a two-patch, sink–source system with no economic heterogeneity, and Huffaker et al. [10] and Skonhøft and Solstad [21] investigate optimal management in a two-patch setting for terrestrial species. Janmatt [11] finds qualitatively similar results to ours when studying the optimal spatial management for a northeast Atlantic clam fishery. None of these studies investigates all three ecological systems, and compares spatially differentiated with nonspatially differentiated uniform controls.

inability) of the regulator to directly control fishing effort. Similar to these analyses, the regulator is assumed to be knowledgeable, understanding entry/exit dynamics of the industry and population dynamics and dispersal mechanics of the biology, with perfect foresight. While some of these assumptions are obviously simplistic, this is a logical first step to developing a broader theory of the implications of spatially explicit management in fisheries that would include more realistic processes.

3. Optimal spatial policies

In order to solve for the optimal spatially explicit taxes that might be used in regulating this system, we set the problem up as a linear in controls problem. This is accomplished by specifying rents in patch i as $R_i(x_i, E_i, \tau_i, \pi_i) = [(p_i - \tau_i) h_i(x_i, E_i) - (c_i + \pi_i) E_i]$, where p_i is the ex-vessel price and c_i is the per-unit effort cost. The marginal costs of fishing effort can differ across patches due to biogeographic and oceanographic factors that affect the fishing operation. For example, a protected cove with a sandy bottom may have different costs for a vessel that pulls large nets along the benthic habitat (bottom trawler) than in the exposed open ocean with a rocky seafloor. Ex-vessel prices could differ based on product quality differences across the areas and transportation costs to processors and markets. The current valued Hamiltonian for this problem is

$$H = \sum_{i=1}^n \{ [p_i h_i(E_i, x_i) - c_i E_i] + \lambda_i [x_i f_i(x_i) + N D_i(\cdot) - h_i(E_i, x_i)] \\ + \varphi_i [s_i R_i(E_i, x_i, \tau_i, \pi_i) + \sum_{\substack{j=1 \\ j \neq i}}^n s_{ij} (R_i(E_i, x_i, \tau_i, \pi_i) - R_j(E_j, x_j, \tau_j, \pi_j))] \}, \quad (3)$$

where $N D_i(\cdot)$ is shorthand notation for the net dispersal function.

This is a problem with $2n$ controls, $2n$ state variables, and $2n$ costate variables. We will assume that there are upper and lower bounds on the controls and that negative taxes (or subsidies) are feasible if warranted. In general, there will be some restrictions on parameter values that assure nonnegative fishing effort and biomass levels in each patch; we assume these hold without computing the explicit restrictions.¹⁰

Since the problem is linear in the controls, we can first rearrange the Hamiltonian to isolate the control variables. Once this is done, we observe that there are switching functions in the Hamiltonian that we designate as

$$\sigma_{\tau_i}(t) = -h_i(E_i, x_i) \left\{ \varphi_i \left(s_i + \sum_{\substack{j=1 \\ j \neq i}}^n s_{ij} \right) - \sum_{\substack{j=1 \\ j \neq i}}^n \varphi_j s_{ji} \right\}, \\ \sigma_{\pi_i}(t) = -E_i \left\{ \varphi_i \left(s_i + \sum_{\substack{j=1 \\ j \neq i}}^n s_{ij} \right) - \sum_{\substack{j=1 \\ j \neq i}}^n \varphi_j s_{ji} \right\}. \quad (4)$$

¹⁰See Sanchirico and Wilen [19] for the restrictions that must hold for nonnegative biomass and fishing effort levels under open-access conditions, which is special case of the above model.

These switching functions are the time-varying coefficients that multiply each of the controls $\tau_i(t)$ and $\pi_i(t)$ in the rearranged Hamiltonian. By the Pontryagin necessary conditions, each control must be chosen to maximize the Hamiltonian at each instant. Since controls enter the Hamiltonian linearly, the optimal levels of the $2n$ control instruments must satisfy

$$\tau_i = \begin{cases} \tau_i^{\max} & \text{as } \sigma_{\tau_i}(t) > 0, \\ \tau_i^* & \text{as } \sigma_{\tau_i}(t) = 0, \\ \tau_i^{\min} & \text{as } \sigma_{\tau_i}(t) < 0, \end{cases} \quad (5)$$

$$\pi_i = \begin{cases} \pi_i^{\max} & \text{as } \sigma_{\pi_i}(t) > 0, \\ \pi_i^* & \text{as } \sigma_{\pi_i}(t) = 0, \\ \pi_i^{\min} & \text{as } \sigma_{\pi_i}(t) < 0. \end{cases} \quad (6)$$

When a switching function is positive, the optimal control for that patch is set at its maximum and when the switching function is negative the control must be set at its minimum allowable value. If the switching function is zero, the control must be set at its “singular value” τ_i^* or π_i^* , which is to be determined as discussed below. In addition to Eqs. (4)–(6) the necessary conditions include the biomass and effort state equations along with the costate equations. With respect to the latter, by the Pontryagin conditions, we have

$$\begin{aligned} \dot{\lambda}_i - \delta \lambda_i = -\frac{\partial H}{\partial x_i} = & -\left\{ (p_i - \lambda_i) \frac{\partial h_i}{\partial x_i} + \lambda_i \left(x_i \frac{\partial f_i(x_i)}{\partial x_i} + f(x_i) + \frac{\partial ND_i}{\partial x_i} \right) + \sum_{\substack{j=1 \\ j \neq i}}^n \lambda_j \frac{\partial ND_j}{\partial x_i} \right. \\ & \left. + (p_i - \tau_i) \frac{\partial h_i}{\partial x_i} \left(s_i \varphi_i + \sum_{\substack{j=1 \\ j \neq i}}^n s_{ij} \varphi_j - \sum_{\substack{j=1 \\ j \neq i}}^n s_{ji} \varphi_j \right) \right\}, \end{aligned} \quad (7)$$

$$\begin{aligned} \dot{\varphi}_i - \delta \varphi_i = -\frac{\partial H}{\partial E_i} = & -\left\{ (p_i - \lambda_i) \frac{\partial h_i}{\partial E_i} - c_i \right. \\ & \left. + \left((p_i - \tau_i) \frac{\partial h_i}{\partial E_i} - c_i - \pi_i \right) \left(s_i \varphi_i + \sum_{\substack{j=1 \\ j \neq i}}^n s_{ij} \varphi_j - \sum_{\substack{j=1 \\ j \neq i}}^n s_{ji} \varphi_j \right) \right\} \end{aligned} \quad (8)$$

with $i = 1, 2, \dots, n$. Here, λ_i is the marginal value of another unit of biomass in patch i , and φ_i is the marginal value of another unit of effort in patch i .

The typical procedure for solving a problem with one linear control is to characterize conditions that must hold on the singular interval where the switching function is identically zero for some finite period. This involves setting the switching function and its higher-order derivatives equal to zero, inserting Pontryagin conditions where appropriate, and solving for the singular value of the

control or a singular path of the biomass. One then completes the solution by synthesizing the pattern of extreme and singular controls over the whole time horizon.

With more than one control, the problem of synthesizing the complete pattern of optimal controls for the approach path and equilibrium is considerably more complicated because the optimal transition path can involve sequences of extreme and singular controls for various combinations of controls over different parts of the horizon. We ignore the synthesis problem of characterizing transition path controls and focus attention on “interior” equilibrium solutions. These solutions involve singular controls for all instruments so that the switching functions for all n patches are simultaneously zero. We assume that parameters and control bounds are such that singular solutions exist for all controls simultaneously and that these involve positive levels of harvesting and biomass at steady states.¹¹

By solving for the full system of singular controls at interior equilibria, we are left with a system of $6n$ equations in $6n$ unknowns ($x_i, E_i, \tau_i, \pi_i, \lambda_i, \varphi_i$). The system includes costate Eqs. (7) and (8), state equations for effort and biomass, together with the switching functions (Eq. (4)) that are zero at the interior equilibrium. Setting these costate, state, and switching equations to zero describes the equilibrium steady-state solution for the optimally managed renewable resource with spatial dynamics.

The equilibrium solution for the general problem depends critically on the characteristics of the net biological dispersal function. An ecological system with links between and among all patches would generate an optimal solution that is fully integrated in the sense of being simultaneous. On the other hand, a closed system with no biological dispersal can be solved as a set of n independent patches in equilibrium. Finally, a sink–source dispersal system where dispersal flows in one direction is also interdependent.

To interpret the economic intuition embedded in the equilibrium solution, note first that along a singular interval with the system of switching functions (4) identically equal to zero, the shadow values of effort are simultaneously zero ($\varphi_i^* = 0$) since h_i is positive for all i by assumption. Intuitively, if φ_i^* is not equal to zero, then the marginal value of a net change in reallocating effort either across space or to other fisheries would be nonzero $s_i\varphi_i + \sum_{j=1, j \neq i}^n (s_{ij}\varphi_i - s_{ji}\varphi_j)$ and it would pay to change the tax levels to capture these arbitrage possibilities. Thus, at an interior equilibrium with all policy instruments at non zero values, landings taxes and effort taxes will be used to guide the system into a steady-state equilibrium in which there is no additional value to adding or relocating effort. With $\varphi_i^* = 0$ for all i , the Pontryagin necessary conditions simplify to:

$$\dot{\varphi}_i \stackrel{\text{set}}{=} 0 \Rightarrow (p_i - \lambda_i) \frac{\partial h_i}{\partial E_i} = c_i, \quad (9)$$

$$\dot{\lambda}_i \stackrel{\text{set}}{=} 0 \Rightarrow (p_i - \lambda_i) \frac{\partial h_i}{\partial x_i} = \lambda_i \left[\delta - f_i(x_i) - x_i \frac{\partial f_i(x_i)}{\partial x_i} + \frac{\partial ND_i}{\partial x_i} \right] - \sum_{j=1, j \neq i}^n \lambda_j \frac{\partial ND_j}{\partial x_i}, \quad (10)$$

¹¹In a fully general setting, the solution might also involve corner solutions, with no harvesting in some patches and biomass levels in those patches at their carrying capacity levels. The model is therefore able to consider when a complete closure of a particular area is optimal. Many marine scientists are calling for the creation of no-take (closed) areas as a means to increase fish stock abundances (see, for example, the special issue of *Ecological Applications* (13(1) Supplement: 2003) entitled, “The Science of Marine Reserves”).

$$\dot{x}_i^{\text{set}} = 0 \Rightarrow x_i f_i(x_i) + ND_i(\cdot) - h_i(E_i, x_i) = 0, \quad (11)$$

$$\dot{E}_i^{\text{set}} = 0 \Rightarrow (p_i - \tau_i)h_i(E_i, x_i) - (c_i + \pi_i)E_i = 0. \quad (12)$$

Eq. (9) shows that in each patch, the last unit of effort is such that the net value of marginal product (net of the shadow value of the biomass) is equal to its marginal cost of effort. Eq. (10) shows that the marginal unit of equilibrium biomass in each patch satisfies a relationship balancing the direct value of another unit in production (the left-hand side) with its marginal user cost (right-hand side). The marginal user cost, in turn, reflects the discount rate and the patch biological rate of interest as well as terms involving the value of the marginal unit of biomass in its role on net system-wide dispersal. In general, the equilibrium marginal user cost at each patch may be adjusted upward or downward by the marginal value of the contribution of another unit of biomass to the dispersal process. So, for example, in a system where dispersal is dependent on relative densities, the “own” dispersal effect would be negative (higher biomass levels cause out-migration from patch i) and the “other” dispersal effects would be positive (higher biomass levels in patch i cause in-migration to other patches j). The last unit of biomass added to patch i just balances the immediate value in production with its contribution to steady-state system rents, which include its role in dispersal over the whole system, captured by the sum of marginal physical effects multiplied by the patch-specific shadow prices (marginal profits).

Finally, Eqs. (11) and (12) show that the equilibrium involves zero net after-tax rents in each patch and a biological equilibrium in which harvest in each patch is exactly equal to own growth and net dispersal. Note that the population is sustained in what might be called a *flux equilibrium*, in the sense that a flow of dispersal is necessary in the steady state to keep biomass in each patch constant. This is atypical in nonspatial dynamic economic problems and is associated with the fact that flows of dispersal may be needed to sustain steady-state biomass levels in each patch.

At an interior equilibrium, the optimal landings tax is equal to the steady-state shadow value of the biomass ($\lambda_i^* = \tau_i^*$). In addition, because this is assumed to be a system in which open access incentives drive entry/exit, the optimal effort tax extracts the rent wedge between the marginal and average products of effort at the optimum, so that

$$\pi_i^* = (p_i - \tau_i^*) \left[\frac{h_i(E_i^*, x_i^*)}{E_i^*} - \frac{\partial h_i(E_i^*, x_i^*)}{\partial E_i^*} \right] \quad (13)$$

as shown by (9) and (12). This additional instrument applied to effort arises because open access entry incentives must be choked off at the equilibrium to eliminate rent dissipation. An alternative setup might approximate a regulator who can choose effort without sluggishness. In that approach, the equilibrium would involve solving only for the optimal biomass shadow price trajectories, and effort in each patch would be functions of the costate and biomass levels.

3.1. Characteristics of optimal spatial management

The analysis above characterizes the optimal steady-state solution to the regulated open access problem with a patchy biological system. In general, without further specification of the dispersal system, one cannot characterize the features of this equilibrium. In what follows, we specify several explicit dispersal systems and illustrate how a spatially optimized patchy system compares

with one managed with a nonspatial or uniform instrument. For tractability, we consider two-patch cases parameterized using typical assumptions for fisheries models. In particular, assume that the production functions for each patch are Schaefer functions so that $h_i = q_i E_i x_i$, where q_i is the catchability coefficient in patch i .

Per capita biological growth is assumed to be a linear function of the level of current biomass relative to a carrying capacity biomass, as specified in Section 2. We also normalize the populations in each patch by their carrying capacities, implying that x_i is the density of biomass in the patch. The normalization requires the growth rates and catchability coefficients to be rescaled appropriately.¹² The net dispersal function will henceforth be assumed *linear* so that, for example, in patch i it is $ND_i = d_{ii} x_i + d_{ij} x_j$, where d_{ii} is the rate of emigration out of patch i ($d_{ii} < 0$), and d_{ij} is the dispersal rate from patch j to i . We make a standard “adding up” assumption that whatever leaves patch i for patch j arrives in patch j from patch i [8]. This assumes no mortality in the dispersal process and no deviations in movement along the dispersal route. The specific restrictions on the d_{ij} for each ecological structure are discussed below.

These assumptions reduce our analysis to the simplest but still interesting patchy system that can be examined. With a linear harvest function, the value of marginal product with respect to effort equals the value of average product. This makes (13) identical to zero and hence the solution requires only a single instrument (landings taxes) to achieve the optimized equilibrium level of effort. Under these assumptions, the solution to Eqs. (9)–(12) yields equilibrium values for effort, biomass and the shadow price of biomass and (12) solves for the optimal tax rates, which are $\tau_i = p_i - c_i/x_i$.

Under these more specific assumptions, the necessary conditions for the two singular equilibrium biomass densities, Eqs. (9)–(12), can be reduced to the following two nonlinear equations:

$$\begin{aligned}\Phi_1(x_1) &\equiv \left(p_1 - \frac{c_1}{x_1}\right) \left(\delta - x_1 \frac{\partial f_1(x_1)}{\partial x_1}\right) - p_1 f_1(x_1) = d_{11} \left(p_1 - \frac{c_1}{x_1}\right) + d_{21} \left(p_2 - \frac{c_2}{x_2}\right) + \frac{c_1}{x_1^2} (d_{11} x_1 + d_{12} x_2), \\ \Phi_2(x_2) &\equiv \left(p_2 - \frac{c_2}{x_2}\right) \left(\delta - x_2 \frac{\partial f_2(x_2)}{\partial x_2}\right) - p_2 f_2(x_2) = d_{22} \left(p_2 - \frac{c_2}{x_2}\right) + d_{12} \left(p_1 - \frac{c_1}{x_1}\right) + \frac{c_2}{x_2^2} (d_{22} x_2 + d_{21} x_1).\end{aligned}\tag{14}$$

This formulation emphasizes that the biomass levels in each patch that optimize the problem without dispersal ($d_{ij} = 0$ for all i, j) are given by values that satisfy $\Phi_i(x_i) = 0$ in each of the above equations. The solution with $\Phi_i(x_i) = 0$ is the solution to what is known as the *closed biological system*.¹³ As Clark [6] has shown $\Phi_i(x_i) = 0$ depicts the standard single patch condition that the net marginal value

¹²This is not equivalent to saying that the carrying capacities are equal across the patches. Any differences are captured in the rescaled intrinsic growth, dispersal, and catchability coefficients. To reduce the number of parameters, we assume that the rescaled catchability coefficients are equal to one. This assumption does not affect the qualitative nature of our solutions.

¹³In the closed case, even with harvest linked over space and time by economic arbitrage opportunities, the optimal solution involves moving to a steady state in which the biomass in each patch satisfies: $x_i^c = 1/(4r_i p_i)((r_i - \delta)p_i + c_i r_i + \sqrt{8\delta c_i p_i r_i + ((\delta - r_i)p_i - c_i r_i)^2})$. The optimal biomass densities are functions only of own-patch specific economic and biological parameters (left-hand sides of Eq. (15)), a result well known from Clark [6]. The comparative static results in this case are easily shown, namely that the optimal biomass levels are inversely related to the price/cost ratio and the discount/growth rate ratio. We also know that the optimal biomass levels could be above or below the maximum sustainable yield ($MSY_i = 1/2$ under our assumptions) depending upon the degree of stock dependence in harvesting costs.

of another unit of biomass in any patch is zero. In this case, the optimal biomass would be the level that just makes the marginal “liquidation” value of an instantaneous reduction equal to the marginal loss in present value from a long-term reduction in the steady-state biomass.¹⁴

Eq. (15) shows that, in the nondegenerate spatial case with dispersal, there are additional impacts from reducing biomass at the margin in any patch, namely the net aggregate impacts via dispersal on the optimal biomass levels and hence profitability of all connected patches. Eq. (14) also shows that when dispersal is present ($d_{ij} \neq 0$ for some i, j), the solutions for steady-state system are integrated in the sense that the system solution is simultaneous. It also can easily be shown that, with all biological and economic parameters equal and the dispersal matrix symmetric, the optimal biomass levels will be identical across the patches.

The interpretation of the right-hand sides of Eq. (14) can be thought of as the instantaneous changes in system-wide profits via dispersal associated with changes in biomass at the margin in some patch i , holding other things constant. The first term, $d_{11}(p_1 - c_1/x_1)$, is the change in marginal profits in patch 1 associated with a one unit sustained reduction in biomass. The change in biomass in patch 1 may induce a change in dispersal between patches 1 and 2, which will then have an impact on patch 2’s marginal profits, indicated by the second term $d_{21}(p_2 - c_2/x_2)$. Finally, a marginal change in patch 1 biomass (holding patch 2 biomass constant), will also affect fishing costs since average costs are density dependent. This impact on costs is given by the third term $(c_1/x_1^2)(d_{11}x_1 + d_{12}x_2)$, where average costs are weighted by net dispersal. Similar interpretations hold for the three right-hand side terms in the second equation in (15). Intuitively, optimal management of biomass dispersal trades off the loss in marginal profits from a fish leaving, the gain in marginal profit from the fish being caught in another area and the change in average costs of catching fish due to the reallocation of the stock.

To flesh out the implications of different types of system dispersal, we next derive the optimal biomass levels for two special cases of biological dispersal. In one case, we assume dispersal depends upon *relative densities*. The other case is a *sink–source* case that assumes dispersal is unidirectional, flowing from the source to the sink in amounts dependent upon source patch density only. After analyzing first-best system optimal policies, we investigate and compare the implications of implementing nonspatial or second-best policies.

3.2. Relative density-dependent biological systems

What are the explicit equilibrium characteristics of an optimally managed system with relative density-dependent dispersal? In particular, how does the dispersal part of the system modify the above results for the closed system? To answer this question, we begin with the simple one-parameter net dispersal function used by Clark [6] in his inshore/offshore dispersal model, namely $ND_i = b(x_j - x_i)$, where b is a common dispersal rate. In this system net dispersal into patch i will be

¹⁴To see this, let $(1/\delta)R_i(x_i) = (1/\delta)[p_i - c_i/q_i x_i] x_i f_i(x_i)$ equal the present value of the steady-state rents associated with some sustained yield policy $h_i = x_i f_i(x_i)$ at x_i , and let $R'_i(x_i)$ equal the derivative of that function. Let $Z(x_i) = \int_{x_i(0)}^{x_i} [p_i - (c_i/(q_i \varepsilon))] d\varepsilon$, or the amount that one would derive from an instantaneous reduction in the biomass from $x_i(0)$ to x_i . The optimal steady-state biomass trades these two functions off at the margin, so that the optimal biomass satisfies $Z'_i(x_i) - (1/\delta)R'_i(x_i) = 0$, where $\Phi_i(x_i)$ is equal to $Z'(x_i) - (1/\delta)R'_s(x_i)$.

positive if the relative density level in patch j is greater. To highlight the particular role of cost parameters, it is also assumed that prices are equal and there is no biological heterogeneity so that the intrinsic growth rates are the same across patches.

These assumptions allow us to focus on the manner in which economic heterogeneity affects the optimal solution by varying only the patch-specific costs. This is important, since, as we will show, the optimal solution involves adjusting biomass over space so that harvest is concentrated in high profit (here low cost) patches. In addition, the general system in (14) is quartic and not solvable analytically. By focusing only on economic (cost) heterogeneity, we are able to graphically represent the optimal equilibrium in a single representation comparing the relative density-dependent case, with both the closed and sink–source systems. Under these assumptions about dispersal, the right-hand side of Eq. (15) reduces in patch i so that

$$\begin{aligned}\Phi_1(x_1)x_1 &\equiv x_1 \left[\left(p - \frac{c_1}{x_1} \right) \left(\delta - x_1 \frac{\partial f_1(x_1)}{\partial x_1} \right) - p f_1(x_1) \right] = b \left(\frac{c_1 x_2}{x_1} - \frac{c_2 x_1}{x_2} \right), \\ \Phi_2(x_2)x_2 &\equiv x_2 \left[\left(p - \frac{c_2}{x_2} \right) \left(\delta - x_2 \frac{\partial f_2(x_2)}{\partial x_2} \right) - p f_2(x_2) \right] = -b \left(\frac{c_1 x_2}{x_1} - \frac{c_2 x_1}{x_2} \right).\end{aligned}\quad (15)$$

The right-hand side of Eq. (15) can be rearranged so that we have $\Phi_1(x_1) = g(x_1, x_2)/x_1$ and $\Phi_2(x_2) = g(x_1, x_2)/x_2$, where $g(x_1, x_2) \equiv [(c_1 x_2/x_1) - (c_2 x_1/x_2)]$.

Fig. 1 graphs vertical and horizontal lines representing the optimal steady-state biomass levels for the closed system without dispersal ($b = 0$), that satisfy $\Phi(x_i) = 0$ and (15) for each patch. The optimal *closed system* equilibrium is denoted by the number 1. Panel I of Fig. 1 illustrates the case where costs in patch 1 are lower than in patch 2, and patch 2 therefore has higher optimal biomass levels. In panel II of Fig. 1, the costs are reversed. In both panels, $g(x_1, x_2) = 0$ is graphed under the respective cost assumptions.

Under assumptions made here, the $\Phi_i(x_i)$ functions are increasing at a decreasing rate as they cross zero at the closed system equilibrium for each patch. As Clark [6] has further demonstrated in his model of inshore/offshore dispersal, by inspection of the graph and the signs of the

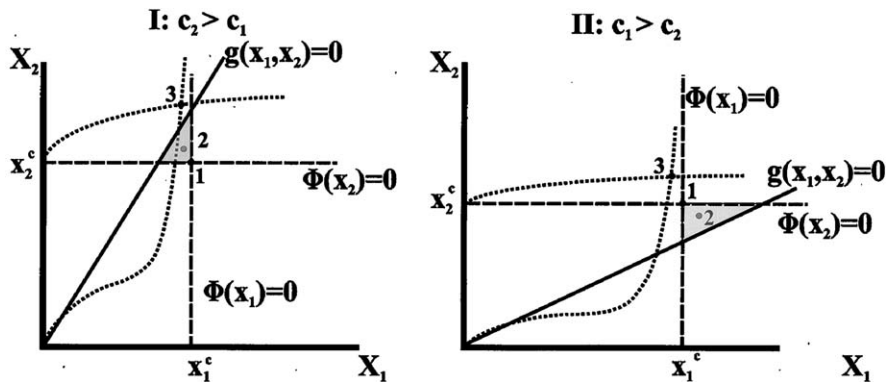


Fig. 1. Optimal spatial equilibrium biomass density levels. *Note:* Point 1 corresponds to the equilibrium in a closed system, point 2 corresponds to the equilibrium in a relative density-dependent dispersal system, and point 3 corresponds to the equilibrium in the sink–source system. In both cases, patch 1 is the source, and patch 2 is the sink.

functions in Eq. (15), it can be seen that the optimal steady-state solution with dispersal lies in the shaded feasible region (as labeled with point 2) vis-à-vis the closed case equilibrium. That is, if marginal costs of harvesting in patch 2 exceed those of patch 1 (panel I), the solution accounting for dispersal falls to the northwest of the intersection of the solutions that satisfy $\Phi_1(x_1) = 0 = \Phi_2(x_2)$, and to the southeast if patch 2 costs are lower than patch 1 costs. Thus with higher costs in patch 2 relative to patch 1, ceteris paribus, the optimal biomass in the system with dispersal involves more biomass in patch 2 and less in patch 1, relative to the case where dispersal is ignored. The intuition for this result is straightforward, namely the optimal solution requires “shifting” biomass to the high-cost patch because marginal units of biomass in patch 2 cause dispersal to flow into patch 1, and this supports a marginally higher level of harvesting in the higher profit patch 1.

Note that the increased optimal level of biomass in patch 2 in order to generate dispersal is *in addition* to the already higher level associated with cost differences that is reflected in the $\Phi(x_1) = 0 = \Phi(x_2)$ condition not being on the 45-degree line. At the margin, storing more biomass in situ in patch 2 increases rents, because patch 2’s higher relative density generates flows of dispersal into the more profitable patch 1. In other words, the regulator optimally “farms” the system by turning the high-cost patch into a de facto source of biomass for the low-cost patch where it is more profitable to harvest. It is easy to show that the higher the dispersal rate, the more the optimal spatially differentiated solution diverges from the closed system solution. The reallocation of biomass across the system is implemented with optimal differential landings taxes that affect effort levels, which in turn influence harvest and biomass levels.

Note too that the optimal landings tax case is equivalent to a spatially explicit marketable permit or individual transferable quota (ITQ) solution, with patch-specific quotas set at optimal levels. Suppose that the optimal harvest level is determined for each patch and that the regulatory authority requires each vessel to have a unit of quota to land a unit of harvest. Suppose further that permits are leased from the regulatory authority and that permits are patch-specific, so that a fisherman must have a patch 1 permit to land a pound of harvest from patch 1, and so on. Then the permit lease price will be bid up to the same level as the optimal tax determined above, since the tax is the marginal value of another unit of harvest at the optimum. In this case, the equilibrium value of a permit to land a pound of fish in the low-cost patch will be larger than the value in the high-cost patch.

3.3. Sink–source biological system

We now investigate the optimal distribution of biomass under a sink–source ecological structure, where we assume without loss of generality that patch 1 is the source and patch 2 is the sink. The net dispersal function in patch 1 is $ND_1 = d_{11} x_1 = -bx_1$ and in patch 2, it is $ND_2 = d_{21} x_1 = bx_1$ (b is the common dispersal rate). In this representation, biomass flows out of patch 1 into patch 2 at a rate proportional to the density level in patch 1 only. Without the flow dependent on *relative* density levels, there will always be greater flows of biomass leaving patch 1 and entering patch 2 compared with the relative density-dependent case, everything else being equal. Therefore, the sink–source case bounds the dispersal flow that can exist in the relative density-dependent case, for example, when patch 2’s population is zero and patch 1’s is nonzero.

Under these assumptions, Eq. (14) becomes:

$$\begin{aligned}\Phi_1(x_1) &\equiv \left(p_1 - \frac{c_1}{x_1}\right) \left(\delta - x_1 \frac{\partial f_1(x_1)}{\partial x_1}\right) - pf_1(x_1) = -b \left(\frac{c_2}{x_2}\right), \\ \Phi_2(x_2) &\equiv \left(p - \frac{c_2}{x_2}\right) \left(\delta - x_2 \frac{\partial f_2(x_2)}{\partial x_2}\right) - pf_2(x_2) = b \left(\frac{c_2 x_1}{x_2^2}\right).\end{aligned}\tag{16}$$

Since $\Phi(x_i)$ is increasing, Eq. (16) implies that the optimal equilibrium biomass in the source (patch 1) will be less than the closed system ($b = 0$) equilibrium, whereas the optimal sink patch equilibrium biomass will be higher than the corresponding closed system level.

We graph the solution of Eq. (16) in both panels of Fig. 1.¹⁵ Point 3 in the graph denotes the optimal sink–source equilibrium. The optimal equilibrium level in the sink must be greater than the level in closed case for any source population, because the sink receives biomass from the source independent of its bioeconomic structure. In addition, the level in the source will be lower than the closed case due to dispersal out of the source.

The sink–source case can be compared with the relative density-dependent case by examining the right-hand sides of Eq. (16) compared with the corresponding right-hand sides for the density-dependent case (15). It can be seen that the right-hand side for patch 1 in the sink–source is algebraically smaller than that for the relative density-dependent case and negative. Thus, the optimal source population under a sink–source system is smaller than for the density-dependent system and also smaller than the closed system. The right-hand side for patch 2 can be seen to be larger than for the corresponding right-hand side for the density-dependent case and positive. Thus, the sink patch (patch 2) is larger than the density-dependent case and larger than the closed case. It is important to note that with price heterogeneity, the optimal source patch biomass may be higher or lower than the closed case. These results are shown in Fig. 1, which graphs the relative positions of the closed, the density-dependent, and the sink–source cases, respectively, for both cost configurations.

The intuition behind the ordering and placement of the positions of equilibria can be understood by noting that the optimal solutions reflect the interplay between an economic gradient (i.e., spatial direction of highest profits) and biological gradient (i.e., spatial direction of biological dispersal). Overall system profits are highest when the biological gradient aligns with the economic gradient. In a relative density-dependent system, biomass levels can be adjusted to cause flows to move in either direction, so that biomass can be made to flow in the direction of lower cost patches. But in a unidirectional sink–source system, flows can only move in one direction. When dispersal is unidirectional (sink–source), the equilibrium will necessarily reflect the direction of the immutable biological gradient. So with patch 1 the source, the optimal biomass distribution will involve higher levels in the sink (patch 2) and lower levels in the source (patch 1) and hence lie to the northwest of the closed system. This reflects a physical constraint on dispersal direction that does not come into play with relative density-dependent dispersal.

Both panels of Fig. 1 illustrate that the density-dependent equilibrium are to the northwest of the closed system equilibrium when patch 2 costs are relatively high, and to the southeast when

¹⁵This is done by rearranging the two equations to isolate either x_1 or x_2 on the left-hand side. The graphs of these lines are illustrated in the figure where the intersection represents the solution.

patch 2 costs are relatively low. When dispersal flows in a sink–source manner from patches 1 to 2, the optimal equilibrium will involve more patch 2 biomass and less patch 1 biomass. This sink–source equilibrium will be closer to the optimal density-dependent equilibrium when the natural biological gradient lines up with the economic gradient or when the source patch costs are high relative to the sink patch costs. It will be farther from the optimal density-dependent case when source patch costs are low. In that case, the biological and economic gradients are working in opposite directions since profits dictate adjusting biomass in the direction of the source whereas the biology dictates that biomass must flow away from the source.

4. Second-best solutions: nonspatial uniform taxes

In this section, we consider second-best solutions (uniform fiscal instrument) to the spatial problem when spatially differentiated policy instruments cannot be used. As discussed in the introduction, this is closer to the norm in real marine systems, and it reflects information gaps as well as enforcement and other transactions costs associated with accounting for spatial detail. Comparing first- and second-best optima is becoming more relevant as information enabling spatial management continues to accumulate. For the second-best spatially uniform instrument problem, we set up the Hamiltonian as above, except that we impose the constraint that the controls (taxes) are equal ($\tau_1 - \tau_2 = 0$) [12]. The constrained Hamiltonian (L) is then $L = H + \mu(\tau_1 - \tau_2)$, where μ is the marginal value (cost) in terms of fishery-wide gross rents from imposing a uniform policy (tax) on the system. Appending this constraint only modifies the relevant switching functions while the other necessary conditions are qualitatively identical.

With a uniform harvest tax, we again consider the singular case where both switching functions vanish, taking into account the shadow value on the control constraint. In this case, the switching functions for patches 1 and 2 are:

$$\begin{aligned}\sigma_1(t) &= -x_1 E_1 \{\varphi_1(s + s_{12}) - \varphi_2 s_{12}\} + \mu = 0, \\ \sigma_2(t) &= -x_2 E_2 \{\varphi_2(s + s_{21}) - \varphi_1 s_{21}\} - \mu = 0.\end{aligned}\tag{17}$$

Unlike the previous results where the only solution to Eq. (4) is when the shadow values on effort in patches i and j are simultaneously zero, the solution to (17) involves non-zero shadow values ($\mu \neq 0$). Inspection of Eq. (17) suggests that the sum of the switching functions must vanish along the singular path as compared to the first-best case where each are equal to zero. Under these new second-best assumptions, the necessary conditions for an interior steady-state solution including Eq. (17) are:

$$\begin{aligned}\dot{\varphi}_i &= 0 \Rightarrow \varphi_i = \frac{(p - \lambda_i)x_i - c_i}{\delta}, \\ \dot{E}_i &= 0 \Rightarrow \tau = p - c_i/x_i, \\ \dot{x}_i &= 0 \Rightarrow E_i = f_i(x_i) + d_{ii} + d_{ij} \frac{x_j}{x_i}, \\ \dot{\lambda}_i &= 0 \Rightarrow (p + (p - \tau)(\varphi_i(s + s_{ij}) - \varphi_j s_{ji}) - \lambda_i)E_i + \lambda_i(f_i(x_i) - x_i \frac{\partial f_i(x_i)}{\partial x_i} - \delta) + d_{ij}\lambda_j + d_{ii}\lambda_i = 0.\end{aligned}\tag{18}$$

The solution to these necessary conditions yields the optimal singular uniform tax level and the corresponding singular biomass and effort levels in this second-best setting. In a two-patch case and with the switching functions, there are 10 equations and 10 unknowns.

Since the “double” singular solution no longer requires that the individual shadow prices of effort be zero, the set of Eq. (18) differs from the necessary conditions for the spatial optimal (Eqs. (9)–(12)) in a couple of ways. First, the $\dot{\lambda}_i = 0$ equation will reflect not only the value of net biological dispersal, but also the costs of the misallocation of effort.¹⁶ Interestingly, for the second-best equilibrium solution, these costs (shadow prices φ_i) are weighted by the fleet dispersal and entry/exit rates that do not appear in the first-best equilibrium solution. The slower these rates (the fleet responds only sluggishly to profit opportunities), the lower the instantaneous costs of the misallocation of fishing effort, because the fleet is assumed unable to move at a speed fast enough to make the discounted efficiency costs large, everything else being equal. On the other hand, the faster that arbitrage opportunities are seized upon both in dispersal and entry/exit, the larger the efficiency costs of being unable to spatially differentiate effort more precisely. Second, the $\dot{\varphi}_i = 0$ equation implies that the net marginal value of effort will be negative in equilibrium in the patch with too much effort ($\varphi_i < 0$) and that there will be a divergence between the biomass shadow prices in each patch and the uniform landings tax rate.

From the $\dot{E}_i = 0$ Equation in (18), the optimal landings tax must be equal across patches and equal to the marginal profitability in each individual patch. With uniform output prices, this requires equalizing average (and marginal) costs of the last unit harvested so that the optimal biomass densities must satisfy $x_2 = (c_2/c_1) x_1$. Thus, the single tax (second-best optimal) biomass levels are in the same proportion as the ratio of cost coefficients and must lie on the ray from the origin whose slope equals the ratio, regardless of the dispersal system. We also know that the slope of this line is greater (smaller) than the slope of $g(x_1, x_2) = 0$ when the costs in patch 2 are greater (smaller) than patch 1. Under these assumptions, the points along the $x_2 = (c_2/c_1) x_1$ ray are in the same ratio as the open-access equilibrium biomass levels ($x_i^\infty = c_i/p$).¹⁷ Therefore, as the uniform landings tax goes to zero, the second-best equilibrium biomass levels approach the open-access levels while maintaining a constant ratio.¹⁸

Fig. 2 graphs the optimal ratios of second-best biomass densities when the cost in patch 2 is greater than in patch 1 for the closed and relative density-dependent system (sink–source is discussed below). We also illustrate the first-best (point 2) and open-access equilibrium as benchmarks, where point A is the open-access equilibrium level that results from solving Eqs. (1) and (2). Where is the second-best equilibrium located on the $x_2 = (c_2/c_1) x_1$ ray? Although an analytical solution to the system of equations in (15) is not feasible, we can determine relative positions as follows. Suppose that an optimal (first-best) spatially differentiated individual

¹⁶The misallocation of effort in this second-best setting is analogous to the “hotspot” effect discussed in the pollution permit literature. In that case, if higher abatement costs firms are geographically concentrated their purchase of pollution permits will increase emissions in the local area. It is possible that the increase in emissions might be greater than what would otherwise be optimal, if the markets were more spatially explicit. In our system, if the regulator were not constrained to imposing a uniform tax, she would find it profitable to reallocate the effort from the patch with too much to the patch with too little effort, everything else being equal.

¹⁷To prove this result, employ our assumptions and solve Eqs. (1) and (2) with the tax levels set to zero.

¹⁸The corollary is that with any positive tax the equilibrium population levels in both patches will be greater than under open-access levels.

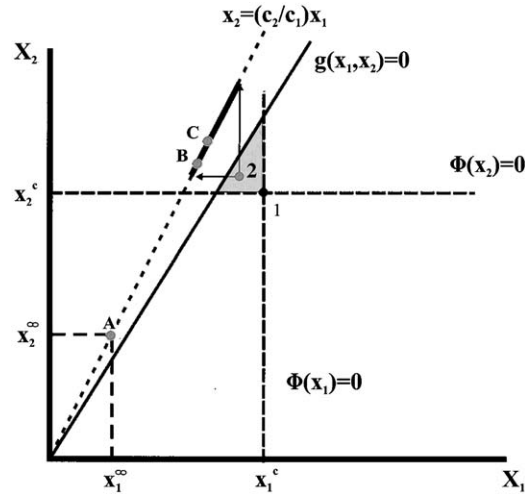


Fig. 2. Optimal spatial and uniform equilibrium in closed and density-dependent systems with $c_2 > c_1$. *Note:* We represent the open-access equilibrium with point A (x_1^∞, x_2^∞), the spatial equilibrium in a closed system and density-dependent system with points 1 and 2, respectively. A potential candidate for the equilibrium in closed and density-dependent system when implementing a uniform tax is illustrated with points B and C, respectively. We also show the feasible region for a uniform equilibrium in a density-dependent system as represented by the darkened portion of the line $x_2 = (c_2/c_1)x_1$.

transferable harvest quota program is in place, with quota lease prices higher in patch 1 because of higher marginal profits there. If fishermen were allowed to trade these quota permits across patches, permits would begin to flow at the margin from patch 2 to 1. This would make harvests rise and biomass fall in patch 1 and harvests fall and biomass rise in patch 2. Ultimately, this homogenization of the transferable harvest quota system would equalize shadow values across the two patches, leaving an equilibrium solution to the northwest of the spatially differentiated system. At this equilibrium, second-best biomass is larger in patch 2 and smaller in patch 1 than first-best optimal. In addition, the resulting common quota price equalizes at some “averaged” price between the first best low and high quota prices in the two respective patches.

Potential candidate optimal second-best taxes are illustrated with the points B and C, which lie to the northwest of the first-best optimal levels, where point 1 represents the first-best closed case and point 2 represents the first-best relative density-dependent system. In the density-dependent case, the set of feasible biomass levels resides in the range of points along the ray bounded by the arrows northwest from point 2. Therefore, an inference that can be drawn is that, relative to the optimal (first-best) spatially differentiated taxes and management, the distribution of biomass in the uniform (second-best) tax case is skewed towards lower biomass in the lower cost (higher profit) area.

Thus, an important conclusion is that the inability to implement spatially explicit landings taxes leads the regulatory authority to “over- conserve” the high-cost patch and “under- conserve” the low-cost patch. The inefficiency arises in this case because after-tax marginal rent equalization with a common landings tax can only be achieved with biomass ratios equal to the cost ratios. Steady-state rents are lower for the whole system, of course, since first-best regulation requires

adjusting the optimal biomass ratios to different levels. Relative total harvests under the two systems cannot be easily determined or compared.

The degree of over- and under-conservation depends on the degree and nature of connectivity in the system. For example, relative to the density-dependent case, a uniform tax in the closed case under (over) conserves the population in the low (high) cost patch to a greater (lesser) extent. In the density-dependent system, dispersal from patch 2 to 1 offsets some of the decrease in patch 1 population levels from the increase in fishing effort and catch in patch 1. Without dispersal, the shift of fishing effort and resulting lower population levels are not offset and therefore, there is a larger decrease in the patch 1's population level. This is illustrated by the relative placement of points B and C on the ray; if point C corresponds to the second-best equilibrium with relative density dependence, the equilibrium in the closed system might be at a point like B.

Although not surprising, it is important to point out that when the biological and economic system is homogenous the first- and second-best optimal densities levels are equal in the closed and density-dependent system and across the two systems. Within each system, costs are the same and the optimal first-best taxes are identical to each other and therefore equal to the uniform tax level. There is also no difference between the closed and relative density-dependent systems, because with densities equal, dispersal is zero.

4.1. Second-best taxes in sink–source system

We now turn to an analysis of uniform taxes in the sink–source system. The second-best solution is similar to that for the closed and relative density-dependent systems because the equilibrium will also fall on the $x_2 = (c_2/c_1)x_1$ ray. However, the “uncontrollability” of the dispersal process does create some important (and unique) differences.

We begin by illustrating in Fig. 3 where costs in the source are greater than in the sink—biological and economic dispersal gradients are aligned. Fig. 3 also illustrates, for points of

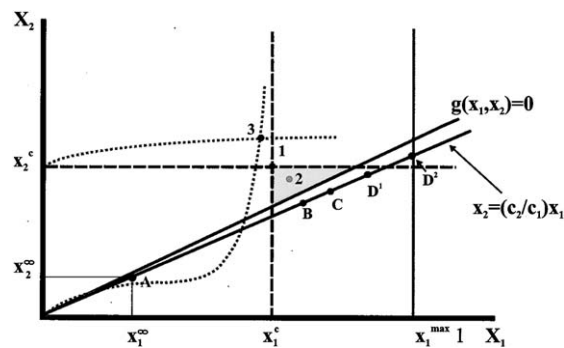


Fig. 3. Optimal spatial and uniform equilibrium in sink–source system with $c_1 > c_2$. Note: Numbers correspond to spatial optima with closed (1), density dependent (2), and sink–source (3). Letters correspond to second-best optima, except A which is the open-access equilibrium. B is a potential candidate optima in the closed, C in the density dependent, and D¹ and D² in the sink–source. The $\Phi = 0$ lines are represented and intersect the graph at the closed solution but are not labeled. x_1^{\max} is the endogenous carrying capacity of the source patch when the source is not fished ($x_1^{\max} = (1-b/r)$).

reference, the closed, density-dependent, and sink–source first-best optimal solutions with points 1, 2, and 3 respectively. Second-best equilibria for the density-dependent (point C) and closed (point B) case lie on the ray to the southeast of point 1, whereas second-best equilibria for the sink–source case lie southeast of point 3 (points D^1 and D^2). Under similar reasoning used for the closed and density-dependent cases, the second-best solution using a uniform instrument will fall within the quadrant delineated by right-angle vertices originating at the first-best sink–source solution and encompassing the ray determined by the cost ratios.

The ordering of the uniform equilibria along the ray depends upon the extent to which it is possible to exploit the alignment of the biological dispersal and economic gradients. Recall that the absolute level of biological dispersal in the sink–source system is greater than in the density-dependent case, everything else being equal. Given the dispersal flows, point D^1 lies to the northeast of point C, because the greater dispersal flow (larger biological gradient) makes it profitable for greater amounts of fishing effort to shift over to patch 2. This “hot spot” effect results in lower levels of population in patch 2 and higher levels in patch 1 relative to the density-dependent case. The same logic applies to the relative positions of points B and C and points B and D^1 .

Before discussing the case where c_1 is less than c_2 , we should note that it may be optimal under some circumstances to have “corner solutions” in which there is no exploitation of some patch.¹⁹ Conditions for a corner solution can be thought of as parametric conditions that make the optimal equilibrium greater than or equal to natural unexploited equilibria.²⁰ In Fig. 3, point D^2 illustrates that it is possible that second-best equilibria might lie on the upper bound for patch 1 biomass, when first-best optima are interior.²¹ This is an interesting finding in light of the recent interest in using marine reserves to manage fisheries. While most of the marine reserve arguments are based on biological arguments with little attention to economics, these results suggest that there are circumstances in which a marine reserve (here a corner solution) is an economically optimal policy. The circumstances we highlight here that make marine reserves more likely as an optimal policy are: when the reserve candidate is a source in a natural sink–source system, when

¹⁹Brown and Roughgarden [4] investigate optimal management in the presence of larval dispersal where each subpopulation is managed privately but the larvae disperse to a common pool before redistributing uniformly across the patches. They find it pays to close off areas to fishing when larval production exhibits increasing returns to scale, even if spatially differentiated controls are available. Janmatt [11] also found that closing a source could be first-best optimal when the dispersal rate is stock dependent. Sanchirico and Wilen [20] investigate the effects of marine reserve creation in open-access fisheries and find that there are bioeconomic conditions that result in a win–win situation (harvest and biomass increase after an area is closed).

²⁰The additional fact to note here is that the equilibrium biomass levels in both patches are bounded by fundamental carrying capacities as well as by the dispersal structure. For the density-dependent system, x_1 and x_2 are bounded by carrying capacities (identically one in this case), the largest values that would emerge without exploitation. For the sink–source system with patch 1 the source, the largest values are: $x_1^{\max} = 1 - \frac{b}{r}$, $x_2^{\max} = \frac{1}{2} + \frac{1}{2r}\sqrt{r^2 + 4br(1 - b/r)}$.

²¹This is possible for both the density-dependent and sink–source systems, but it is more likely in the sink–source case for two reasons. First, the upper bound for patch 1 is smaller under the sink–source than in the density-dependent case. Second, the first-best solution to the sink–source problem involves equilibria to the northwest of these for the density-dependent case and so the triangle originating at point 3 encompasses more potential candidate values for the second-best solution to patch 1. With a wider range of candidate values, there are more circumstances under which the indicated second-best optimum is infeasible, suggesting that patch 1 will be unexploited and left to serve as a sink for the higher profit patch 2.

fishing costs are high in the source, when the dispersal coefficient is relatively large, and when enforcement/information costs prevent first-best policies.

What happens when the biological and economic gradients are opposing one another or when c_1 is less than c_2 ? Before we answer, it is instructive to consider the case where the costs are equal, as illustrated in panel I of Fig. 4. As mentioned previously, the spatial and uniform equilibrium in both the closed and density-dependent case are equal (point labeled 1, 2 & B, C) and the $x_2 = (c_2/c_1)x_1$ ray is the 45-degree line. However, even with costs being equal, the optimal spatial equilibrium for the sink–source (point 3) is characterized by greater densities in the sink and less in the source. This is due to the unidirectional flow of dispersal. In Fig. 4 panel I, point D represents the optimal uniform equilibrium. It diverges from the spatial equilibrium, because even without habitat heterogeneity, dispersal affects the average costs of fishing in patch 2 by reducing average costs at the margin. Therefore, fishing effort reallocates towards the sink patch to capture these cost gains, lowering the density in the sink and increasing the density in the source patch. Relative to the first-best sink–source optimum, however, the amount of fishing effort in patch 2 is too high (negative shadow price of effort) and in patch 1 is too low (positive shadow price of effort) with a uniform tax.

In panel II of Fig. 4, we illustrate the case where there is a slight difference in the cost coefficients across the two patches, and therefore the ray lies to the northwest of the 45-degree line. The optimal uniform equilibrium in the closed (point B) and density dependent (point C) cases provide reference points. In this case, the slight difference in the costs is not enough to outweigh the biological gradient's effect on average density-dependent fishing costs. Therefore, even if the cost coefficient is higher in patch 2, dispersal causes high-biomass density and lower per unit harvesting costs in patch 2. At the optimum, there is a negative shadow value of effort in patch 2, because the economic gradient is outweighed by the biological gradient.

As we increase the relative differences in the cost coefficients, the ray out of the origin crosses the optimal spatial equilibrium and in fact, there is a cost ratio where the ray exactly intersects this equilibrium. At this cost ratio, which we denote Ω it can also be shown in the sink–source system that the biological and economic gradients cancel each other out, and the optimal spatial and uniform equilibria coincide.²² That is, there is no efficiency loss in terms of steady-state rents associated with implementing a uniform tax when the cost ratio equals Ω , even though costs are different and there is an asymmetric dispersal processes. We illustrate this case in panel III of Fig. 4 where the spatially differentiated and uniform equilibria in the sink–source are illustrated by the point labeled 3&D. Not only are the first- and second-best instruments equal at this cost ratio, this ratio also corresponds to a point at which the ordering of the equilibria shift relative to the origin across the three ecological systems. This is evident by inspecting the ordering of the equilibria in panels I, II, and III, and is due to the exogenous directional component of the dispersal gradient in sink–source systems.

Finally, in panel IV of Fig. 4, the relative differences in cost coefficients are larger. Unlike in panel II, where there was too much effort operating in the sink patch relative to the optimal, in

²²Because analytical solutions are not feasible, this result was proven numerically and it holds for absolute levels of cost coefficients where fishing is economically profitable. That is, for high costs when very little (if any) fishing is occurring, Ω does not exist, because even for slight differences in costs, the optimal uniform equilibrium consists of closing the high-cost patch to fishing.

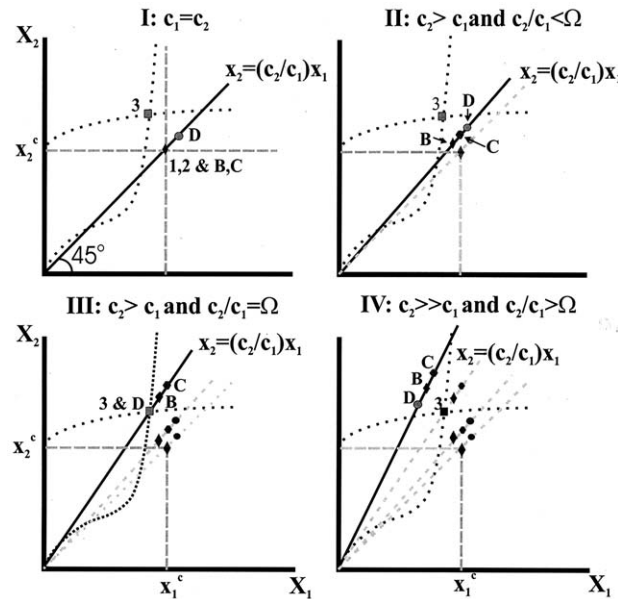


Fig. 4. Optimal spatial and uniform equilibrium in sink-source system. *Note:* In all panels, the points B (diamond), C (hexagon), and D (circle) represent the optimal uniform equilibrium in the closed case, density-dependent, and source-sink case, respectively. Point 3 (square) is the optimal spatial equilibrium in the source-sink case. In panel 1, the optimal and uniform equilibrium in the closed and density dependent are all equal where numbers correspond to optimal spatial equilibrium, respectively. Panel III represents the bifurcation case, defined when the cost ratio equals Ω where the optimal spatial and uniform equilibrium are identical in the sink-source case. The $\Phi_i = 0$ lines are represented and intersect the graph at the closed solution but are not labeled, and we also represent the prior (in numeric order) panel's solution for reference. (Note point A (open-access) is not represented on this graph.)

this case the shadow price of effort in the source (sink) is now negative (positive). The economic gradient now exhibits more influence than the biological gradient and therefore, under the uniform tax, fishing effort shifts into the source to catch the fish before they disperse to the sink. This results in lower source densities, as shown by the position of the uniform and optimal equilibrium, and higher densities in the sink, everything else being equal.

In sum, if the influence of the biological gradient outweighs the economic gradient, quota will flow from the source to the sink once trading is allowed to occur across the two areas with a trading ratio of one. There exists a cost ratio Ω that bifurcates this system where no trading or reallocation will occur from the spatial differentiated system. At cost ratios greater than Ω quota will flow into the source rather than the sink, because it is more profitable to catch the fish before they disperse to the higher cost sink area.

It is also worth highlighting that the distance between first- and second-best solutions is either large, or small, depending upon whether patch 1 costs are large or small relative to patch 2 costs. This again has to do with the fact that the system has asymmetric properties because the dispersal direction is not “controllable.” When economic and biological gradients are opposed to one another, first- and second-best solutions will be relatively close together, indicating modest gains

from spatial differentiation. The gains are modest because it is physically infeasible to shift the direction of dispersal to patch 1, which is the high-profit patch. On the other hand, when economic and biological gradients are in alignment, there are larger gains to fine-tuning and hence greater distance between first- and second-best optima.

5. Discussion

This paper combines a model of a spatially linked biological population with a spatial/dynamic model of open access user behavior that accounts for the incentives to arbitrage over space as well as time. To correct for the dynamic inefficiencies caused by myopic behavior of open access participants, the regulator can implement a first-best set of spatially differentiated landings and effort taxes. Under general assumptions, effort taxes are needed to choke off excess entry in each patch, and a landings tax is needed to correctly price the productive role of biomass in the system's overall production. Optimal spatially differentiated landings taxes must be set equal to the shadow value of the marginal unit of biomass in each patch, evaluated at optimal levels over the whole system. In addition to own patch specific prices and costs, own biological growth, and the discount rate, the shadow value of biomass in each patch accounts for the role of the last unit in the dispersal process in the spatially linked system. At the margin, the economic value of biological dispersal trades off the losses from not being able to harvest the fish that left the patch against the marginal returns of harvesting an additional fish in the receiving patch plus the reductions in the marginal costs of fishing from fish entering the patch.

In an ideal world in which information is perfect and transactions costs are zero, it would be economically optimal to design management policies that account for spatial interconnections within and among patches by utilizing separate instruments for each spatial unit. In an imperfect world in which it is costly to implement such programs, it is still possible to take into account biological information about spatial interconnections and design second-best policies that maximize rents given the necessity of undifferentiated instruments. An important question is how these first- and second-best policies differ in their impacts on rents, harvests, and biomass levels. Our results accord with intuition in the sense that optimal second-best policies average or blend the differentiated results. With an inability to utilize spatially differentiated instruments, the system cannot be as finely tuned as with first-best instruments. As a result, rents are lower, total effort is mismatched over space, and the biomass levels are not optimally adjusted to take advantage of the possibility of “farming” the system or aligning the dispersal and economic gradient.

Overall, economic and biological heterogeneity in fundamental bioeconomic parameters make it worthwhile to differentiate policy instruments. The dispersal process, however, plays a vital role in determining how closely second-best policies approximate first-best policies. For example, in the sink–source case the dispersal direction is not controllable as it is in the relative density-dependent case. Hence the sink–source, second-best spatially uniform policy will deviate from the first-best differentiated policy to a significant degree when biological and economic gradients are aligned.

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