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Spatial Behavior, Marine Reserves, and the Northern California Red Sea Urchin Fishery

By

Martin Daniel Smith
B.A. (Stanford University) 1992

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Agricultural and Resource Economics

in the

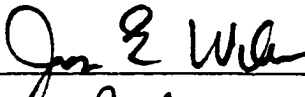
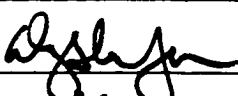
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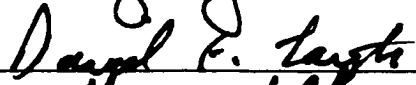
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MARTIN DANIEL SMITH

2001

Spatial Behavior, Marine Reserves, and the Northern California Red Sea Urchin Fishery

ABSTRACT

Resource scientists have recently shown virtually unqualified support for managing fisheries with marine reserves, signifying a new resource management paradigm that recognizes the importance of spatial processes in both untouched and exploited systems. Biologists promoting reserves have based such support on simplifying assumptions about harvester behavior. This thesis shows that these naïve assumptions about the spatial distribution of fishing effort before and after reserve creation severely bias predicted outcomes, generally overstating the beneficial effects of reserves.

This thesis presents a fully integrated, spatial bioeconomic model of the northern California red sea urchin fishery. The model is the first attempt to marry a spatially explicit metapopulation model of a fishery with an empirical economic model of harvester behavior. The biological model is calibrated with parameters representing best available knowledge of natality, growth, mortality, and oceanographic dispersal mechanisms. The model of spatial behavior is estimated using a large panel data set of urchin harvester decisions, which are recorded in logbooks and on landings tickets.

The economic model tracks repeated decisions that take place on different time and spatial scales. Harvesters make daily decisions about whether to fish and where to fish, conditioned on home ports. On longer time scales, harvesters select a home port, choose between northern and southern California regions, and decide whether to drop out of the fishery. Combining a Random Utility Model with Seemingly Unrelated Regressions, the model predicts the aggregate supply response of fishing effort and the spatial allocation of effort as a function of relative economic payoffs. The economic model is integrated with the biological model to endogenize effort, harvest, biomass levels, and reproductive performance of the population.

The integrated model is used to explore the efficacy of marine reserve formation under realistic assumptions about the determinants of total effort and its spatial distribution. Contrary to the dominant biological modeling conclusions based on naïve assumptions, realistic behavioral assumptions lead mostly to pessimistic conclusions about the potential of marine reserves. The thesis results ultimately cast doubt on many of the arguments made by those who advocate closures to enhance fisheries.

Acknowledgements

My biggest thanks go to my thesis advisor Jim Wilen. Jim has been an outstanding intellectual mentor throughout graduate school and a true friend. His combination of analytical rigor, institutional knowledge, and pragmatism are inspiring, while his subtle ways of sparking creativity are truly amazing. Jim also encouraged me and showed tremendous patience at times when I pursued research interests beyond the scope of my dissertation. I will always be proud to be a student of Jim Wilen.

I also thank the rest of my committee. Doug Larson helped me to shape my thesis prospectus, encouraged me to get involved in real-world fisheries policy, showed great confidence in me from the beginning of graduate school, and provided another expert voice on marine issues. Dave Layton was extremely helpful with my econometric work and planted many seeds for future empirical analyses of the sea urchin data. Jeffrey Williams consistently asked the hardest questions throughout the dissertation. My work benefited greatly from answering some of them, though I regret that a few questions are left unanswered.

I am also indebted to the remainder of the faculty, our wonderful librarians, the computer support staff, and the administrative staff in the Department of Agricultural and Resource Economics. I am especially grateful to Julian Alston for his comments in my brown bag seminars and his sense of humor, to Karen Klonsky for friendship and collegiality, to Kim Brobeck for her assistance with graphics and overheads, and to Kathy Edgington for her programming help in SAS and in just about every other software package I use.

Many thanks are due to the folks in the Department of Wildlife, Fish, and Conservation Biology who have made it possible to embark on this interdisciplinary project. In particular, I wish to recognize Lou Botsford, the graduate students in his lab, and other scientists working on sea urchins. I also especially want to thank Dale Lockwood for all of his hard work coding BigUrchin, for his willingness to incorporate economic models iteratively, and for his patience with my limited understanding of the C programming language.

Thank you ARE graduate students! My fellow students have been great friends and colleagues throughout my five years in Davis. They have made Davis a fun and intellectually stimulating place to be. While I am tempted to list everyone, I will refrain and acknowledge especially Dawn Parker, Alan de Brauw, Jenni James, Jonathan Kaplan, and all of my office-mates that have made SS&H 2154 a great place to work: Shi-Ling Hsu, Norbert Wilson, Atle Guttormsen, Camille Tribble, and Rocio Uria.

I also want to acknowledge faculty and students in other departments around campus who have made Davis so enjoyable and have contributed to this rich intellectual experience. In particular, thanks to the departments of History, Economics, Environmental Science and Policy, and Statistics.

Thanks also to my students in ARE 100A during fall quarter, 1999. These students helped me to realize how much I enjoy teaching.

This research was partially funded by a grant from the National Sea Grant College Program, NOAA, U.S. Department of Commerce, under Grant No. NA66R G0477, Project No. R/F-169. Thank you for this support.

And to my softball team, High Anxiety, thank you for providing a true escape from the stresses of doing a dissertation.

Thank you to all of my friends and family outside of Davis. My parents, Dan and Erin Smith, have been supportive throughout graduate school. I appreciate their confidence in me and their trust that I have chosen the right profession. And to my fabulous in-laws, Doctors John and Kay DuVal, thank you for all of your encouragement and empathy. Thanks too to the great brother-in-law and Ozark craftsman Niell DuVal.

To my wife Kathleen DuVal, thank you for all of your love and the joy that you have brought to my life. These years in Davis have been the happiest in my life. And thanks for convincing me to go to graduate school in the first place. After all, it was your idea. There's just one last thing I have to say. Seeing your passion for history and your devotion to your research has truly been my greatest inspiration.

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Chapter 1

Marine Reserves:

A New Tool for Fishery Management?

In May of 2000, President Clinton signed an executive order that directed the Departments of the Interior and Commerce to develop plans for an extensive network of marine reserves in the coastal waters of the United States. The order was hailed by marine ecologists and conservation biologists as a bold step towards sustainable management of the marine environment. On the surface, the order suggests that many of our most important coastal ecosystems are potentially threatened by human actions, and marine protected areas, like terrestrial parks, can secure access for present and future generations to unique aquatic ecosystems and the non-consumptive services that they provide. Creating a comprehensive system of reserves, however, goes beyond recognizing non-market values and anthropogenic threats to the marine environment. The order explicitly acknowledges that marine resources are geographically diverse as

well as spatially interdependent, and successful management of these resources involves spatially explicit tools.

While non-market existence or bequest values are at the heart of conservationists' support of marine reserves, fisheries scientists have also suggested that carefully designed protected areas could benefit fisheries. Indeed, language within Clinton's executive order uses presumed fishery management benefits to promote and justify marine reserves, mentioning "economically sustainable use of the marine environment for future generations." Proponents of reserves as a management tool assert that protected areas will house a higher abundance of more mature and fecund individuals, and the larvae and egg production from protected organisms will disperse to surrounding areas.

This distinctively spatial view of population dynamics is part of a larger transformation in ecological paradigms. The older viewpoint treats natural resources as uniformly distributed across space, while contemporary thinking emphasizes the patchiness and spatial heterogeneity of resources. Some recent ecological studies of the marine environment adopt metapopulation models that depict marine resources as discrete and heterogeneous patches of biomass that are linked through highly unpredictable oceanographic processes including upwelling, currents, wind, and advection (Quinn et al. , 1993; Botsford et al. 1999). The conclusions of metapopulation studies are consistent with the possibility that marine reserves could enhance overall biological productivity in systems.

Biologists and marine ecologists have contributed most of the literature promoting the use of marine reserves for fisheries management. Much of the scientific justification for marine reserves that has had an impact on national policy is thus primarily based on

biological research. Of paramount importance, however, is that most biological modeling makes simplifying assumptions about fishing effort that inaccurately characterize economic behavior. Fishing effort is simply the amount of time spent fishing and is typically measured in hours or fishing trips. As such, effort is an indicator for the intensity of harvest pressure on the resource. Many biological models assume that after a closure that establishes a reserve, the effort in the remaining open areas will remain the same as before reserve establishment. Others assume that displaced effort will proportionately relocate to open areas. Few biological analyses recognize the important fact that the geographical location of fishing effort before and after reserve establishment will be driven by economically-motivated behavior of harvesters, and none have put together a biological model with an empirical economic model (Botsford et al., 1993; Botsford et al., 1999; Walters, 2000). Thus, aside from normative considerations, the most prominent and broadly accepted predictive conclusions about the formation of a marine reserve may be suspect.

Since biologists and ecologists stress that marine ecosystems are complex and must be studied carefully, the same normative reasoning should apply to the economic components of exploited systems. After all, economic behavior is also complicated and has a profound impact on the systems of interest. While detailed study of biological and oceanographic characteristics that are spatial in nature has generated support for spatial management of fisheries, a detailed study of the spatial behavior of harvesters may reinforce or subvert this support. Moreover, analysis of spatial behavior may also lead to support for other types of regulatory tools in addition to or in place of marine reserves.

Fortunately, fisheries scientists and regulators often have the means to study the behavioral side of the problem in some spatial detail. In particular, fishing logbooks contain key geographical harvesting information and landings tickets contain the essential economic data. This thesis makes use of such data sources for the California red sea urchin fishery. Using conceptual and empirical metapopulation models together with an empirical economic study of the northern California fishery data, the thesis examines the implications of ignoring real patterns of spatial behavior in the harvest sector and the likely behavioral responses to spatial management practices. As this thesis demonstrates, when spatially explicit economic behavior of harvesters is considered, whether reserves will prove beneficial to a fishery depends in complicated ways on biological and economic parameters, institutions, and dynamic mechanisms that link aggregations of abundance and harvesters.

An important theme of this thesis is that naïve assumptions about economic behavior sometimes generate the most optimistic predictions about marine reserves. In particular, marine reserve scenarios that appear to give rise to an increase in aggregate steady-state harvest are often based on unrealistic behavioral assumptions, including a fixed aggregate fishing effort and a uniform distribution of that effort across space. These typical assumptions are inaccurate because they characterize harvesters as being unresponsive to economic incentives that vary across space, time, and different policy regimes. Empirical analysis of the California red sea urchin industry clearly demonstrates that urchin harvesters do, in fact, respond to spatially and intertemporally varying economic opportunities. An assessment of spatial management that accounts for these facts differs substantially from one that does not. In many circumstances, the

typical simplifying behavioral assumptions in the biological literature bias results in predictable ways that make reserves seem more beneficial biologically and economically than they actually would be.

Marine Reserves in the Biological Literature

Despite being a relatively new topic, the biological literature on marine reserves and marine protected areas is extensive. A keyword search for either “marine reserve” or “marine protected area” in the online database of *Fish & Fisheries Worldwide* (produced by the National Information Services Corporation) yielded 545 distinct references. In addition to justifications based on preserving pristine ecosystems for their intrinsic values or for research, many of these papers outline arguments for why marine reserves would be useful for managing commercial fisheries. This literature in general proposes several biological justifications for marine reserves as a fishery management tool.

Biological analyses of marine reserves outline five interrelated justifications for using marine reserves to manage commercial fisheries. Reserves can **rebuild** overexploited areas (Polacheck, 1990; DeMartini, 1993; Bohnsack, 1993), take advantage of **dispersal** mechanisms in boosting system-wide biological production (Davis, 1989; Polacheck, 1990; DeMartini, 1993; Bohnsack, 1993; Carr and Reed, 1993; Lauck et al., 1998), encourage **returns to scale and size** in system-wide production (Roberts and Polunin, 1991; DeMartini, 1993; Bohnsack, 1993), preserve the natural **life cycle** of an organism (Polacheck, 1990; Bohnsack, 1993; Carr and Reed, 1993), and provide a **hedge** against stock collapses (Bohnsack, 1993; Carr and Reed, 1993; Clark, 1996; Lauck et al., 1998; Hastings and Botsford, 1999). This section describes these arguments and makes use of some economic terminology to clarify them.

The most basic biological justification is that reserves may be used to rebuild overexploited stocks. This argument presupposes that the fish stock is overexploited under the existing management regime. A reserve then sets aside an area in which harvesting is prohibited. Over time, it is anticipated that stocks within the reserve return to a healthy level, at which point exploitation could possibly resume.¹ The rebuilding argument thus focuses on the use of closed areas to manage biomass **within** the area designated as a reserve.

In contrast, other arguments for reserves focus on using reserves to generate benefits **outside** the reserve area. Dispersal is the mechanism that links a reserve with the remaining open areas. Specifically, many biologists support reserves as a management tool because they believe that reserves can augment resource stocks in the remaining areas open to exploitation through dispersal processes. This notion has arisen from metapopulation frameworks that identify some areas as “sinks” and others as “sources.” Sinks are locations (or patches) that naturally can absorb relatively more larvae or adult organisms, while sources are places that naturally export larvae or adult organisms. As such, conventional wisdom suggests that sinks are candidates for open fishing grounds and sources are candidates for reserves.² The main theme of this second justification is that reserves may enhance fishable biomass by linking fishery management to migration patterns of organisms and taking advantage of sink/source dynamics. Much of the literature has focused on larval dispersal of sedentary organisms such that adult stocks within a reserve build up and continuously export larvae to the open fishing grounds.

¹ Alternatively, closed areas could be maintained indefinitely to avoid recurrence of the problem. When managers are concerned only about what happens within a reserve, this would come about only if there were non-fishery benefits from protecting the area.

² Of course, a source as a reserve still must have some replenishment to maintain its export of organisms.

The life cycle justification for a reserve contends that a reserve permits at least a fraction of an exploited population to survive through a full life cycle, and hence that fraction achieves natural and healthy age and size distributions of organisms. An exploited fishery without a reserve, in contrast, truncates the age and size distributions, as most fishing gear selects for larger organisms. In extreme cases, the fishery removes virtually all of the population of organisms larger than the age or size of full selection to the fishing gear. By permitting more organisms to survive through a full natural life cycle, a reserve may enhance biological productivity. In addition, a reserve may provide protection against selection pressures that emerge when exploitation alters the age and size distribution.

The stock rebuilding, dispersal, and life cycle justifications for a reserve all form the basis for a further argument based on returns to scale and organism size. The idea is that a reserve takes advantage of non-convexities that can exist in the production functions for offspring. These non-convexities may increase system-wide production relative to a system without a reserve. Here we consider three types of non-convexities in the production sets of biological offspring, the first two of which are known as *Allee effects* (Allee, 1931). Allee effects are density-dependent mechanisms that may lead to population extinction at low population densities.³

The first potential non-convexity arises from density-dependent spawning. A primary explanation for Allee effects is the inability for organisms to find mates at low population densities. At higher densities, there is more reproduction per organism. In particular, if larval production as a function of biomass within an area is increasing and

³ Mathematical bioeconomic models sometimes use “depensation” and “Allee effect” interchangeably. See Clark (1990) for a detailed discussion of different depensation mechanisms.

convex (has positive first and second derivatives), doubling the number of organisms and holding fixed the size distribution more than doubles the production of offspring. Thus density-dependent spawning may create increasing returns to scale in the production of offspring.

The second potential non-convexity arises from density-dependent settlement. There is evidence that for some species juvenile organisms take refuge with adults,⁴ so increasing the number of adults may also increase the success of juvenile settlers. Over some range of low densities, this creates a convex functional relationship between population density and settlement. So, again the Allee effect creates increasing returns to scale.

The third possible non-convexity stems from the interaction of age, size, and fecundity. Specifically, older and larger organisms in many populations are disproportionately more fecund. By permitting a full life cycle, a reserve increases the share of these more fecund individuals, potentially capitalizing on returns to size of organisms. Within this context, organism "size" should be thought of as an input in the production function for offspring. In other words, fixing the number of organisms, and varying the sizes of organisms, affects the number of offspring. With increasing returns to the size input, doubling the sizes of organisms more than doubles the larval production.

Increasing returns to scale and organism size depend on the stock rebuilding, life cycle, and dispersal arguments. Returns to scale as a result of Allee effects typically apply to low-density populations. As such, a reserve would rebuild these stocks. Returns to size hinge on shifting the size distribution towards larger organisms. This is precisely

⁴ In the case of sea urchins, juveniles can be protected from predators in the spine canopies of adults (Tegner and Dayton, 1977).

what results from permitting full life cycles. Finally, for a fishery to reap the benefits of a reserve there must be dispersal. Increased biological productivity within a reserve will not benefit a fishery unless it spills over into non-reserve areas.

The hedging argument for reserves is fundamentally different but draws on the reasoning of other justifications. When exploitation is permitted in all areas, a resource stock is vulnerable to collapse. Indeed we have seen numerous examples of fishery stock collapses throughout the last two centuries. A combination of fundamental ecological uncertainty and unforeseen shocks as well as regulatory miscalculations may precipitate a stock collapse even when the fishery is well-managed. Proponents of this view also point to regulators' inherent inability to control effort perfectly. Under the hedging justification, with a reserve in place, healthy stocks will survive and thrive within the closed area even when there is overexploitation in the open areas. This argument is interconnected with previous ones; to sustain a fishery in the face of a stock collapse outside a reserve, the reserve must export adults or larvae to the open areas. Thus, the hedging argument relies on the notion of dispersal. Moreover, increasing returns to size and scale within a reserve further reinforce the likely augmentation of stocks in open areas and strengthen the hedging argument.

Biological justifications for reserves are strongest under several stylized biological conditions. The first is when adult organisms are sedentary. Sedentary adults allow biomass recovery within the reserve and facilitate complete life cycles among protected organisms. These factors, in turn, may contribute to increasing returns to size and scale. Second, density-dependent spawning is important for increasing returns to scale. As a result, reserves might be especially appropriate for sedentary broadcast

spawning organisms, i.e. organisms that broadcast their gametes into the water. The reasoning is that these organisms cannot effectively move to increase fertilization rates, and unfertilized eggs are unlikely to be fertilized as they disperse in the water away from concentrations of other urchins. Third, dispersal is particularly important for arguments that rely on using reserves to augment areas outside of the reserve continuously and permanently. Without dispersal, a reserve simply could not feed exploited areas. All of these conditions make benthic invertebrates like abalone, crabs, and sea urchins likely candidates for marine reserves. Adults are sedentary, spawning is clearly density-dependent, and larvae disperse in ocean currents.

Table 1.1 classifies some of the biological literature promoting reserves as a fishery management tool and reports the number of times each article has been cited according to the Science Citation Index and the Social Science Citation Index. Dugan and Davis (1993), cited 74 times, tops the list. This paper reviews empirical studies of marine reserves for exploited fish populations. Most of the studies reviewed by Dugan and Davis find that reserves increase abundance and size of fish **within** the reserve. A few studies indicate that fishery yields outside of reserves are enhanced. Consistent with these findings, Russ and Alcala (1996) present empirical results from a marine reserve in the Phillipines. They find evidence that with a reserve, densities of reef fish increase within the reserve. They also find some evidence that densities go up in neighboring non-reserve areas.⁵ One empirical study that finds closures to be ineffective in rebuilding stocks is Tegner (1993). Tegner assesses a 15-year spatial closure for abalone in southern California and attributes its lack of success to low dispersal rates and poaching.

⁵ In an earlier paper, Roberts and Polunin (1991) reviewed empirical marine reserve studies, found similar results but focused almost exclusively on effects within a reserve.

Aside from the two papers by Dugan and Davis and Russ and Alcala, all of the remaining frequently cited papers are simulation or analytical modeling rather than empirical studies.⁶ The most frequently cited of these modeling approaches is Polacheck (1990), which is also the first modeling paper on this topic. Polacheck uses a two-patch Beverton and Holt (1957) model. One patch represents the reserve, and one represents the non-reserve. The model assumes that total fishing effort is unchanged by introducing a reserve, and the effort formerly in the reserve area redistributes uniformly in the non-reserve area. This is a typical assumption in the marine reserves modeling literature, as Table 1.1 indicates. Polacheck demonstrates that with high pre-reserve fishing effort, a reserve can increase the spawning stock biomass as a result of a shift in the age distribution of the population towards older organisms. Under some reserve scenarios, this also can increase the fishing yield per recruit. Using a similar model that adds density-dependent dispersal, DeMartini (1993) finds similar results.

Lauck et al. (1998) develop a stochastic model with biological growth and measurement error that confounds the setting and achievement of sustainable harvest rates. Developing the “hedging” argument, they find that the probability a stock remains above some threshold level increases as the fraction of space in a reserve increases. Hastings and Botsford (1999) make the important point that there is an equivalence in yield between traditional effort controls and a reserve. While their results hinge critically on the assumption that fishing mortality can be expressed as a constant harvest fraction that does not change in response to a reserve, they show that, in principle, there is no difference in yield between controlling system-wide effort with conventional measures

⁶ One notable exception is McClanahan and Kaunda-Arara (1995). These authors collected data on fishers before and after a marine reserve was implemented in Kenya. They found dramatic increases in catch per

(e.g. gear, season length) and controlling effort by restricting access to space. Carr and Reed (1993) make an extreme behavioral simplification, modeling a reserve such that it maintains a constant harvest level. These authors assume that a manager chooses harvested and non-harvested population sizes, and regardless of how large or small the reserve is, fishing effort will simply exhaust the recruits.⁷ Quinn et al. (1993) use a metapopulation model of reserves with constant fishing effort. They find that refuges can protect against stock collapses at limited cost in sustainable catch when fishing effort is low. In contrast to other authors, they also find that with precise controls of fishing effort, managers can obtain higher yields without reserves. Yet, with slight increases in fishing effort beyond these levels, subpopulations can be driven to extinction. Man et al. (1995) also find that reserves can effectively prevent stock collapses. They use a metapopulation model that tracks the proportion of occupied patches and assume a proportionality constant that captures fishing effort, which is not endogenous in their model.⁸

unit effort in areas neighboring the park, but overall total effort and total catch also decreased dramatically.
⁷ As further evidence that these authors ignore economic behavior, Carr and Reed begin the last paragraph of their conclusion with the following statement: "To properly design, manage, and evaluate a harvest refuge will, in most cases, require a multidisciplinary approach involving fishery biologists, oceanographers, ecologists, and population geneticists." (p. 2026) Note that economists are missing from their list.

⁸ Numerous other authors have modeled marine reserves with mathematical models that do not allow for endogenous behavioral response, e.g. Guenette and Pitcher (1999), Mangel (2000). Interestingly, biological modeling of marine reserves also excludes poaching and enforcement costs, two other behavioral aspects of the problem. If a reserve succeeds in rebuilding the biomass in an overexploited area, it would also increase the incentive to poach there. Though modeling efforts have ignored this possibility, Tegner (1993) cites poaching as one possible reason for the inability of reserves in southern California to rebuild abalone stocks.

Table 1.1

Summary of Key Biological Articles

Article	Year	Citation Count	Modeling or Empirical	Pre- and Post-Reserve Effort Assumptions
Dugan and Davis	1993	74	Discussion	none
Polacheck	1990	49	Modeling	fixed total effort and uniform redistribution
Carr and Reed	1993	48	Modeling	constant harvest - no behavior
DeMartini	1993	45	Modeling	fixed total effort and uniform redistribution
Lauck et al.	1998	41	Modeling	random harvest fraction.
Russ and Alcala	1996	39	Empirical	N/A
Quinn et al.	1993	38	Modeling	fixed total effort and uniform redistribution, fishers give up at very low densities
Man et al.	1995	34	Modeling	fixed total effort and uniform redistribution
Bohnsack	1993	30	Discussion	N/A
Hastings and Botsford	1999	14	Modeling	fixed harvest fraction

Although this brief review of the most frequently cited biological articles on reserves does not reveal it, there has been a subtle shift in focus in the literature as biologists have become more active promoters of marine reserves. Most of the early empirical studies and some of the first modeling studies focused on the response to an area closure **within** the area closed. These studies showed the unsurprising result that instituting reserves in an exploited area allows the area to return to a more “natural” state, with more biomass, more fecundity, and broader age and size distributions. In response to concerns by fishermen about how reserves might affect them, the second generation of modeling papers focused on the impacts **outside** of reserves, particularly on aggregate harvest. These studies reveal that it is hypothetically possible that closing a fraction of a fishery to exploitation can increase yields in remaining open areas by enough to compensate for the closure. This historiographical perspective on the biological literature is essential because it reveals how little attention has been given to empirical impacts of reserves outside reserve areas and how little time biologists have had to study this problem.

There are two issues associated with these biological results, both of which are addressed by this thesis. First, since the disparate biological modeling work has not been reconciled or synthesized, it is not exactly clear what features of a system are required to ensure that a reserve will actually enhance fisheries management. Each modeling paper employs different assumptions and methods, and it is not apparent what mechanisms drive results. Second, all of the biological literature employs simplifying and often unrealistic assumptions about effort, both before and after reserve creation.⁹ These

⁹ The one exception to the trend in biological modeling of reserves to ignore economic behavior is Walters (2000). This study describes ECOSPACE as a tool to analyze reserves. ECOSPACE is an ecosystem

assumptions are critical. Economists would argue that effort will respond to economic conditions *ex ante* and *ex post*. We would certainly expect fishermen to reallocate the remaining open areas in response to economic incentives, and simplifying assumptions such as constant effort, constant fishing mortality, or proportional reallocation likely will lead to an incomplete understanding of reserve impacts.

Regulatory Interest in Spatial Management

As biologists have begun to promote the benefits of marine reserves, regulatory interest in spatial management has increased among policy makers and managers. While there are only a few examples of marine reserves used for fishery management from around the world, there has been a growing interest in reserves as a fishery management tool within the United States and elsewhere. Language within Clinton's executive order mentions fishery management using marine reserves. California resource managers have also expressed an explicit interest in marine reserves as a fishery management tool but have recognized that reserves are not a panacea. A recent report of the Resources Agency of California (2000) states:

There is mounting evidence to suggest that certain types of marine managed areas allow exploited, resident species to recover within their borders and may enhance productivity of some species outside their borders. However, these areas should be viewed from the broader perspective as one of many management tools that can be used to protect or conserve marine species, such as measures limiting the number of vessels or types of gear, and establishing seasons or quotas. (p. 2)

Beyond arguments put forward by biologists, there are further reasons that make reserves an attractive option for regulators. Of utmost importance is the idea that a

simulation that includes a spatially explicit behavioral component. The behavioral model, though not a structural model of economic decisions, is a gravity model in which harvesters are more (or less) attracted to a location based on the profitability of the location. A reserve thus has zero profitability.

marine reserve is another tool with which to limit fishing effort. If reserves can sustain higher harvests than traditional tools (due to biological factors), such higher harvests alone may provide ample regulatory justification. But if reserves are found to be only equivalent to other tools, then they must be a less costly way to regulate if a strong case is to be made for their use as a fishery management tool. Roberts and Polunin (1991, 1993) argue that reserves may be useful for managing fisheries in the tropics based on two premises: 1) conventional management is difficult in the tropics due to limited regulatory resources and 2) many tropical fisheries are multi-species reef fisheries, which may be regulated more efficiently with a reserve than with individual single species management schemes. Polacheck (1990) contends that reserves avoid allocation conflicts that are typical of other management tools. However, as in his modeling simplifications, this contention ignores the spatial heterogeneity of harvesters. Given geographic heterogeneity of fishing fleet moorings and processing facilities, the siting of a reserve certainly poses distributive consequences through travel costs.¹⁰

Marine Reserves in the Economics Literature

Because much of this thesis focuses on the impacts of spatially explicit economic behavior on the outcomes of marine reserve creation, it is important to consider what economists have already said on this issue. To date, all of the work in the economic literature has been conceptual. As such, it provides clues about circumstances in which a marine reserve would be a useful fishery management tool. Like biologists, economists find that reserves are beneficial in some settings but not in others. It is thus essential to empiricize existing conceptual bioeconomic analyses in order to evaluate a particular

¹⁰ Bohnsack (1998) lists "reduce conflicts between users" among his "well supported" fishery benefits of reserves. Again, this is based primarily on biological literature that does not explicitly model behavioral

reserve setting. To help summarize the economic literature, a search is conducted in the Science Citation Index and in the Social Science Citation Index for the articles discussed below as in the analysis of biological literature on marine reserves. The numbers of hits appear in brackets and are suggestive of how much attention these articles have received.¹¹

Economists in general have paid little attention to the spatial behavior of resource users. Early economic analyses of marine reserves followed the simplifying assumptions of biologists. Holland and Brazee (1996) [cites=18] consider the case of fixed total fishing effort to evaluate reserves. Not surprisingly, they conclude that the optimal size of a reserve and the ability of a reserve to insure against stock collapse both depend on that level of fishing effort. Hannesson (1998) [cites=4] also analyzes marine reserves and finds that temporary rents can be generated by the marine reserve as fish disperse outside of it. However, under open access, gains from the reserve are dissipated as in the standard case.¹² The result is not surprising because in Hannesson's model, the reserve does nothing to alter the open access incentive structure outside of the reserve. Brown and Roughgarden (1997) [cites=7] find that a scenario in which it is profitable to harvest only one subpopulation in a metapopulation, which essentially creates a marine reserve in other locations. Sanchirico and Wilen (1999) [cites=6] provide more general biological and economic spatial models based on the assumption that traditional mechanisms of

responses to reserves.

¹¹ In comparison with the biological literature, the citation indices reveal that the articles are all fairly recent and have not had sufficient time to accumulate numerous citations.

¹² The "standard case" is rent dissipation under open access. Gordon (1954) uses a static model to describe how an open access institutional setting leads to a rent dissipation process in which overexploitation of a fishery can occur. The basic idea is that when access to a natural resource is not limited or controlled, harvesters will exploit the resource until it is no longer individually profitable for them to do so. The aggregate level of exploitation can thus exceed the socially optimal level of exploitation. Smith (1968) generalizes this result in a dynamic setting.

open access continue to operate when a resource is spatially heterogeneous. In their case, temporary rents appear as spatial arbitrage opportunities that arise due to the spatial character of biological dynamics and are dissipated due to open access.¹³

Although conceptual analyses predict that an open access institutional setting eventually dissipates economic rents that arise with a marine reserve, there is uncertainty about what will happen to the biological health of a system with a marine reserve. Specifically, how do aggregate biomass, harvest, and egg production respond to reserves? Simple models have produced a few propositions. For example, Sanchirico and Wilen (2000) derive conditions under which a system with a reserve will generate more sustainable harvest than one without a reserve. The requirements are that: 1) there is some biological dispersal mechanism; 2) economic behavior of harvesters responds to relative rents; 3) the biological dispersal rate is neither too high nor low; and 4) the bioeconomic ratio (cost/price ratio) in the reserve patch is relatively low. The first three conditions enable abundance growth in the reserve to spill over into the remaining open areas, whereas the last condition implies that the opportunity cost of foregone harvest in the reserve patch will be low. The analysis by Sanchirico and Wilen and previous works on marine reserves are conceptual and stylized, using simple *ad hoc* assumptions about factors and mechanisms that drive spatial behavior of harvesters as well as simplifying assumptions about the biological mechanisms and institutional setting.¹⁴ Thus it is worth examining whether their conclusions hold in more realistic settings. Given that future

¹³ Two other conceptual models of marine reserves in the economic literature are Conrad (1999) and Pezzey et al. (2000). Conrad divides the fishery into reserve and non-reserve areas and finds that the present value of a reserve policy, optimizing over the size of the reserve, is lower than the present value of optimal fishery management without a reserve. By introducing stochastic growth into the model, marine reserves can lower variability in fishable biomass. Pezzey et al. use their conceptual model to find that reserves can increase equilibrium catch if the pre-reserve biomass is less than half of the carrying capacity.

management of marine ecosystems almost certainly will involve marine reserves, it is essential to conduct a more robust analysis of reserves in a multitude of settings.

The Importance of Space in Ecology and in Natural Resource Economics

The larger context of this dissertation is the growing importance of spatial considerations in studying natural resources. Ecologists, though long concerned with the geography of ecosystems, have placed greater emphasis on spatial heterogeneity and spatial interactions in recent years. Recognizing the importance of realistic depictions of natural systems, resource economists have followed suit. This dissertation is part of a movement to incorporate space more systematically into models of natural resource use.

Space is naturally an important theme in ecology. Many topics in ecology explicitly incorporate spatial heterogeneity and interactions. Historically, the sub-field of biogeography has analyzed the spatial distribution of plants and animals. Dating back to the 19th century, biogeography primarily has studied species on a macro scale, e.g. across continents (Stilling, 1992). Within the field of population biology, the sub-field of metapopulation ecology has emerged over the past thirty years to study explicitly the spatial structure of populations on a more micro scale. Metapopulation models incorporate not only the spatial heterogeneity of habitat but also the spatial dispersal of organisms.¹⁵

With developments like metapopulation ecology, spatial considerations have become increasingly important in the ecology literature in recent years. A simple review of abstracts in the journal *Ecology* demonstrates this trend. A search of *Ecology* abstracts

¹⁴ Homans and Wilen (1997) demonstrate that modeling regulation in a fishery that is otherwise characterized by open access leads to different predictions than the pure open access model.

in five year increments for the words "spatial" and "metapopulation," counting the number of articles in which either of these words were found, is summarized in Table 1.2.¹⁶ Beginning in the late 1970s and through the early 1990s, the importance of space in the literature shows a dramatic increase, though interest seems to have waned somewhat in the late 1990s.

Table 1.2
Occurrences of "Spatial" or "Metapopulation" in Article Abstracts in *Ecology*

From	To	Articles Meeting Search Criteria	Article Count Index	Adjusted Articles
1965	1969	16	137	16
1970	1974	16	150	15
1975	1979	34	163	29
1980	1984	74	177	57
1985	1989	88	190	64
1990	1994	125	203	84
1995	1999	65	216	41

In contrast with ecology, spatial considerations have played a far less central role in natural resource economics over the same period. The core models in both non-renewable and renewable resource economics depict a single resource stock that is generally assumed homogeneous across space.¹⁷ Arguably the most important contribution to neo-classical resource economics across these different areas is the systematic incorporation of intertemporal dynamics into conceptual models of resource

¹⁵ See Hanski (1999) for a detailed treatment of metapopulation ecology. Hastings (1990) categorizes models of spatial heterogeneity in ecology into diffusion models and patch models, and argues that these two types of models apply to different spatial and temporal scales.

¹⁶ Because the total number of articles in the journal increased over time, an article count index was created by counting total articles in 1965 and in 1994 and interpolating for other years. The article index generated a weighted number of articles in which spatial or metapopulation appeared in the abstract.

¹⁷ Certainly at the heart of non-renewables is the Hotelling (1931) model that derives the price path for a homogeneous exhaustible resource over time. In the sustainability and intergenerational equity literature, we also find core models with a single homogeneous resource (Solow 1974, Hartwick 1977). At the center

use. Beginning in the late 1960s, there was considerable qualitative insight to be gained from dynamic treatments of different resource extraction problems that used a single state variable to depict a homogeneous stock, a simplification that provided for analytical tractability and elegance. In a survey article of renewable resource economics, Brown (2000) argues that incorporating the spatial dimension of resource problems may eventually provide similarly important insights.¹⁸

Modifications of core resource economics models frequently involve multiple resource stocks but do not typically account for spatial relationships explicitly. Many developments in exhaustible resources and in forestry, for instance, involve sequencing of heterogeneous resource pools. In fisheries, extensions of the core model sometimes involve age- and size- structured populations or predator-prey models of multiple populations.¹⁹ Even though resource economists often study the same natural systems as ecologists, historically there has been a strong tendency in economics to abstract away from spatial heterogeneity and linkages. The research in this dissertation is part of the movement to extend traditional renewable resource models in economics to incorporate the spatial dimension systematically.

Although it is not a core concept in neo-classical natural resource economics models, spatial heterogeneity is by no means new to resource economists. David Ricardo, arguably the first resource economist among the classical economists, implicitly recognized the importance of spatial heterogeneity in his treatment of land use. In particular, Ricardo argued that rent arises from heterogeneous qualities of land and

of fisheries economics are the Gordon (1954) and Smith (1968, 1969) models, while in forestry economics we have the Faustmann (1849) rotation problem.

¹⁸ Wilen (2000a) emphasizes the importance of accounting for space explicitly in fisheries models.

scarcity of the highest quality. Moreover, Ricardo extended his analysis to mineral and even to environmental resources, writing, "If air, water, the elasticity of steam, and the pressure of the atmosphere were of various qualities; if they could be appropriated, and each quality existed only in moderate abundance, they, as well as land, would afford a rent, as the successive qualities were brought into use."²⁰ Resource economists since Ricardo have applied this reasoning in a number of settings. Nevertheless, most models of land use and land heterogeneity have been static and we are left with a small literature in resource economics that is both spatial and dynamic.²¹

Outline of Chapters

Chapter 2 presents a simple conceptual model of marine reserves in a two-patch system with logistic growth. The emphasis is on the steady-state production surface under various assumptions about dispersal and total fishing effort. Unlike previous bioeconomic analyses, there is no explicit optimization imposed on the system. Thus, it provides a means to evaluate naïve behavioral assumptions typically invoked in the biological literature.

Chapter 3 introduces the empirical setting for this dissertation. It provides industry background for the California red sea urchin (*Strongylocentrotus franciscanus*) fishery and highlights some aspects of the sea urchin biology. As such, these descriptions justify the sea urchin fishery as an ideal test case for evaluating the performance of

¹⁹ Wilen (2000b) describes the history of renewable resource models in economics. He argues that as ecologists and other scientists began to incorporate more realistic depictions of populations, economists continued to focus on simple conceptual models in order to ensure tractable analytical solutions.

²⁰ Ricardo (1821, p. 39).

²¹ Following the *Ecology* abstract search, abstracts of two resource economics journals were searched for the words "spatial" and "metapopulation." In the *Journal of Environmental Economics and Management*, there are five articles with either word between 1990-1994, and in the interval 1995-1999, there are seven articles with either word. A similar search in *Land Economics* reveals three articles each in the 1985-1989 and 1990-1994 intervals, and four articles in the 1995-1999 interval.

marine reserves. Chapter 3 then describes the raw data for the sea urchin fishery and elucidates the spatial dimensions of harvester behavior. Finally, the chapter analyzes harvester attrition with a duration model and characterizes several aspects of harvester heterogeneity.

Chapter 4 presents a discrete choice model of sea urchin harvester participation and location choice. It uses the Nested Logit specification to estimate how sea urchin divers respond to time-varying and location-specific characteristics. Estimates are used to simulate short-run behavioral responses to spatial closures.

Chapter 5 analyzes another dimension of spatial behavior: the choice of a fishing port. This chapter uses a Seemingly Unrelated Regression (SUR) model to allocate urchin divers between the northern California and southern California urchin fishery. Then a second SUR model allocates northern California divers among the northern California fishing ports. Both models include partial adjustment structures to account for sluggish responses to spatially varying harvesting revenues. For a fixed number of total harvesters (as there would be in a limited entry program), the SUR models together can generate predictions about the number of participants in each possible fishing port.

Chapter 6 describes an age- and size-structured metapopulation model of sea urchin biology. It uses individual Beverton-Holt models for each subpopulation and links the subpopulations through larval dispersal. It then presents a conceptual analysis of how the spatial distribution of fishing effort will likely affect the outcome of a marine reserve. The chapter next simulates marine reserves and other spatially explicit effort reductions under different parameterizations of recruitment with a simple uniform larval dispersal mechanism. For each scenario, it compares the steady-state system-wide catch under for

different values of fishing effort in an experimental patch, including the reserve case of zero fishing effort.

Chapter 7 integrates the behavioral models of Chapters 4 and 5 into the metapopulation model. In essence, these steps make fishing effort endogenous, whereas fishing effort in the biological model of Chapter 6 is considered to be exogenous. Recognizing that there is substantial scientific uncertainty about some parameters in the model, the fully bioeconomic model is calibrated using simulations that include best assessments for biological and oceanographic parameters that characterize the northern California red sea urchin fishery. The calibrated model is then used to explore the implications of marine reserves for managing the fishery.

Chapter 8 presents further analysis of marine reserves with and without the fully integrated bioeconomic model. Specifically, the simulations compare results with and without the behavioral components to assess the importance of behavioral modeling in the context of marine reserves.

Chapter 9 summarizes the results and conclusions of the dissertation.

Chapter 2

Evaluating Reserves without Optimization

One important observation about biological models of marine reserves is that assumptions about fishing effort drive the conclusions. In particular, both the level of aggregate effort and its assumed distribution over space, before and after reserve formation, are critical to the question of whether a reserve can be beneficial to fisheries yield. Each biological model of reserve formation assumes a distribution of fishing effort that is allocated across space in some ad hoc way. Then the modeling question becomes: do reserves pay off relative to some baseline spatial distribution of effort? Assumptions about total fishing effort, or in some cases pressure on the resource, come in various forms. One type of assumption is a constant fishing mortality exponent, e.g. Polacheck, 1990; DeMartini, 1993; Man et al, 1995. Another type is a constant harvest fraction, e.g. Botsford and Hastings, 1999. Still others assume various forms of constant fishing pressure such as constant harvest (Carr and Reed, 1993) and a random harvest fraction with a constant mean (Lauck et al.).

Using a biological model similar to that of Sanchirico and Wilen (1999), this chapter presents a simple example that demonstrates three points about these biological models, each of which evaluates reserves without performing an explicit optimization. First, in the absence of dispersal and assuming biological production that exhibits decreasing returns,¹ a reserve will paradoxically only pay off in a **lightly** exploited system. This result, while counterintuitive, would never be a cause for regulation because it would not reasonably arise in a situation without regulation.² Second, the only reasonable scenarios in which reserves pay off are ones in which the pre-reserve system is in a state of **overexploitation**. Third, beneficial reserve scenarios tend to arise when the initial allocation of fishing effort lies in a non-convex region of the production set. This is the case even in a simple model in which the biological production set is convex within each patch. In this setting, it is the dispersal of organisms across space and the possibility of localized extinctions that gives rise to these non-convexities.^{3,4}

¹ Throughout this chapter, we refer to different production technologies with the following convention. A convex technology implies a convex production set. This is the standard case of decreasing returns technology. As such, a functional representation of the production frontier is a concave function. Conversely, a non-convex production technology implies a non-convexity somewhere in the production set. This corresponds to increasing returns technology, which can be represented by a convex production function.

² We will see that unreasonable scenarios can arise because a system is so lightly exploited that harvest is maximized by allocating all effort to one location. A marine reserve in this setting would constitute regulatory redundancy because even under open access, and assuming no costs, we would expect such an allocation to come about naturally. There would be no incentive for individual agents not to allocate themselves into this de facto reserve scenario.

³ Local extinction means simply that biomass is driven to zero in at least one of the patches. We will also see that if we assume that free disposal of fishing effort is possible, production set non-convexities may result. However, when free disposal of effort is prohibited, these non-convexities are infeasible and the only remaining non-convexities are attributable to dispersal and local extinction. Free disposal in this chapter means that for a given allocation of fishing effort, if effort in one patch drives that patch to extinction, then effort in that patch can be thrown away. Thus, extinction in one patch does not make continuing to harvest the other patch infeasible. In terms of what happens to the fishing fleet, it means that all vessels in the extinct area exit the fishery and either sit idle or fish for another species; none of them reallocate to the other patch.

⁴ In contrast to Sanchirico and Wilen (1999), this chapter does not explicitly model behavioral responses. Later chapters will present empirical behavioral models that are spatially explicit. The intent here is to provide a means to evaluate biological claims about reserves and shed light on why biological modelers of reserves reach the conclusions that they do.

The model in this chapter does not nest all of the modeling approaches in the biological literature, but it illustrates the tautological nature of many biological studies of reserves. After all, if a system is severely overexploited, then a dramatic reduction in exploitation through any means, including instituting a reserve, is likely to improve upon the situation. It is important to note that in these extreme cases, even a reallocation of the **same** system-wide total fishing effort can reduce the overall level of overexploitation. In this context, however, a reserve is not necessarily optimal. That is, there might be another reallocation of fishing effort that increases harvest more than the reserve scenario. A reserve may thus be a second best, for the optimal allocation may not be obtainable with existing management tools. However, a reserve may also be a second worst in the sense that all but one other allocations of the same aggregate fishing effort produce more harvest. In this situation, it is essential to ask whether the single allocation that a reserve improves upon is at all a realistic one. The bottom line is that the benchmark allocation of fishing effort to which we compare a marine reserve has a substantial impact on whether our predictions favor reserves.

A Two-patch Model of Marine Reserves

The model in this section presumes, in order to mimic much of the biological literature on reserves, that total fishing effort is fixed. In a two patch setting, choice of effort in one patch thus determines the level of effort in the other. Our focus is the essential question: for a given amount of fishing effort and an initial allocation of that effort, under what circumstances will reserves lead to an increase in aggregate steady-state harvest?

Consider first the case of two patches with no dispersal. Biomasses in patch 1 and 2 are X and Y respectively. Fishing effort in patch 1 is e , while total fishing effort is \bar{e} . Ignoring catchability coefficients, we can express system-wide harvest (H) as:⁵

$$H = eX + (\bar{e} - e)Y. \quad (2.1)$$

Now suppose that natural growth and mortality in each patch are defined by $F(X)$ and $G(Y)$, respectively. The following two differential equations then describe the evolution of biomass in the exploited system:

$$\dot{X} = F(X) - eX, \quad (2.2)$$

$$\dot{Y} = G(Y) - (\bar{e} - e)Y. \quad (2.3)$$

For a given feasible choice of e , equilibrium in the system is defined by $\dot{X} = \dot{Y} = 0$. If we were interested in maximizing total harvest in the steady-state and could choose both e and \bar{e} , then we would simply choose such that X and Y corresponded to maximum sustainable yield values. Instead, we are interested in the common case in the biological literature in which total effort is given and we evaluate different allocations of that effort.⁶

A way to think of this allocation question is a simple analogue of production with a single input. Suppose that there are two factories (A and B) that produce a single output from a single input. For a given amount of available input, under what circumstances would one choose to run only one factory? If we assume **free disposal** of the input, we would only optimally choose to run one factory under a limited set of circumstances. Specifically, we would turn on and allocate only to Factory A when the

⁵ This is essentially a two-patch version of the Schaefer (1957) model but suppressing the catchability coefficient, q .

⁶ One possible case is an \bar{e} such that it is the sum of patch-specific maximum sustainable yield efforts.

marginal product of the last unit of input in that factory exceeds the marginal product of the first unit of input allocated to Factory B. With strictly decreasing returns production in both plants, as the total available input increases, eventually we would reach a point at which we would turn on Factory B. If A and B had the same production technology, then it would never be optimal to run just one factory. Alternatively, if one or both factories has increasing returns to the input, i.e. a non-convex production technology, then it might always be optimal just to run one factory.

Suppose we interpret total fishing effort as the input and harvest as the output. Under the free disposal and convexity assumptions in the preceding paragraph, a reserve would only be optimal at low levels of effort, i.e. in a lightly exploited system. Without free disposal of effort, however, the results can become more complicated, particularly with biological production systems for which marginal product is not just diminishing but actually becomes negative at high levels of exploitation.

To be more formal, suppose that $F(X)$ and $G(Y)$ are concave functions, i.e. the biological production set in each patch is convex. Thus, the aggregate production set is convex under free disposal. This assumption is sufficient for non-increasing returns to hold. Intuitively, we would expect aggregate steady-state harvest to peak when an equimarginal condition holds even if total effort is not chosen optimally. In particular, by adding (2.2) and (2.3), solving for total harvest, differentiating with respect to e , and setting the result equal to zero:

$$F'(X)\frac{dX}{de} = -G'(Y)\frac{dY}{de}. \quad (2.4)$$

In words, for an arbitrary amount of total effort \bar{e} , if the allocation of effort between two patches is chosen to maximize system-wide harvest, then the change in patch 1 growth

for a decrease in X due to more harvesting pressure should be offset at the optimum by minus the change in patch 2 growth for an implicit decrease in harvesting pressure in patch 2.

It is possible that this condition does not define an interior optimum if the first term is always greater (or less) than the second. This would be a circumstance for which a reserve would apparently be globally optimal even with convex production technology. Importantly, however, this case is somewhat artificial because we would not expect harvesters to allocate themselves to two patches naturally in this setting. If the average benefit of harvesting in patch 1 always exceeds that of harvesting in patch 2, even if there is no activity in patch 2, then everyone would allocate themselves naturally to patch 1. Thus, we have identified a situation in which a reserve pays off with a fixed amount of total effort, but it is one in which there would be no need for a reserve as a harvest maximization management tool.

To fix these ideas more clearly, consider next a numerical parameterization of the model above. That is, we define the following:

$$F(X) = a_1X - b_1X^2 \quad \text{and} \quad G(Y) = a_2Y - b_2Y^2. \quad (2.5)$$

where $a_1 = 0.7$, $a_2 = 0.5$, and $b_1 = b_2 = 0.001$. Figures 2.1–2.4 plot system-wide harvest against values of e . Each figure corresponds to a different total effort level, \bar{e} . The first figure shows how a reserve in patch 2 is actually optimal, in terms of maximizing harvest, for an extremely low level of total effort. This certainly is not the typical finding in the biological literature, but it has a simple explanation. As e is reduced to zero, the system-wide harvest decreases from the global optimum. The marginal harvest from effort is higher in patch 1 even when effort in patch 2 is zero. This corresponds to the

case discussed above in which a reserve arises naturally without any regulation. The incentives of individual harvesters, even under open access, coincide with allocating all effort to one patch. Thus, this case has little interest for regulators.

Figure 2.2 depicts a case with a larger overall exploitation rate. Here the optimal allocation of effort across patches lies in the interior. Figures 2.3 and 2.4 depict still larger total effort levels. These are all characterized by the fact that at such high overall levels, some allocations of that effort drive at least one of the patches to extinction. In these figures, therefore, we distinguish between feasible allocations with and without free disposal of effort. The solid lines assume that once a patch is driven to extinction, effort can still be allocated to it. The hatched lines indicate zero system-wide harvest for these cases because they are infeasible. Here we define feasibility to mean that harvests in both patches are greater than or equal to zero. For infeasible allocations, effort levels predict negative harvest in at least one patch. With free disposal, we can see the total yield associated with the separate growth functions bifurcate as total effort increases. This spreading apart causes a non-convexity in the system-wide harvest function when we permit free disposal, and it simply shrinks the feasible region when we do not permit free disposal. At high levels of exploitation, reserves are not feasible without free disposal. That is, reallocating a feasible allocation to one with a reserve will not always lead to a steady-state harvest that is positive if we prohibit free disposal. In Figure 2.4, we see that total effort is so high that no allocations are feasible.

The possibility of free disposal in this setting, which highlights the mechanisms driving results in the biological literature, is an interesting one. If we permit free disposal of effort, then we presume that the regulator can control the spatial allocation of effort;

for we know that no harvesters would visit a site continually when the site has been driven to extinction. Thus, the only way to achieve some of these allocations is to control precisely the effort in the patch that is still harvested. The conceptual problem with free disposal in this setting is that if this were true, then the regulator could always dispose of effort in each location that exceeded maximum sustainable yield effort levels. So, with globally concave growth functions and no dispersal, the only justifiable reserve case would be one of low exploitation. Notice that the effort/harvest transformation is always globally concave in the feasible region if we only consider feasible allocations under the assumption of no free disposal.

Figure 2.1

Harvest in Two-Patch Model with No Dispersal $\bar{e} = 0.025$

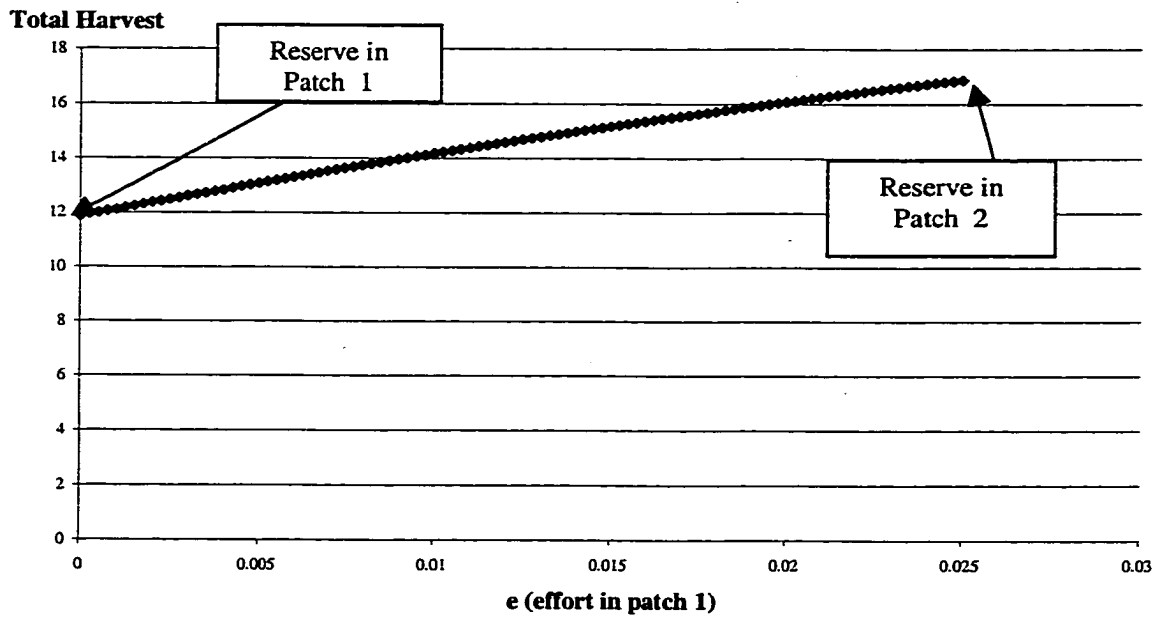


Figure 2.2

Harvest in Two-Patch Model with No Dispersal $\bar{e} = 0.3$

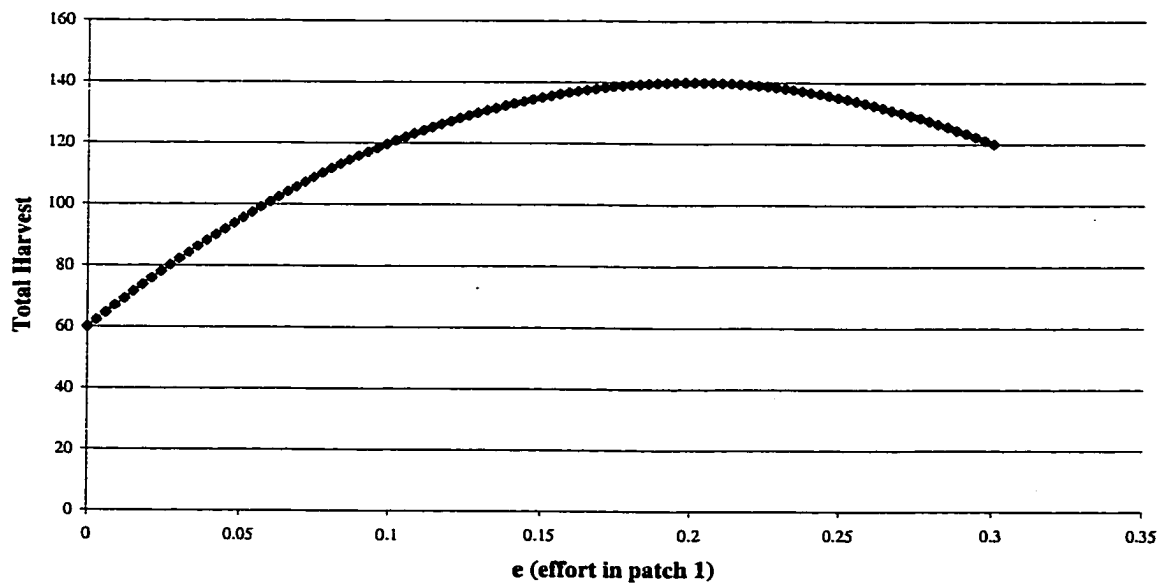


Figure 2.3

Harvest in Two-Patch Model with No Dispersal $\bar{e} = 0.8$

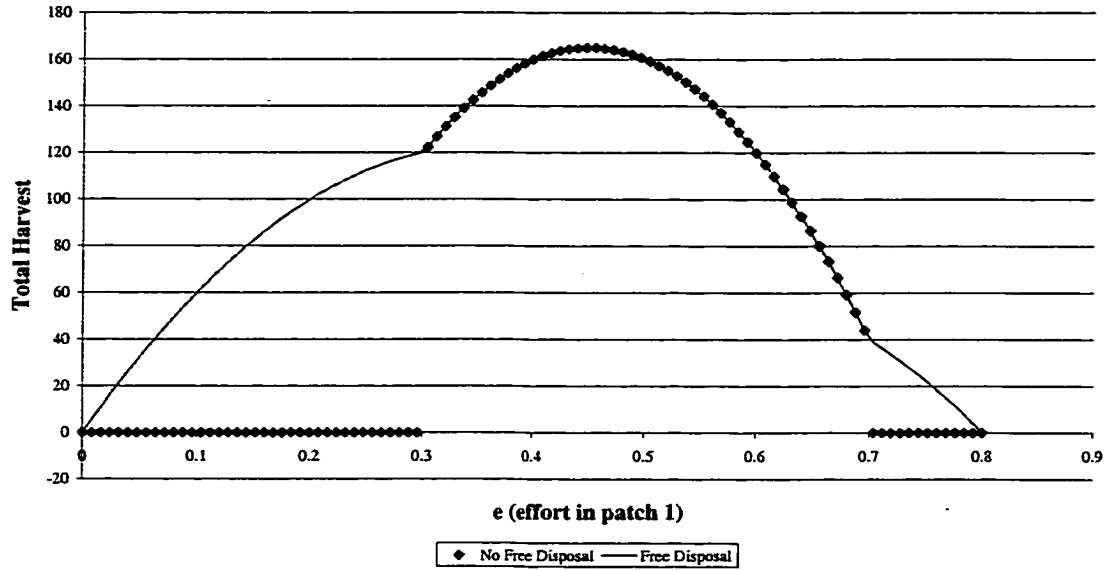
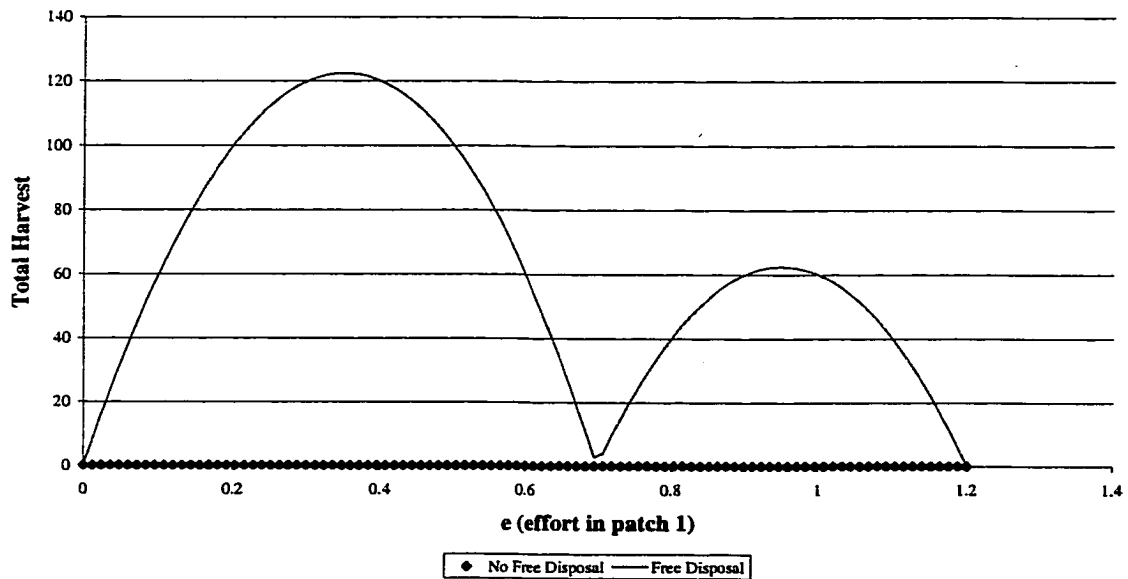


Figure 2.4

Harvest in Two-Patch Model with No Dispersal $\bar{e} = 1.2$



Uni-directional Dispersal

Now suppose that we add uni-directional dispersal to the model above. This corresponds roughly to what ecologists call a sink-source system. One patch is a source of biomass for the other. Here we modify (2.2) and (2.3) to be as follows:

$$\dot{X} = F(X) - eX - \delta X, \quad (2.6)$$

$$\dot{Y} = G(Y) - (\bar{e} - e)Y + \delta X. \quad (2.7)$$

Thus, patch 1 is a source and patch 2 is a sink. As such, higher biomass in patch 1 creates a positive externality for patch 2.

Using the same parameterization as above, and setting $\delta=0.4$, Figures 2.5-2.8 depict results for the same four different levels of total effort as Figures 2.1-2.4. Interestingly, in Figure 2.5 we see that a reserve scenario is optimal at a low exploitation rate, but one would choose the opposite reserve configuration. Previously, we would optimally choose to harvest only X, since the intrinsic growth rate is higher. Here, however, one would harvest from Y because X exports sufficient organisms to Y to boost the marginal product of effort in Y above that of effort in X at the boundary. In other words, we would choose to implement a reserve in X because X is a source.

Figure 2.6 depicts the moderate exploitation case in which harvest is globally concave in e . Clearly, neither reserve scenario is optimal. Yet, due to the high dispersal rate from X to Y, the reserve scenario beats many other allocations of effort. Again, we ask the question of how realistic these allocations would be in an actual fishery. Specifically, would harvesters allocate themselves across space such that total harvest is below the level with a reserve in patch 1? The answer is clearly no. Without costs and for a given level of total effort, individuals would equate average products across space

even with no other institutional constraints.⁷ This would lead naturally to an allocation that for this case maximizes system-wide harvest. Thus, the fact that reserves appear superior to some scenarios in these hypothetical biological modeling exercises does not suggest that reserves will perform better in any reasonable real world scenarios with these basic features.

Figures 2.7 and 2.8 correspond to still higher levels of total effort. Like in Figures 2.3 and 2.4, we see that increasing total effort spreads the individual patch harvest curves apart. In contrast, the cases with dispersal spread the curves more at the same levels of total effort. As a result, none of the allocations depicted in these figures are feasible without free disposal.

⁷ In our simple example, marginal and average products of effort are equal.

Figure 2.5

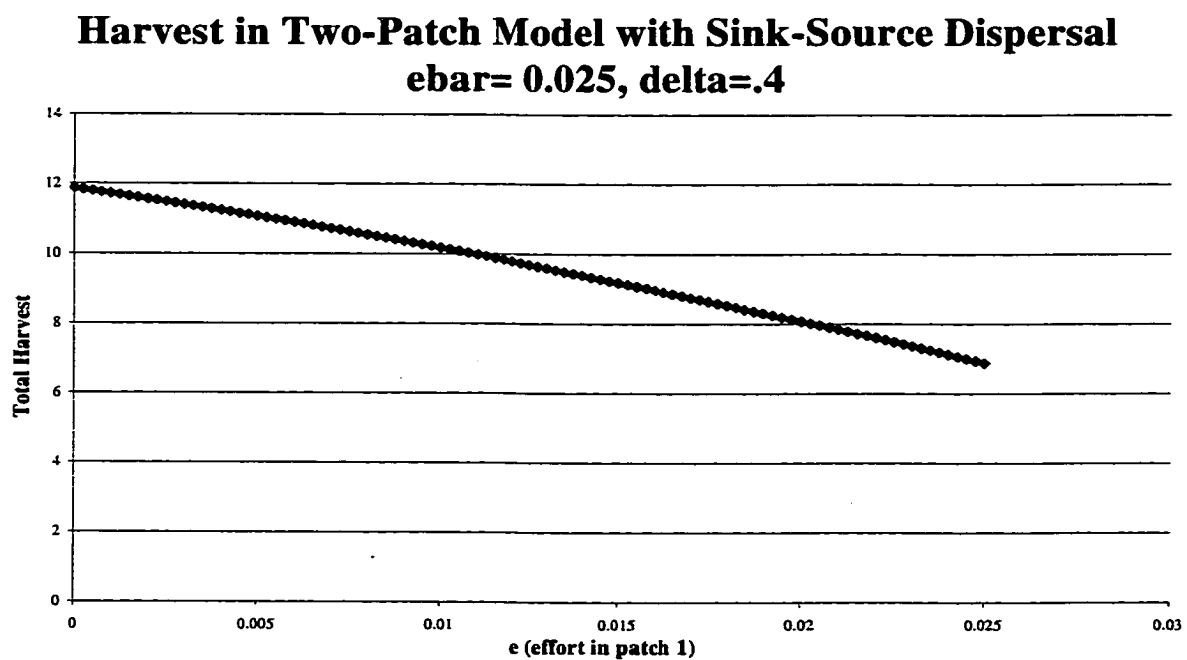


Figure 2.6

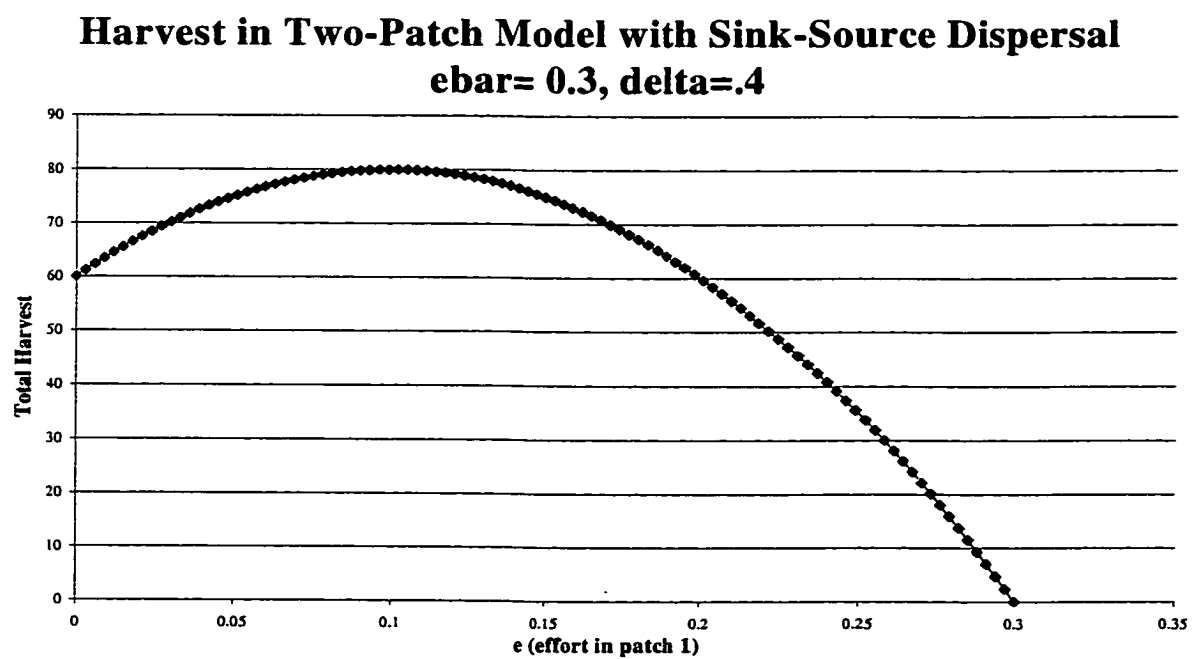


Figure 2.7

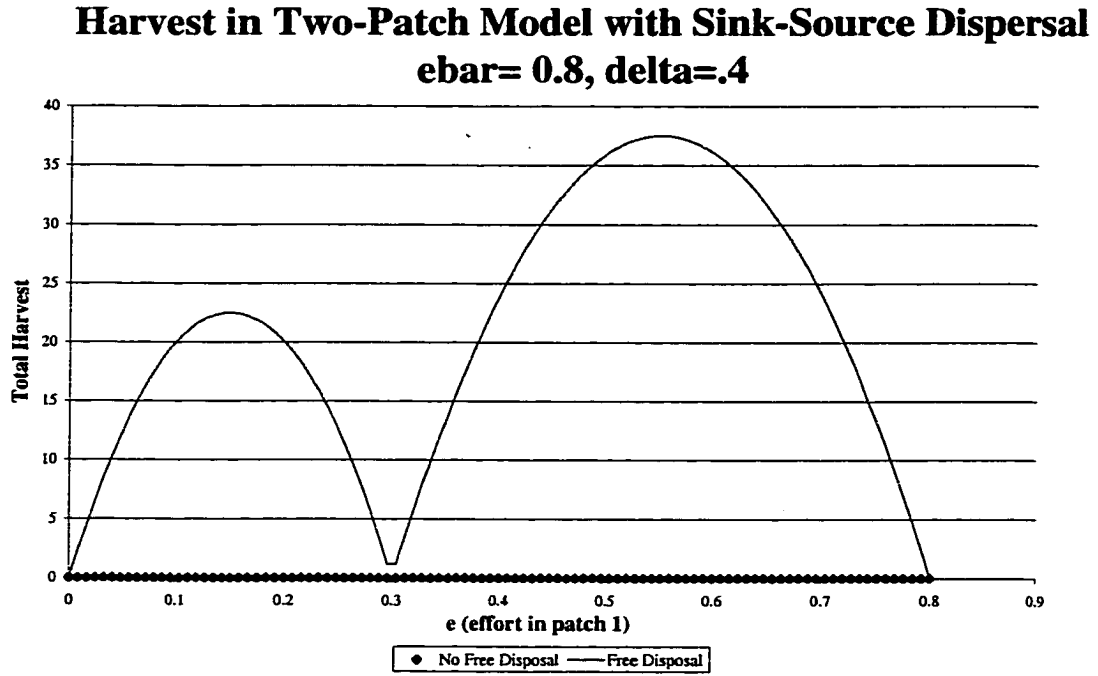
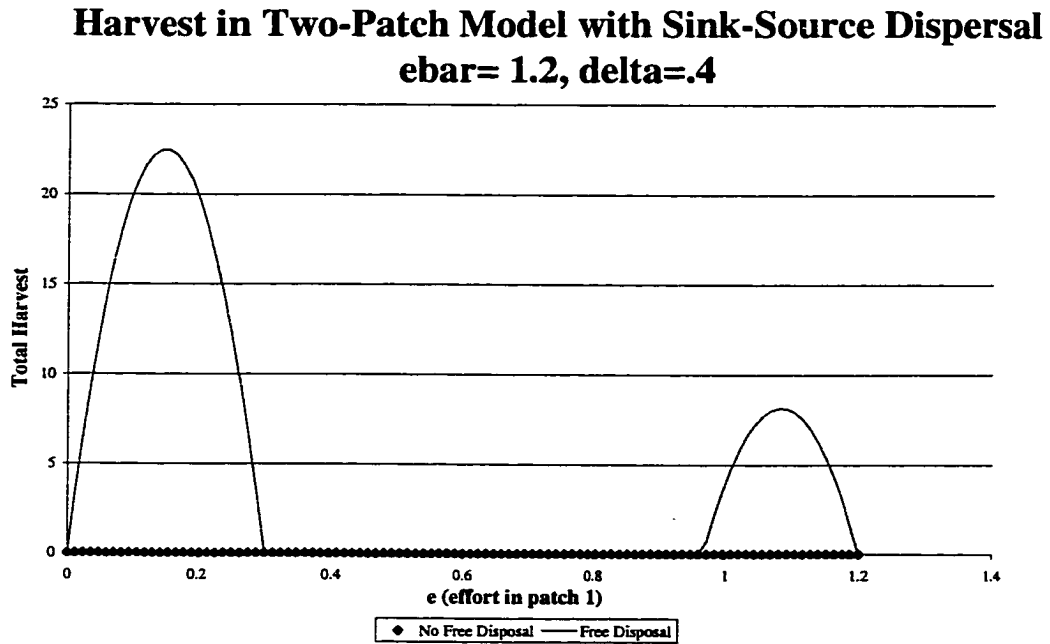


Figure 2.8



Bi-Directional Dispersal

Introducing bi-directional dispersal changes the analysis somewhat. For simplicity, we enter this dispersal such that it is dependent upon relative abundance in the two patches but not density-dependent within each patch.⁸ Thus, the state equations are:

$$\dot{X} = F(X) - eX + \delta(Y - X), \quad (2.9)$$

$$\dot{Y} = G(Y) - (\bar{e} - e)Y + \delta(X - Y). \quad (2.10)$$

Setting the state equations equal to zero and using the quadratic parameterization from above, we can solve for the roots of the steady-state. First, solve for Y in terms of X:

$$Y = (-\delta)^{-1}[(a_1 - \delta - e)X - b_1 X^2]. \quad (2.11)$$

Next, substitute for Y in the other state equation to obtain an implicit function in terms of X:

$$X \left\{ \phi\gamma + \delta + \left(\phi b_1 - \frac{b_2 \gamma^2}{\delta^2} \right) X + \left(\frac{-2b_2 \gamma b_1}{\delta^2} \right) X^2 + \left(\frac{-b_2 (b_1)^2}{\delta^2} \right) X^3 \right\} = 0, \quad (2.12)$$

where

$$\phi = \frac{a_2 - \delta + e - \bar{e}}{\delta} \quad \text{and} \quad \gamma = \delta + e - a_1. \quad (2.13)$$

Using the parameter values above, for given values of e and \bar{e} , we can solve for the three non-zero roots of X , select the root that is positive and real (if one exists), find the corresponding Y , and compute harvest.⁹ If no real positive root of X exists, we know that $X=0$ is a root (by inspection). We can then check to see if there is a corresponding positive root for Y .

⁸ This dispersal pattern differs from Sanchirico and Wilen (1999) only in that each state variable is not divided by the corresponding patch's carrying capacity parameter. The reason for this simplification is that bioeconomic equilibria comparable to those in Sanchirico and Wilen are not sought in this analysis.

We perform the simulations for four different dispersal values, $\delta \in \{0.1, 0.2, 0.3, 0.4\}$. At low levels of \bar{e} , the results are qualitatively similar to those described above. A reserve only pays off at extremely low levels of exploitation, and individual harvester incentives would bring about such a reserve without exploitation. At moderate exploitation levels, the reserve beats some allocations, is not globally optimal, but again the incentives for harvesters to allocate themselves optimally exist already.

Only at high levels of \bar{e} do we see some results that diverge. Specifically, at high levels of total effort, some allocations that were infeasible with no dispersal or unidirectional dispersal are now feasible. Increases in total effort still serve to spread individual patch harvest curves apart, but the edge regions can give rise to sustainable harvest levels even if the middle regions do not. Figures 2.9-2.12 illustrate this point. They depict aggregate harvest as a function of e for four combinations of δ and \bar{e} . At higher levels of overexploitation, a reserve beats a larger share of other feasible allocations. Moreover, at higher levels a reserve is more likely to be globally optimal. We also see that reserves are more likely to pay off at a higher dispersal rate. This result is consistent with much of the biological and economic literature. That is, reserves tend to perform better as a management tool when dispersal rates are high. Conversely, low dispersal rates have been cited as a reason for reserves not performing well.

Another way of viewing Figures 2.9-2.12 is to see them as depicting non-convexities in the total harvest transformation function. Reserves are more likely to pay off in terms of higher steady-state harvest when there are non-convexities in the biological production set. The larger the share of the production space that is

⁹ For these simulations, GAUSS was used to find the roots.

characterized by non-convexity, the more possible it is that a reserve improves on a large share of all possible allocations. Intuitively, if our benchmark for comparison to a reserve is an allocation in some trough depicted in one of these figures, then of course we will find that a reserve improves on that allocation. This fits with conventional wisdom of production economics. When there are non-convexities, equimarginality will not necessarily define the optimum as in the case of two production facilities with increasing returns to a fixed input.

Existence of non-convexities is thus essential for the policy relevance of marine reserves in biological models with simple assumptions about effort and its spatial allocation. In our first results, we find some reserve scenarios that seem to pay without non-convexities. However, we also argue that in these cases “reserves” would arise naturally without regulation, since harvesters would independently be attempting to equalize average products across space, leading to the optimal allocation. If that allocation occurs at one of the corners, then economic behavior creates a de facto “reserve” without the help of regulators. In the face of non-convexities, however, the situation changes dramatically. With a non-convexity, it is not necessarily the case that individual harvesters smoothly reallocate to equalize average products across space. For instance, if the system were on a trajectory to reach the right-hand side hump in Figure 2.9, it would not be individually rational for harvesters to reallocate effort marginally to jump to the left-hand side hump. For proof, consider a system at rest on the left side of the right-hand side hump and an individual with a tiny amount of effort that is all in patch 2. If the individual reallocates to patch 1, total harvest decreases, and harvest for the individual decreases as well. Thus, the individual’s average product actually would

decline and it would not be individually rational to reallocate in this way. Only a global reallocation of all harvesters would be able to jump the non-convexity. This scenario is analogous to under provision of a public good and provides justification for the regulator to act in creating a reserve.

The extreme case is one in which the steady-state biomass in both patches is driven to extinction. Clearly, there would be a role for regulators in the creation of a reserve here. Even in the less extreme cases, the system could come to rest at an allocation that provides less total harvest than a reserve scenario, again justifying some action by the regulator. We thus conclude that for a setting in which total effort is fixed before and after reserves, without increasing returns production technology and without free disposal, a reserve will only be a reasonable management strategy at high levels of fishing effort. Hence, a condition for reserves to pay is that, to begin with, the system must be relatively overexploited. It is the combination of high levels of overall effort and dispersal that creates non-convexities of the type that favor reserves.

Figure 2.9

Harvest in Two-Patch Model with Bi-directional Dispersal
 $\bar{e} = 1.2$, $\delta = 0.1$

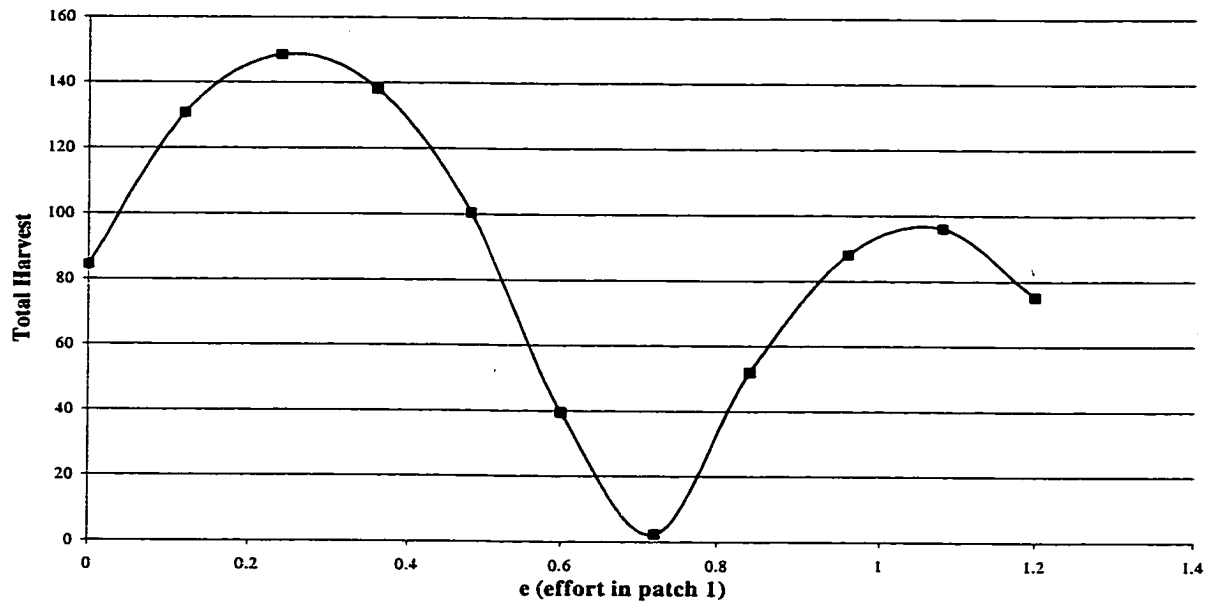


Figure 2.10

Harvest in Two-Patch Model with Bi-directional Dispersal
 $\bar{e} = 1.2$, $\delta = 0.4$

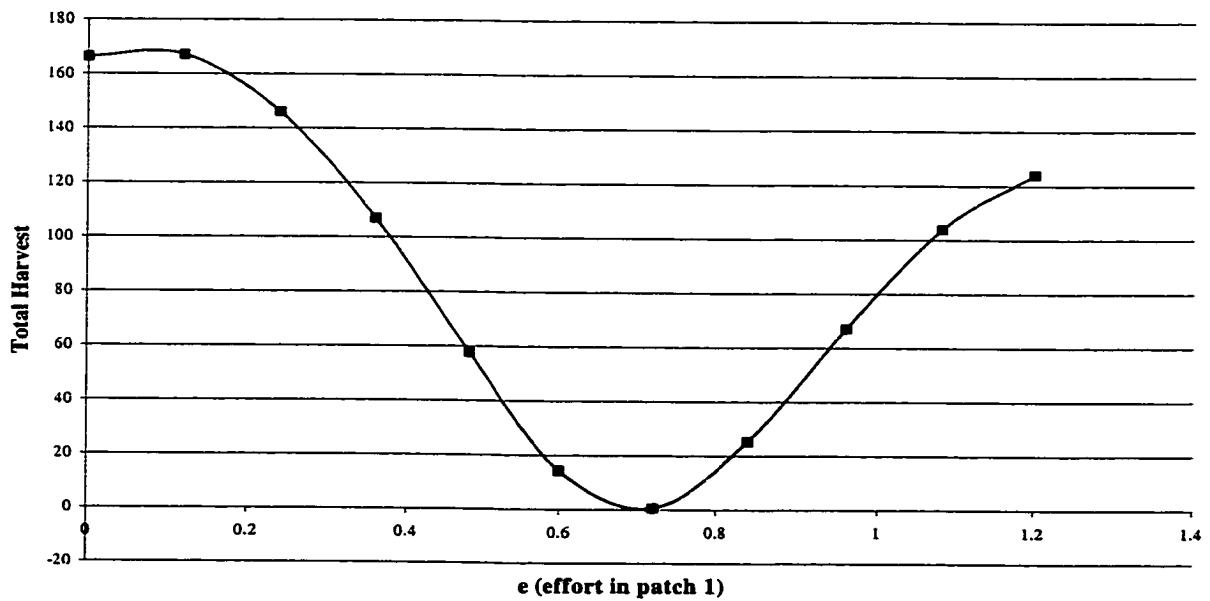


Figure 2.11

Harvest in Two-Patch Model with Bi-directional Dispersal
 $\bar{e} = 2.0$, $\delta = 0.1$

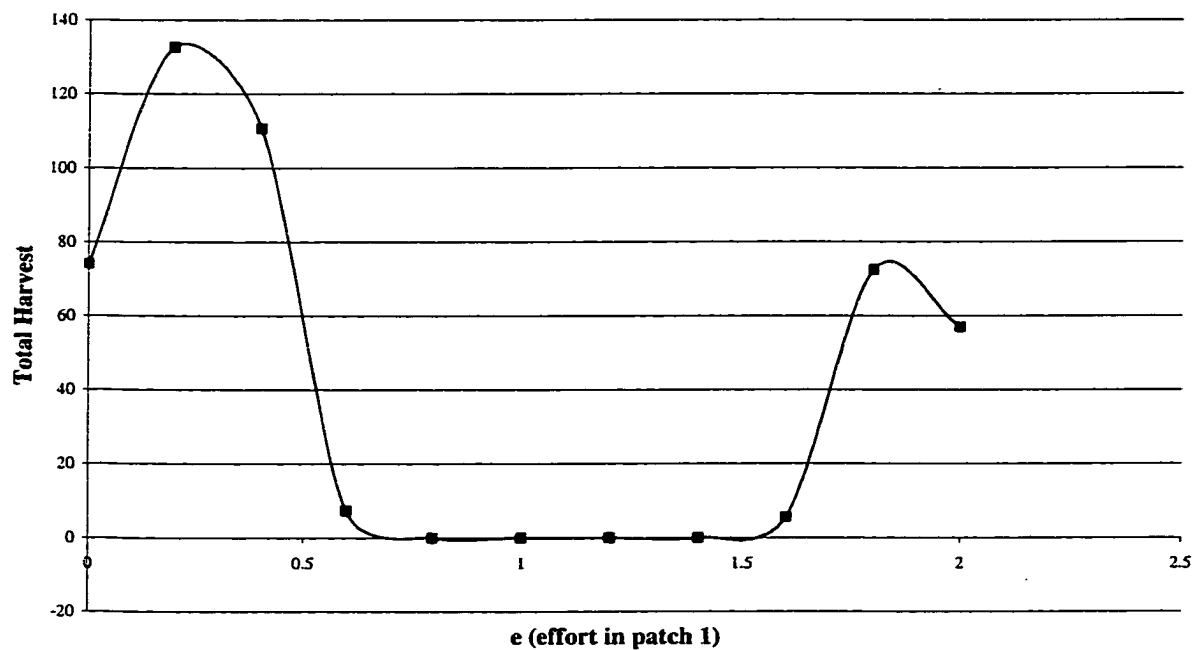
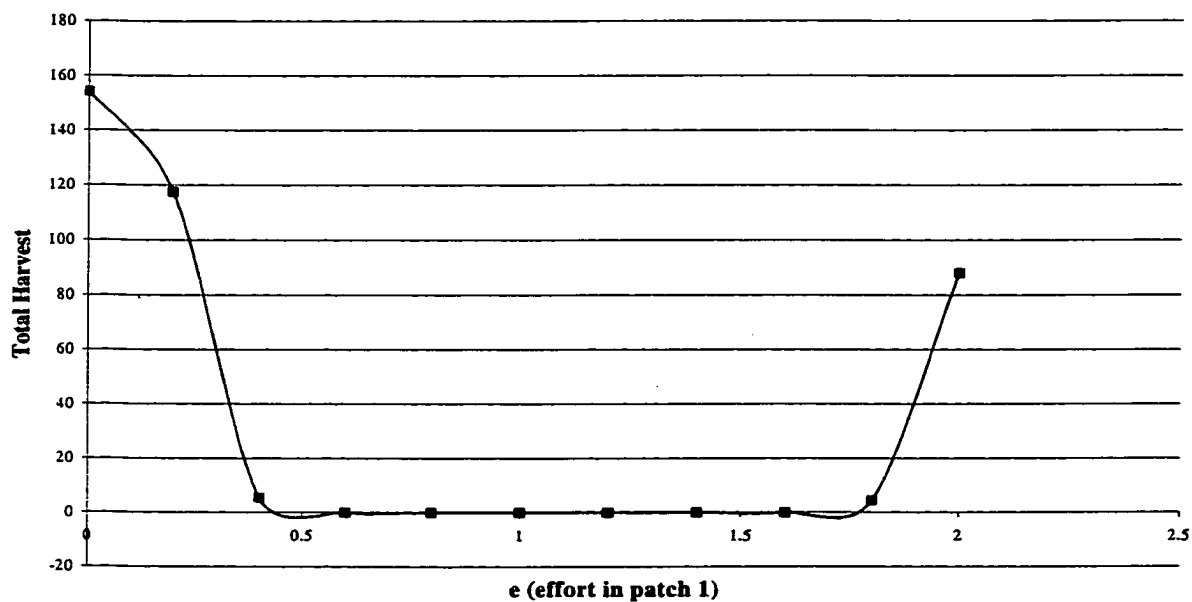


Figure 2.12

Harvest in Two-Patch Model with Bi-directional Dispersal
 $\bar{e} = 2.0$, $\delta = 0.4$



Conclusions: Marine Reserves as a Second Best or a Second Worst?

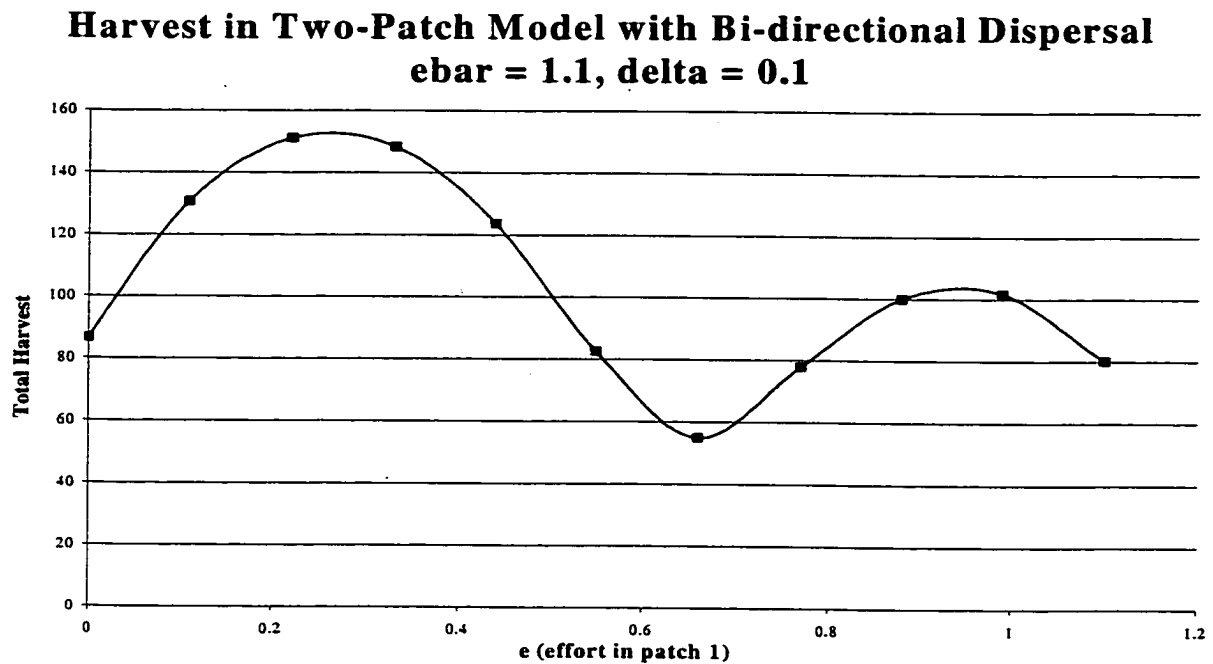
The analysis above demonstrates that for a fixed amount of total effort and decreasing returns production technology in each patch, a reserve can lead to a higher steady-state harvest than many shared allocations of this effort. Many of these shared allocations are unreasonable as *ex ante* allocations in the sense that they would never arise from individual optimizing behavior. However, we have found some feasible allocations that could arise and that clearly are worse than instituting a reserve.¹⁰ A range of allocations, for example, can lead to extinction in both patches if total effort is high enough. Nonetheless, reserves are usually not optimal in terms of system-wide aggregate harvest. Even at high levels of total effort, there is often another allocation that can increase total harvest. As a practical matter, these optimal allocations may be difficult to implement, and in this sense, a reserve can be thought of as a second best. If the regulator cannot feasibly obtain an optimum, it may be feasible to improve on the non-regulation allocation by instituting a reserve.

At the same time, a marine reserve might also constitute a second worst under some circumstances. Does a reserve lead to a higher steady-state harvest than some arbitrary allocation of fixed total effort? If the answer is yes, then a reserve has only been proven to be at least second worst, since the arbitrary allocation could have been the worst outcome. Figure 2.13 depicts a situation in which the reserve beats a narrow range of allocations. Here a reserve improves on $e \in [0.55, 0.825]$ and $e \in [1.05, 1.1]$. Of course, the allocation space is continuous. But loosely speaking, a reserve for these parameter values is not much better than the worst allocation. From the shape of this

curve and from Figures 2.9-2.12, we can imagine a case in which a reserve literally is the second worst.

The important point is that in Figure 2.13, as e is reduced to zero, the system-wide harvest decreases from the global optimum. If a reserve were implemented and the steady-state reached, holding total effort fixed, removing the reserve would increase harvest. That is, the individual incentives for harvesters would drive them to climb the hill towards the optimal allocation, increasing their average products by reallocating effort. Once the top of the hill is obtained, negative marginal products would prevent further reallocation because at the top of the hill, any reallocation would reduce average products for individuals.

Figure 2.13



¹⁰ That these allocations “could arise” indicates that they are stable in the steady-state, not necessarily that these steady-states would arise under normal economic incentives. For instance, in Figure 2.11, an equal division of effort leads to the stable outcome of extinction in both patches.

Ultimately, it is the control of **total** fishing effort and **allocation** of that effort that is at issue in determining whether a reserve will increase harvest with fixed effort. If the regulator can control total fishing effort, then under the assumptions above, allocation of that effort is not a problem. A de facto “reserve” could arise spontaneously at low levels of exploitation, so creating one in this situation would be regulatory redundancy. At moderate levels of exploitation, a reserve would not be optimal, and harvester incentives would promote equalization of average products across space, bringing about the optimum. By assumption, if the regulator is able to control total fishing effort, the regulator would not allow the system to be in a state of overexploitation. Thus, a regulatory impetus for a reserve would not arise in this setting. On the other hand, if the regulator cannot control total fishing effort, then a reserve can be justified under some circumstances. Yet, it is possible that a reserve would be second worst. A reserve might be a temporary means for the system to recover, but afterwards, individual harvester incentives might lead harvesters to reallocate to an improved second best, or even the optimal solution.

This simple modeling exercise demonstrates the importance of economic behavior for evaluating marine reserves. Whether a reserve is more akin to a second best, a second worst, or simply not worth doing hinges on the total level of fishing effort and its spatial distribution. Perhaps most importantly, many predictions about the efficacy of reserves will be determined by the assumed benchmark distribution of fishing effort. In many cases, a reserve is actually worse in terms of steady-state harvest than having no reserve. In some cases, a reserve that seems favorable relative to the benchmark effort allocation is a straw man argument because the benchmark would never arise naturally with existing

economic incentives. In a handful of cases, a reserve is globally optimal, but regulatory action is unnecessary because economic incentives would lead naturally to this allocation. All of these conceptual issues ultimately demonstrate the need for an empirical study of spatial behavior. Only a careful analysis of actual fishing behavior will be able to identify realistic characterizations about fishing effort, its spatial distribution, and its responsiveness to economic incentives.

Chapter 3

The Red Sea Urchin Fishery: Empirical Background and Data

As policy makers around the world show more interest in marine reserves, there is a growing need for comprehensive empirical studies that address spatial decision-making and spatial management. California regulators have demonstrated an explicit interest in spatial management of the northern California red sea urchin fishery. Concerned about a possible collapse of the urchin fishery and prospects for management with marine reserves, regulators have collected an extensive data set that tracks harvester behavior in spatial detail. Not only are regulators concerned about a possible collapse, but there are also compelling biological reasons for managing urchins with spatial closures. At the same time, the fishery data demonstrate clearly that economic behavior is spatially motivated. This chapter summarizes the motivations for studying spatial policies in the sea urchin context and presents the essential empirical background used in later chapters.

The first section describes the sea urchin fishery in California and its regulatory history. Drawing on this backdrop and on biological characteristics of sea urchins, the next section outlines behavioral, biological, and regulatory aspects of the fishery that make it an ideal test case to study spatial behavior and policy. The third section describes the raw data for the sea urchin fishery. These data are used throughout the dissertation. The fourth section presents several different spatial views of the fishery data that confirm the importance of space. These exploratory analyses highlight the patchiness of sea urchin abundance as well as the spatial heterogeneity of harvesters. The last section examines the persistence of harvesters in the fishery and further explores harvester heterogeneity. It finds evidence that spatial adjustment is a key determinant of the success of fishers.

The California Red Sea Urchin Fishery: Industry Background

Sea urchin roe is a traditional delicacy in Japanese cuisine. The highest quality roe, called uni, is served fresh and is among the most expensive items on most sushi menus. In California, divers harvest red sea urchins in areas off the coast down to 100 feet in depth. Divers make day trips, transporting the product while the urchins are still alive to processing plants where the shells (tests) are cracked and the roe is extracted, cleaned, and packed. Processors ship most of the roe by air to Tokyo, where it is sold wholesale and can fetch prices in excess of \$100 per pound. A growing share of product is marketed domestically to supply Japanese restaurants in the United States. Kato and Schroeter (1985) provide a useful summary of urchin biology and the early history of the California fishery. Much of the descriptive information in this section draws from their work.

Sea urchins are in the phylum Echinodermata along with starfish and sea cucumbers. They have hard shells, known as tests, and long protruding spines that protect the organisms from predators. Urchins feed primarily on kelp. An urchin's mouth is on its underside, and the inside of an urchin test consists mainly of its gonads (roe) along with the digestive tract and a water vascular system. There are two common species in California waters: red sea urchins (*Strongylocentrotus franciscanus*) and purple sea urchins (*Strongylocentrotus purpuratus*). Purple urchins are smaller and less valuable than their red counterparts. The red sea urchin is among the largest urchin species in the world and can grow to have an 18 cm test diameter.

Divers harvest sea urchins on one-day trips from California ports using simple technology. Typically divers use handheld rakes to remove urchins from the rocky ocean bottom and place them in mesh bags. The divers are attached to the surface with air hoses, which pump compressed air from their boats on which a dive partner or tender manages the compressor. When a bag is full, a diver attaches and fills a flotation device, bringing the urchins to the surface. Typical vessels are 8-9 meters in length with diesel engines, can travel 15-20 knots per hour, and hold up to 3 tons of urchins. The physical strain of diving as well as weather conditions limit the amount of time that harvesters can operate on any given day.

Processors purchase raw urchins at fishing ports and transport them to factories that extract, clean, and pack the roe. In the processing facilities, workers split urchin tests and remove the roe with a spoon. The roe is washed in salt water in plastic strainers and then bathed in alum to help make it firm. After a final rinse, roe is packed in small wooden trays that typically hold 250 g. The wooden trays are bundled and mostly

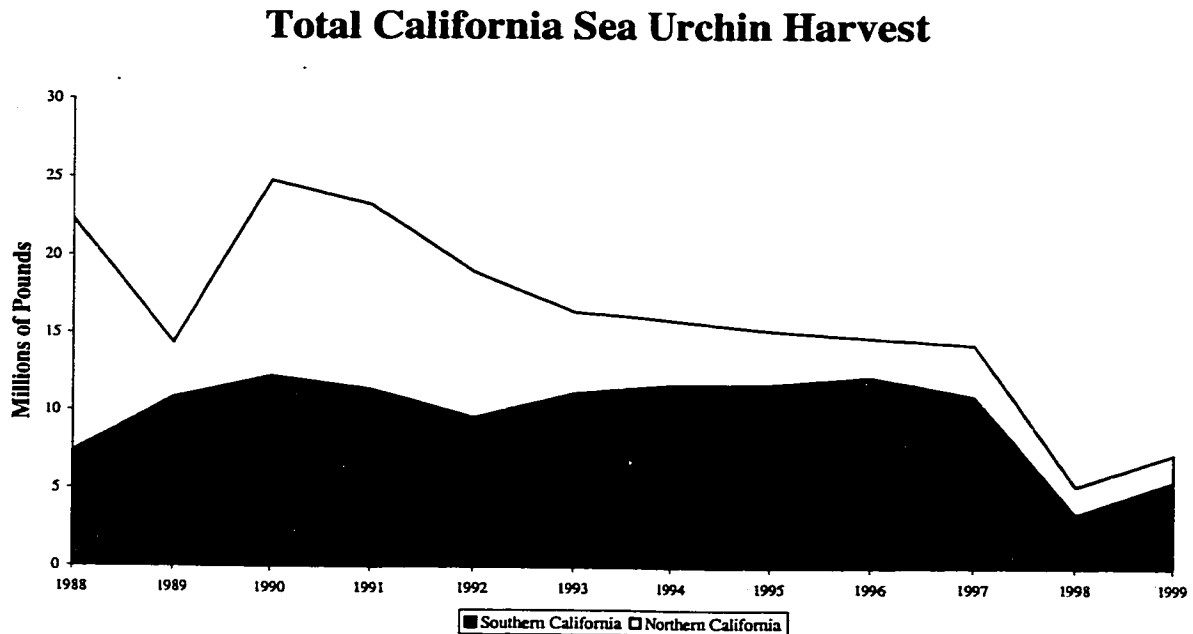
shipped to Japan. The packaged roe is often shipped on midnight flights from California so that it can arrive in Japan before dawn and clear health inspections the same day. Most fresh roe is sold in lots via auction at the Metropolitan Central Wholesale Fish Market in Tokyo. Processors do not typically ship fresh roe on Fridays since it would arrive when the auction is closed on Sundays and would have to wait an extra day to be auctioned.¹

The sea urchin industry is relatively new in California, with the first commercial harvests taking place off the south coast in the 1970s. In the late 1960s, urchins were mainly considered pests and initial experimentation with commercial harvests was motivated partly by a desire to thin urchin populations. Urchins contributed to overgrazing of giant kelp forests, which provide habitat for numerous fish species, and urchins competed directly with abalone for habitat and food. The strong demand for urchin products in Japan and the 1972 opening of a fresh roe processing facility in Los Angeles sparked the initial growth of the urchin industry. The fishery expanded to northern California in the mid 1980s, after the Japanese stocks declined and the Japanese exchange rate provided extremely favorable market conditions for the California urchin fishery. By the early 1990s, sea urchins were California's highest revenue-producing fishery. According to a report prepared for the Pacific States Marine Fisheries Commission (Radtke and Davis, 2000), ex-vessel revenues from sea urchins on the U.S. west coast exceeded those of all other individual fish categories (e.g. pacific whiting, salmon, crab and lobster, shrimp, and halibut) except groundfish in 1991. By 1997, sea urchins still accounted for 5% of total landed value of U.S. West Coast fisheries.

¹ Processors also produce baked roe, salted roe, steamed roe, and frozen roe, though high quality fresh roe generates the most value.

Reasoning from catch per unit effort data and sub-tidal surveys of urchin populations, Kalvass and Hendrix (1997) argue that urchin stocks have appeared fairly stable in southern California but have suffered a precipitous decline in northern California. Figure 3.1 shows the sea urchin harvest in California since 1988. The extreme dip in northern California harvest for 1989 resulted from a season closure (nine months of the year). Otherwise, the figure shows a fairly steady decline in northern California but a consistent harvest in southern California. It is not clear whether this decline in northern California represents the normal trajectory of a virgin fishery in transition to a sustainable steady-state or whether the trend signals the transition to a stock collapse. The fishery receipts peaked around \$30 million in 1992 when there were nearly 600 urchin divers. Since then, the number of divers has declined to about 450.

Figure 3.1



Note: Some data are missing for 1998 and 1999. Areas reflect northern and southern California harvests, so the stacked areas are the total harvest.

Regulators use several different mechanisms to promote sustainable harvesting of sea urchins in California. Kalvass and Hendrix (1997) document the regulatory history of urchin fishing in California. In the early years, as it first began in southern California, the fishery was essentially open access. Participants needed only a commercial fishing license. As heavy exploitation began, regulators started to control fishing effort. In 1985, California Department of Fish and Game required urchin harvesters to have permits and two years later put a moratorium on issuing new permits. In 1989, regulators set a 76 mm (3 inch) minimum size limit based on urchin test diameter. The northern California size limit was increased to 89 mm (3.5 inches) in 1990, and the southern California limit went up to 83 mm (3.25 inches) in 1992. A limited entry program was formally introduced in 1989 that grandfathered existing permit holders. This program was changed several years later to steer the long-run number of permit holders towards 300. To maintain a permit, divers now must land at least 300 pounds of urchin a minimum of twenty times during the current or preceding calendar year. When the current number of permits exceeds 300, the program allows one new license to be issued for each ten permits of attrition. The attrition is based on the difference between the current year's number of permits and the total number of licenses issued in 1993-94 (545). Thus, the program is in the process of steering the fishery towards a long-run target of 300 licenses, and the speed at which this target is approached hinges on the speed of attrition within the fishery.

Another important management tool has been the use of season closures. The northern California fishery was closed in 1989 for nine months because it had expanded so rapidly that there was concern about a stock collapse. In 1990, regulators set several

restrictions on the season. July was closed, one week closures per month were introduced for May through September, and the open season days for these months were reduced to four days each week. In 1992, existing season restrictions were maintained, including the July closure, and several additional restrictions were introduced. Four-day week regulations were added for April and October, and open season days were reduced to three per week for June and August.²

The California Red Sea Urchin Fishery: An Ideal Test Case

The sea urchin fishery in California is ideal for studying spatial behavior and marine reserves. Spatial considerations are critical to both the biology and the diver behavior in the fishery, and there exist sufficient data to study the problem. Davis (1989), in an article arguing that marine reserves are the next step in California fishery management, proposes that sea urchins and abalone are ideal species for using reserves. The reasons that this sea urchin fishery is an appropriate application for studying spatial policies fall into three classifications: behavioral, ecological, and regulatory.

The behavioral rationale for analyzing space in the sea urchin fishery arises from the types of choices that harvesters make. There are multiple dimensions to the spatial choices that an individual urchin diver faces. First, the northern and southern California fisheries are divided by the southern sea otter range in central California. Since roughly 200 miles separate the northern and southern ranges, divers must choose to participate in one region or the other, essentially a choice of spatial location on a very large scale. Of course, once they have chosen, they can switch, but the long distance precludes them

² One biological reason for season closures during these times is based on urchin spawning times. Kato and Schroeter (1985) discuss how some urchins in California spawn throughout the year, but most spawning is concentrated in the summer and fall months. Following spawning, the roe yield is considerably lower, and just prior to spawning, the value of urchin roe declines due to uptake of water.

from switching often. Second, within each region, there is a finite number of ports at which it is possible to land sea urchin. The number of possible ports is limited by total existing ports and their proximity to urchin processing facilities. On any given fishing day, a harvester must choose a port from which to fish. Again, this decision is spatial in nature, and thus port switching is a manifestation of spatial behavior. Third, decisions about specific locations in which to dive for urchin are perhaps the most important spatial choices. These choices ultimately affect the pressure on the resource. Because the northern and southern sea urchin ranges are expansive, specific location choices are likely to be limited by travel costs and hence by divers' chosen ports. Finally, harvesting depth is yet another spatial decision. Because urchins live on the bottom, depth is ultimately determined by the specific harvest location. However, the gradient of the continental shelf does vary along the coast. So, choice of a harvest latitude, for instance, may involve consideration of the diving depth.

We can analyze patterns of spatial behavior in the California sea urchin fishery because the data are extremely rich. Divers make repeated spatial decisions, so in principle, behavioral differences across individuals can be separated into individual heterogeneity and responses to dynamic changes in the underlying states of nature. The data set we have assembled, which is discussed below, is extremely large, having panels that are both long and wide. Moreover, the data set contains geographically specific information about each layer of spatial choice, including depth, latitude, port, and region.

The ecological basis for conducting an explicitly spatial analysis of the sea urchin fishery is even more compelling. Sea urchins prefer rocky habitat in kelp forests, particularly in forests of giant kelp (*Macrocystis*). The patchiness of their habitat has been

documented in several studies (Morgan, 1997; Morgan et al., 2000). The abundance of urchin within patches is also heterogeneous. Some areas have dense populations while others have sparse populations. Typically adult urchins can only move short distances. Kato and Schroeter (1985) find that red sea urchins move an average of 7.5 cm per day in areas of high food abundance and 15.0 cm per day in areas of low food abundance. Although adult urchins are relatively sedentary, patches are linked through another set of spatial characteristics, namely oceanographic factors that transport larvae along the coast. In any given year, ocean temperature, currents, advection, and upwelling all contribute to the survival and spatial distribution of larvae in California's coastal waters, though these processes are not yet well understood (Botsford, 1997).

Reproductive characteristics of sea urchins provide further motivation for analyzing urchin fishing in a spatial context. Sea urchins broadcast spawn to produce larvae. As such, if there are males and females in close proximity, more egg fertilization will take place and hence more larvae are produced. Biologists thus believe that it might be more sensible to regulate by closing whole areas for periods rather than regulating to maintain average biomass densities over the whole system. There is also some discussion in the biology literature that high density populations can aid in the survival of larvae because the spine canopies of adult urchins provide refuges from predators. These mechanisms give rise to Allee effects, i.e. non-convexities in the stock-recruitment relationships, that favor on/off harvesting over maintenance of constant average harvest rates. Thus the localized densities of sea urchins are likely to be important factors that determine the health of the resource (Botsford et al., 1993, 1999; Dugan and Davis, 1993; Quinn et al., 1993).

There are several regulatory justifications for studying spatial behavior and management in the sea urchin fishery. The dramatic decline in northern California urchin catch raises concerns about the fishery's sustainability. Though catch has leveled off in recent years, long-run effects of the heavy exploitation phase are not yet known. Given the spatially varying exploitation rates, it is likely that spawning densities have declined in a heterogeneous manner. Managers may wish to enhance spawning densities selectively through spatial management. Indeed, marine reserves are under consideration as a management tool for the northern California urchin fishery, as Davis (1989) proposed and Botsford et al. (1993, 1999) discuss. Finally, spatially explicit biological characteristics, such as density-dependent spawning, are especially poignant in California marine policy because arguably an incomplete understanding of them led to the collapse of California's abalone dive fishery in the 1980s.³ Perhaps ironically, many abalone divers who lost their livelihoods became sea urchin divers. This institutional history creates added pressure on sea urchin regulators to avoid making the mistakes that they may have made in the abalone fishery.

Raw Data on the California Red Sea Urchin Fishery

The fishery data used in this thesis were collected by the California Department of Fish and Game (CDFG) and include 257,000 observations on California urchin dives over the period 1988-1999. The data from 1998 and 1999 are incomplete and have been excluded from the analyses. Most preliminary data analysis was conducted when data were available only from 1988 through 1997 and some of the 1997 data were missing.

³ Managers have experimented with spatial closures to re-build abalone stocks with little success. Tegner (1993) attributes failure of these closures to poaching and low dispersal rates of abalone but argues that prospects are better for sea urchins because they have higher dispersal rates.

We use the updated data for 1997 and most of 1998 and 1999 to calibrate the simulation model in chapter 7.

Information on an urchin dive appears in two different databases: a landings ticket database and a log book database. Landings tickets are filed with CDFG at the port of landing and contain the revenues, actual quantity sold, landing site, and processor and diver license numbers. Log books are maintained on the fishing vessels and for each day report diving location, dive duration, depth, number of divers on the boat, and estimated pounds caught. Table 3.1 presents a sample observation from each database and descriptions of the database fields. The databases were combined using unique combinations of boat codes and dates. In general, for each boat code in the logbook file on a given day, there is one observation in the landings ticket database for each diver present on that boat for that day. The combined record in Table 3.1 represents a single diver who landed 415 pounds of red sea urchin in Fort Bragg on March 15, 1997. The diver spent two hours underwater at approximately 20 feet below the surface and received \$311.25 from the dealer.

We expect that divers record latitude accurately for several reasons. First, other harvesters do not have access to these data, so there is no risk of giving away trade secrets. Second, divers may want to have accurate records for their own benefit. Falsely reporting logbook data to regulators would necessitate maintaining a separate set of logbook information. Finally, latitude is only required to be reported to one minute of precision, which is about one mile. If divers are really concerned about proprietary spatial information, these latitudes are not enough to pin down their exact harvest

locations. Fortunately, they provide enough information to study spatial decision-making.

The fishery data, though extensive, contains little information about costs of harvesting and opportunity costs of diver time. Some costs can be inferred by computing distance traveled and thus fuel usage. As a practical matter, distance traveled is approximately the difference between latitude at the harvest location and latitude at the port of landing. The data do not actually contain port-of-origin, so these calculations assume that port-of-landing and port-of-origin are the same. For opportunity costs of time, there is no explicit information available. In theory, these costs depend on economic opportunities outside the fishery for individual harvesters and on individual values of leisure time. Since opportunity costs are not observed, they will be modeled as unobservable variables in the econometric specifications in later chapters.

Table 3.1
Raw Data Description

Sample Record from Landings Ticket Database

SPECIES	BOAT	DEALER	POUNDS	PRICE	BLOCK	PORT
RED	33450	2366	415.00	0.7500	0262	223
YEAR	MONTH	DAY	LICENSE	VALUE	ANAME	AREA
97	03	15	54065	311.25	FTB	N

Corresponding Record from Logbook Database

PORT	DATE	BLOCK	QUAD	NLAT	LANDMARK	UD
FTB	31597	262	21	3922	CASPAR NORTH	20
LD	AD	DIVERS	HRS	LBS	PURP	BOAT
30	20	1	2.0	400	0	33450

Field Descriptions

Landings Tickets

SPECIES	Red or Purple sea urchin
BOAT	Numeric boat code (unique for each vessel)
DEALER	Numeric dealer code (unique for each dealer)
POUNDS	Number of pounds sold
PRICE	\$ per pound
BLOCK	Geographic information (not used)
PORT	Numeric code for port landed
YEAR	Year
MONTH	Month
DAY	Day
LICENSE	Numeric code (unique for each diver)
VALUE	Dollar value of sale
ANAME	General area (not used)
AREA	N or S (Northern or Southern California)

Logbooks

PORT	Port code (text)
DATE	Text date field (parsed to obtain month, day, and year)
BLOCK	Geographic information (not used)
QUAD	Geographic information (not used)
NLAT	Text latitude field (parsed to obtain degrees and minutes)
LANDMARK	Geographic information (not used)
UD	Upper depth of dive (feet)
LD	Lower depth of dive (feet)
AD	Average depth of dive (feet)
DIVERS	Number of divers on the boat
HRS	Total hours of diving
LBS	Estimated pounds caught
PURP	Purple urchin or not
BOAT	Numeric boat code (unique for each vessel)

We have collected geographically-specific weather data from the National Data Buoy Center. The Sea Urchin Harvester Association newsletter, called *Light and Variable*, alludes to the importance of weather conditions, suggesting, "Weather governs the sea urchin fleet perhaps more than any other fishery, for divers immerse themselves in the elements, harvesting their catch at the mercy of wind and waves." (<http://www.seaurchin.org/L&V/dec97/About-L&V.html>) These data contain hourly observations on variables that affect diving conditions including wave height, wave period, and wind speed. Large values for these variables represent increasing danger of diving and boating. To investigate behavioral responses to weather variables, these data are averaged into daily observations and linked to the urchin databases. Only two buoys in northern California are located near areas that are highly exploited by sea urchin divers. These buoys are Point Arena Buoy (46014 - PT ARENA) and Bodega Buoy (46013 - Bodega). The exact location for Point Arena Buoy is 39.22 N 123.97 W (39°13'00" N 123°57'57" W), and it sits in water of depth 264.9 meters. Bodega Buoy is located at 38.23 N 123.30 W (38°13'37" N 123°19'43" W) and is in water of depth 122.5 meters. Because the water depths are drastically different, the coastal geography differs, and the Point Arena Buoy is in the middle of the northern California urchin fishing range, the discrete choice analysis in chapter 4 uses the Point Arena data only.

Spatial Views of the Data

Figures 3.2 through 3.4 depict diving activity along the California coast for pounds harvested, diving hours, and diving trips respectively. The horizontal axis is latitude converted to a decimal. All of these figures indicate that sea urchin harvest in northern California is patchy and heterogeneous. There are locations in which effort and

harvest are high and other locations in which harvest and effort are low. These outcomes could indicate spatial heterogeneity in sea urchin abundance, spatial heterogeneity in costs of harvesting, or both. In addition, there are places in which no harvesting takes place at all. This suggests that there are breaks in sea urchin habitat or locations that are too costly or too treacherous to visit. The figures also demonstrate that most harvest activity is concentrated in the middle of northern California. Note that the diving hours and trips figures appear the same. An Ordinary Least Squares regression of diving hours on trips yields an R^2 of .964. Moreover, the slope coefficient has a t-statistic of 52.3 and the intercept is not significantly different from zero. As such, it is sensible to focus on the spatial distribution of diving trips.

Figure 3.2

Diving Activity Coastal Histogram
Pounds Harvested 1988-1997

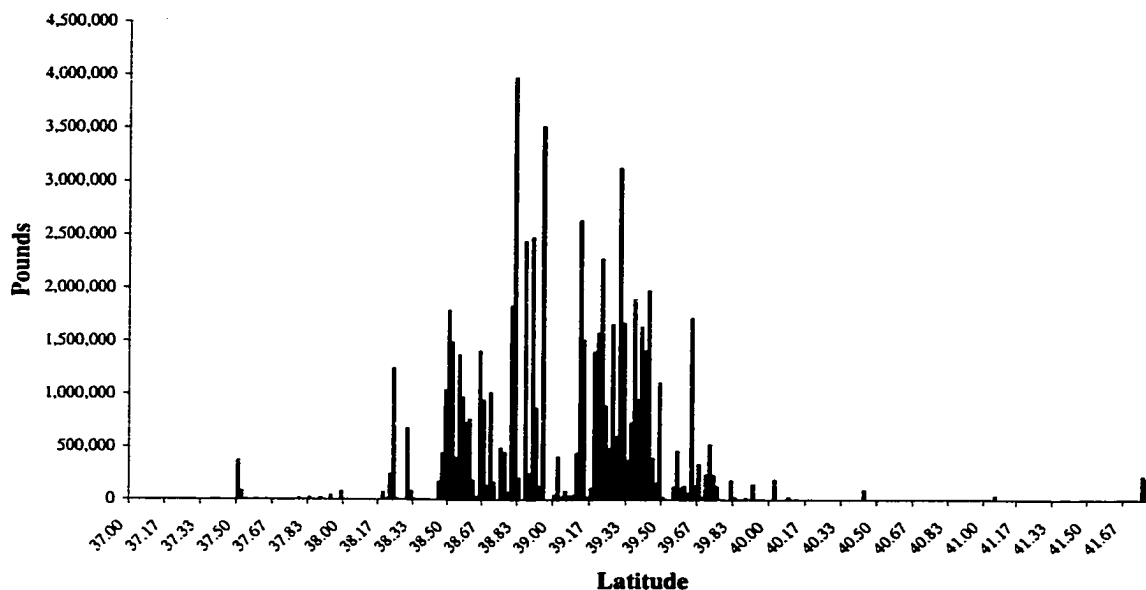


Figure 3.3

**Diving Activity Coastal Histogram
Diving Hours 1988-1997**

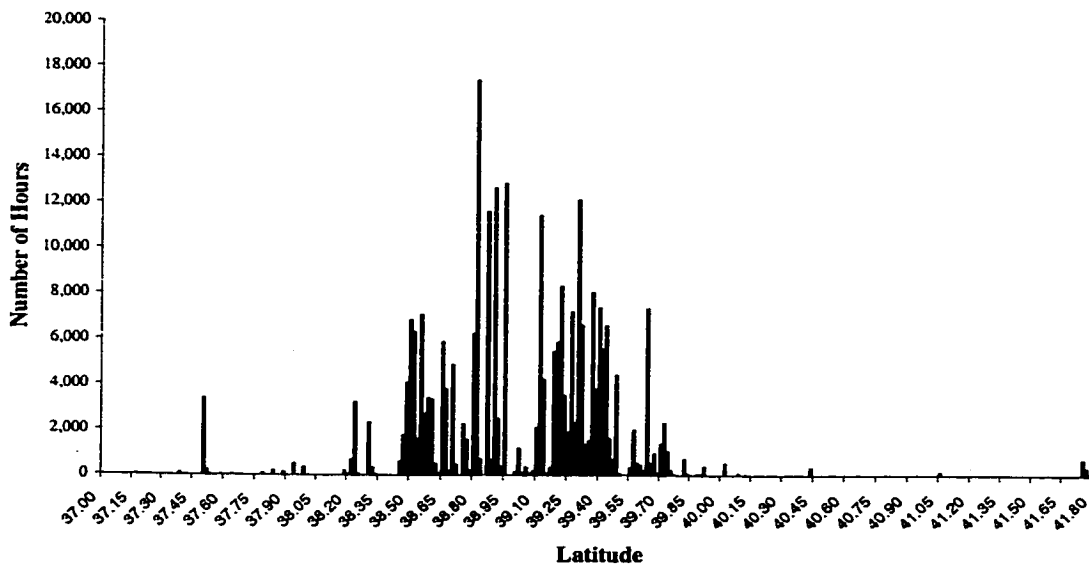
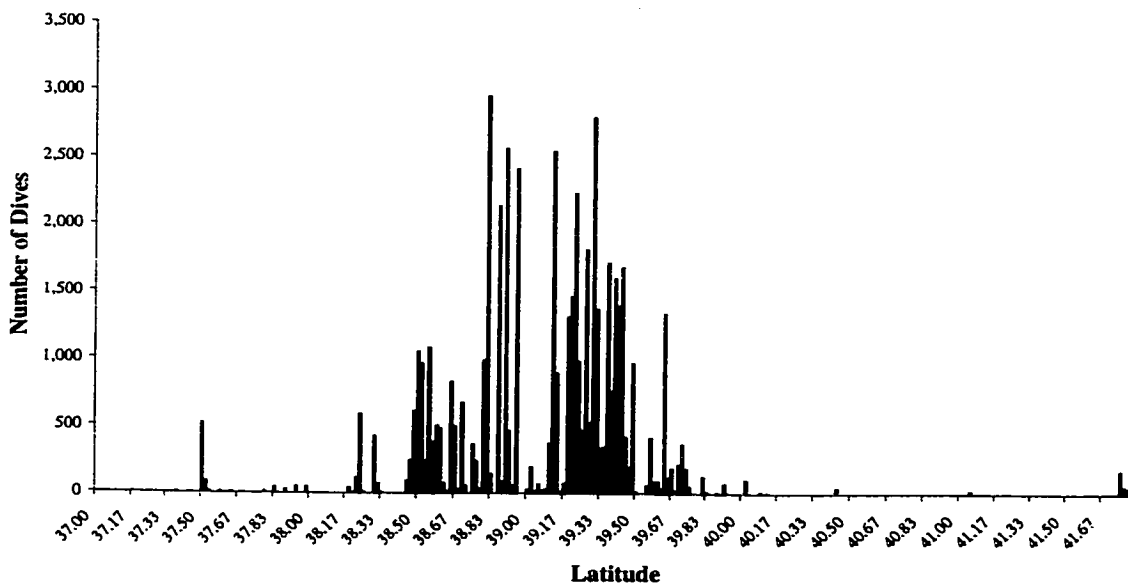


Figure 3.4

**Diving Activity Coastal Histogram
Diving Trips 1988-1997**



There are six ports in northern California at which sea urchins are landed. These include, from south to north, Half Moon Bay (HMB), Bodega Bay (BOD), Point Arena (PTA), Albion (ALB), Fort Bragg (FTB), and Crescent City (CRC). Figure 3.5 shows the locations of these ports on a map of northern California. Most diving activity concentrates around the ports, but some divers do travel relatively far to harvest urchin. The latitude range in northern California was divided into twenty-five bins, each of which is approximately eleven miles of coastline. Table 3.2 reports counts for diving trips from each port to each bin. As shown in this table, the diving effort fans out from each port and generally tapers off quite quickly, but there is considerable overlap for port-of-origin of some bins. For instance, Bin 8 has activity coming from five of the six ports. In contrast, Bin 1 has effort from only one port. The orders of magnitude of the numbers in Table 3.2 are enough to see the spatial pattern without plotting port-specific histograms.

Figure 3.5

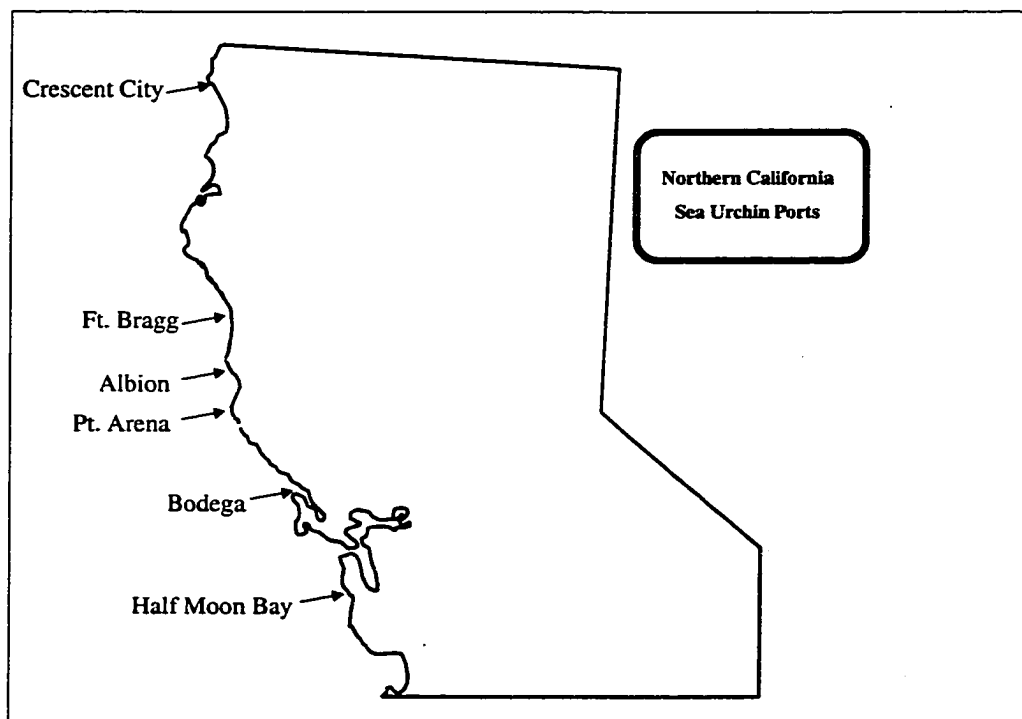


Table 3.2

Number of Diving Trips by Northern California Port 1988-1997

Latitude Bin	HMB	BOD	PTA	ALB	FTB	CRC	Total	% of Trips from Port in Bin
1	3						3	0%
2	572	32					604	95%
3	18	1					19	0%
4	45	32					77	0%
5	28	62	3				93	0%
6	2	748					750	0%
7		596	2	1			599	0%
8	3	6,055	394	10	13		6,475	94%
9		752	5,002	47	119		5,920	0%
10		39	7,556	151	131		7,877	96%
11		9	333	5,416	914		6,674	0%
12		16	104	4,692	8,360		13,172	36%
13		19	41	56	6,589		6,705	98%
14		1	30	19	2,593		2,643	0%
15					217		217	0%
16				2	111		113	0%
18					39		39	0%
21					15	3	18	0%
25		8	1			282	291	97%
Total	671	8,370	13,466	10,394	19,101	285	52,289	49%

Notes:

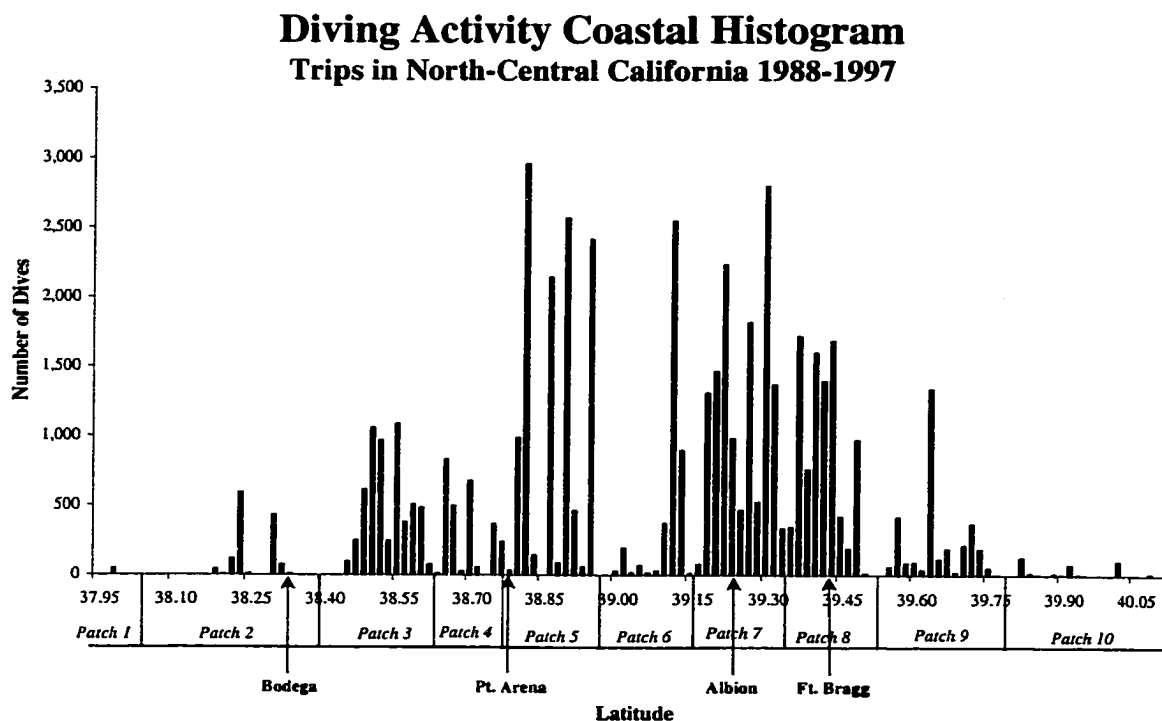
The boxed numbers indicate that the port is located in that bin.

There is no activity in bins 17, 19, 20, 22, 23, and 24.

As a result of this assessment of the geographic distribution of diving activity, northern California is divided into eleven geographically distinct harvest zones that roughly correspond to proposed spatial management zones. These zones are not of equal size as they were in Table 3.2, but instead they attempt to bracket distinct distributions of activity. If sea urchin habitat is indeed patchy, there should be places in which there is no fishing activity or extremely light activity. As such, reasonable places for breaks are

identified between harvest zones as locations with no fishing trips or locations that appear to be in the tail of a fishing activity distribution. Figure 3.6 shows the spatial distribution of effort in north-central California (measured as trips) with patch borders and fishing ports denoted. Though there are six total ports in northern California at which divers land urchin, the four ports depicted in these figures account for more than 90% of northern California catch. Patch 1 extends south all the way to Half Moon Bay, and Patch 10 extends all the way north to Crescent City. The eleventh patch, which is not depicted, consists of the Farallon Islands off the coast of San Francisco. Typical middle patches between Bodega and Fort Bragg average twelve miles in length.

Figure 3.6



The decision about how to define the number and location of patches necessarily involves compromise because management models in this setting bring together disparate spatial scales. “Patches” of sea urchins that affect spawning densities are much smaller

than what divers would consider distinct harvest locations. After all, it is the concentration of spawning urchins within several square meters that affects fertilization. On a somewhat larger scale, urchin divers record distinct landmarks in their logbooks in addition to depth readings and degrees and minutes of latitude. These geographical descriptors may thus encompass many biological patches. Regulatory scale is likely to be larger still because enforcement of many small spatial closures mixed with open fishing areas would be very costly. Perhaps even larger is the oceanographic spatial scale. Sea urchin larvae can travel long distances in ocean currents, though considerable scientific uncertainty remains about these dispersal processes.

The patch divisions in Figure 3.6 bring together these spatial scales in a way that is economically meaningful, practical for regulators, and consistent with sea urchin ecology and oceanography. Patches are large enough that travel distances to the next patch are economically significant but small enough such that individuals sometimes travel across multiple patches. For regulators, the patches are large enough so that visual inspection could determine violations of a marine reserve boundary but small enough that a single patrol boat might be able to enforce a reserve. The patches are also similar to those in Kalvass (1997). In terms of urchin ecology, these divisions assume that within a patch there are sub-patches of sea urchins and that occurrence of these sub-patches is spatially autocorrelated. This is consistent with the pictures of diving intensity that show clear breaks in activity (Figures 3.2 – 3.4). In terms of oceanography, the patches are small enough that they can convey some qualitative information about larval dispersal in currents along California's coast.

Since the goal of patch definitions is to build a bioeconomic simulation model that accounts for harvester behavior as well as sea urchin biology and oceanography, it is important to consider the impacts of patch definitions on this analysis. Simply put, defining patches on a finer spatial scale poses data problems for the key economic variable of interest, expected revenues. In some sense, such problems are unavoidable when we as analysts must rely exclusively on fishery data that is a result of some spatial choice, and not a random transect of the ocean.⁴ With an extremely fine spatial scale, there simply would be no fishing observations on abundance within some patches, and hence no information about expected revenues in those locations. This means that no data would be available for estimating a model of discrete location choice unless the analyst were willing to use estimates of abundance based on spatial statistical methods for producing contour surfaces.⁵ This method, however, is inconsistent with analyzing a patchy environment, which is undoubtedly characterized by discontinuities in the abundance surface. Moreover, it is problematic because it relies on behavioral data rather than random sampling. These data may already have selected for clumps of abundance with nothing between the clumps, or they may be points in larger patches of abundance. In less extreme cases, a fine spatial scale would still pose data problems because only a handful of observations would be available to resolve spatial abundance. At any given time, the expected revenue would then be subject to the idiosyncracies of a particular diver or fishing trip.

⁴ See Smith (2000) for further discussion.

⁵ See Fleming (2000) for discussion of applying spatial statistics to marine fisheries. This comment explicitly assumes that unknown abundance surface is continuous. However, in the case of sea urchins, we know that the surface is patchy, suggesting discontinuities.

Beyond potential data problems, the number of patches is necessarily limited by tractability of the econometric estimations and the dynamic simulations of the sea urchin population. In the next chapter, a discrete choice model is introduced that would be far more difficult to estimate with a proliferation of choices. In later chapters, a dynamic simulation model is introduced with spatial-, age-, and size-structure. Again, the proliferation of patches would make this already complicated model far less manageable.

Figure 3.7 summarizes another spatial dimension, namely, average diving depth (AD). All areas in northern California display depth heterogeneity. There appears to be a strong relationship between average depth and location along the coast, but the relationship is clearly heteroskedastic and non-monotonic as one moves from south to north. The greatest spread of average depths occurs in the middle of northern California where there is the greatest amount of harvest and effort. Greater depth constitutes more physical strain on divers. As such, *ceteris paribus*, one would expect effort to concentrate in shallow depths when urchins are available there. The spatial heterogeneity of average depth, in any event, most likely reflects a variety of factors. First, differences in the physical coastline may lead to the location of urchin habitat at different depths. Second, exploitation of urchins over time may mine the shallow urchins, leaving only ones in deeper water. Third, individual divers may have heterogeneous aversion to diving at deeper depths, and the effects of this heterogeneity may be amplified or dampened over time as the composition of the fishing fleet changes.

Figure 3.7

**Scatter Plot of Average Depth per Trip by Latitude
As Recorded in Diver Logbooks**

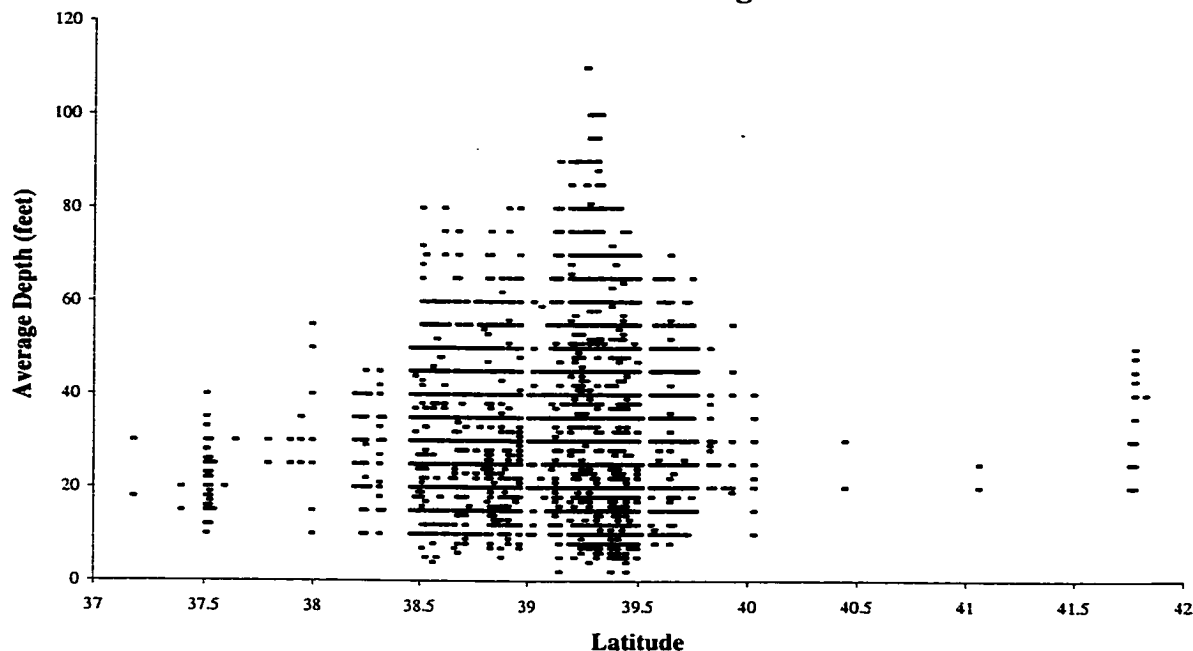


Table 3.3 presents results of a Generalized Least Squares regression of average depth on eight different latitude bins and a time trend. Eight bins are used to divide space equally along the coastline, in contrast to the “patches” or “harvest zones” defined above. The time trend variable is measured in years, with 88.0 being the beginning of the data set. Because a constant is included, one dummy variable is dropped. The regression corrects for groupwise heteroskedasticity, allowing a different error variance in each latitude bin.

Table 3.3
GLS Regression of Average Depth (AD)
Correcting for Group-wise Heteroskedasticity

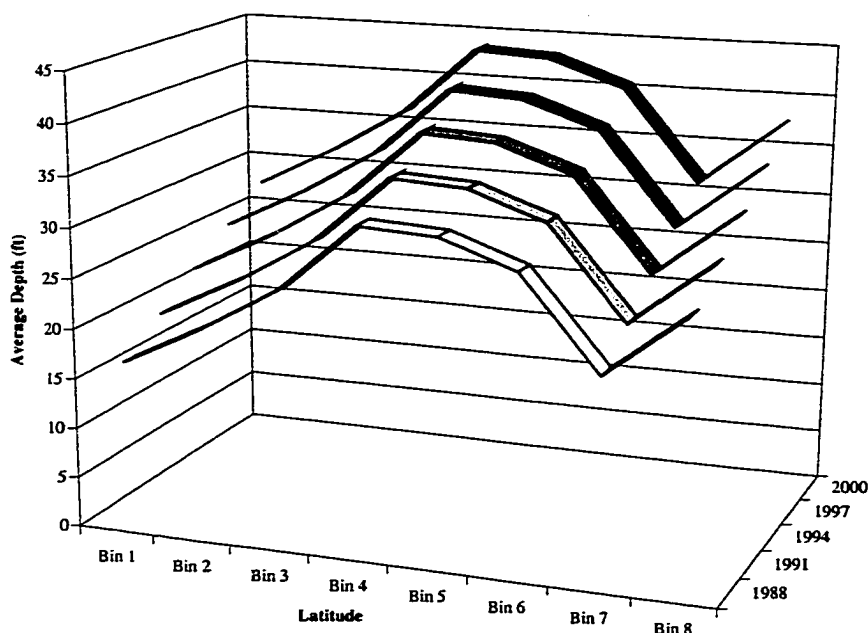
Variable	Coefficient	St. Error	t - statistic	P - value
INTERCEPT	-52.80	2.54	-20.81	0.0001
NUMDATE	0.96	0.03	35.26	0.0001
D1	-15.48	6.97	-2.22	0.0263
D2	-11.51	0.73	-15.74	0.0001
D3	-6.87	0.32	-21.47	0.0001
D4	0.00	-- Restricted for identification --		
D5	-0.40	0.14	-2.82	0.0049
D6	-2.97	0.29	-10.43	0.0001
D7	-12.03	1.58	-7.60	0.0001
D8	-5.80	1.00	-5.79	0.0001
Observations	47,759			
R ²	0.04			
Mean of AD	35.45			

Although the GLS regression in Table 3.3 does not explain much variation in trip-wide AD (R^2 is a mere .04), all coefficients are highly significant statistically. The depth pattern suggests geographic heterogeneity along the coast, but is also consistent with the proposition that divers must go deeper in heavily exploited regions. In particular, the center of the sample (bins 3 and 4) are the most heavily exploited regions and have the deepest predicted depths.⁶ Though the R^2 is low and the numerous observations undoubtedly give rise to such strong statistical significance, the coefficient on NUMDATE (the time trend) is economically significant because it indicates that the average depth has increased over time by about one foot per year. This suggests that the extensive margin for divers has shifted out over time. Figure 3.8 depicts this phenomenon based on predicted values from the GLS regression.

⁶ Since $AD > 0$, the least negative dummy variable indicates the greatest depth, i.e. less depth is subtracted from the normalized baseline depth.

Figure 3.8

Movement of the Depth Extensive Margin



Spatial Decisions and Individual Heterogeneity

Across divers in the northern California fishery, there is substantial variation in participation rates, revenues from fishing, and spatial decision-making. There are 880 distinct divers who fished for sea urchins at least once between 1988 and 1999. The range of participation is substantial, with one as the minimum number of trips and 930 as the maximum.⁷ The average number of trips and standard deviation are 66.76 and 136.49 respectively in the twelve-year period. Annual revenues also exhibit variation across divers. The maximum average annual revenue is \$172,254.72, and the corresponding mean and standard deviation are \$7,543.23 and \$13,980.75. The low means for

⁷ Clearly, many divers fall short of the requirements for license renewal. License codes that have only one trip may indicate individuals who simply tried urchin diving once, but it is also possible that some of these single-dive license codes reflect coding errors in the landings ticket database.

participation and revenues result in part from the large number of individuals who only fished once; for northern California, 354 of the 880 total active divers only went once. Because we expect seasonal revenue and participation to be highly correlated, it is also important to examine whether there is heterogeneity in revenue per trip. The maximum is \$5,570.90, the mean is \$602.04, and the standard deviation of \$594.30. Again these numbers suggest that substantial diver heterogeneity exists.

The spatial behavior of divers also indicates heterogeneity. As shown in Table 3.4, individual northern California divers exhibit different levels of mobility; some divers fish in many locations while others fish in very few locations. In addition, this table shows a slight inverted U-shaped trend in average number of patches visited, suggesting an increase in mobility in the early phase followed by a decrease in mobility in the later phase. The mobility peaks in 1992. Table 3.5 reports how many divers are active in northern and southern California in each year. Though most divers are in one place or the other, some are active in both regions within a given year. As in Table 3.4, there is a U-shaped trend for this mobility, which peaks in 1992.⁸

⁸ Total diver counts in exceed those reported in Kalvass and Hendrix (1997) because these counts include all license codes in the raw landings ticket data. Miscoded licenses would thus appear as additional unique licenses. Later analyses exclude these single-observation records.

Table 3.4
Diver Spatial Mobility Across Patches

Number of Active Divers												
# of Patches Active In	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
1	50	60	146	139	139	99	107	49	37	36	43	43
2	44	51	72	72	62	65	67	48	44	45	33	39
3	20	19	59	60	52	46	45	30	25	33	27	24
4	10	8	36	32	36	32	25	21	21	22	18	9
5	4	0	20	23	38	18	13	15	0	7	5	9
6	1	0	6	12	13	15	13	3	4	3	3	1
7	0	0	2	8	15	9	2	1	0	0	1	0
8	0	0	0	4	3	0	0	1	0	0	0	0
9	0	0	1	3	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0
Total Divers	129	138	342	353	358	284	272	168	131	146	130	125
Weighted Average # Patches	2.05	1.82	2.25	2.53	2.68	2.60	2.33	2.54	2.35	2.51	2.40	2.24

Table 3.5
**Diver Spatial Mobility Across
Northern and Southern Regions**

Number of Active Divers						
Year	Total Divers	Just S. Cal. Divers	Just N. Cal. Divers	Just One Region Divers	Both Regions Divers	Share in Both Regions
1988	210	81	117	198	12	0.06
1989	387	249	113	362	25	0.06
1990	684	342	272	614	70	0.10
1991	735	382	260	642	93	0.13
1992	714	356	250	606	108	0.15
1993	738	454	186	640	98	0.13
1994	826	554	191	745	81	0.10
1995	539	371	106	477	62	0.12
1996	524	393	77	470	54	0.10
1997	525	374	95	469	56	0.11
1998	440	306	109	415	25	0.06
1999	465	336	108	444	21	0.05

A related measure of spatial mobility is frequency of an individual at a particular port. Some divers change ports occasionally, and others fish always from the same port. The number of ports visited by a diver (combining northern and southern California) ranges from 1 to 16. Across divers, the mean and standard deviation are 2.62 and 2.62.

Nevertheless, Tables 3.4 and 3.5 indicate that most divers exhibit some spatial habit persistence or that on average they do.⁹

Heterogeneity and Exit Decisions

The level of commercial exploitation of sea urchin, and hence the sustainability of the fishery, depends critically on the number of active fishers. An individual's harvest is limited not just by the abundance of urchin, but also by the harvest technology, weather conditions, and the physical stress of diving time. Because licenses are non-transferable, there is a natural limit to the aggregate harvest statewide, which is a function of total licenses. As such, the limited entry program that began in 1989 essentially sets an upper bound on the maximum harvest potential for the sea urchin fishery in California. Since the limited entry program allows only one new license for each ten that are retired, the rate of attrition is an essential determinant of the stock of harvesters and consequently the fishery's maximum harvest potential.

Although the requirements to renew a license in the urchin fishery are moderate, participation rates in the first column of Table 3.5 suggest that many divers exited the fishery altogether after the boom phase in northern California ended. The recent trend in attrition raises several important management questions, including what drives the rate of attrition, how many harvesters will remain in the future, and what types of individuals are likely to remain active in the fishery? The first two questions are related. With a sound model of attrition, one can forecast how many divers will remain in active in the fishery and hence the maximum harvest potential. However, it is also important to recognize that diver heterogeneity could have substantial impacts on the health of the fishery. Consider

⁹ It is also possible that there is a sedentary group and a mobile group that together appear to be somewhat sedentary.

two different stylized scenarios for the future urchin fishery that have the same number of harvesters. In the first scenario, harvesters that remain in the fishery are part-time urchin divers. They are also involved in other fisheries and work seasonally as diving instructors. When conditions are good, they dive for urchin, but sea urchin fishing is not their primary source of income. In the second scenario, divers who stay in the fishery are full-time. The divers who exited the industry took full-time jobs in other areas and do not have time and do not maintain equipment to continue diving commercially for urchin. Under these two extreme scenarios, we might see radically different participation levels and impacts on the resource. A population of full-time divers would probably put more pressure on the resource than a population of part-time divers. Thus a model of attrition that accounts for harvester characteristics helps to assess future potential exploitation of the urchin resource.

Duration modeling is an empirical approach that can estimate a trend of attrition and also condition on differences across individuals. The basic idea is that there is some underlying stochastic process that drives *survival times* of individual agents. A survival time in our case is the length of time that an individual stays active in the fishery, i.e. the period between entry and exit. If individuals are assumed to be the same, survival times are typically modeled with a one- or two-parameter probability distribution. If individuals are different, however, the location parameter for the distribution can be made a function of covariates that capture individual heterogeneity. Of course, we also do not observe exit times for individuals who are currently active in the fishery. Duration models explicitly account for this censoring effect much in the way that a tobit model operates.

To perform a basic duration analysis, we must define the survival function, choose a parametric distribution for duration, and choose covariates that may affect survival times. The treatment below follows Greene (1990). A “spell” is the length of time that a diver remains in the fishery, T . It has the following cumulative density function:

$$F(t) = \int_0^t f(s)ds = \text{Pr ob}(T \leq t), \quad (3.1)$$

where $f(t)$ is the underlying probability density function. This gives rise to a survival function, $S(t)$, where

$$S(t) = 1 - F(t). \quad (3.2)$$

The rate at which spells come to an end conditional on surviving to t is the hazard rate,

$$\lambda(t) = \frac{f(t)}{S(t)}. \quad (3.3)$$

A higher hazard rate, *ceteris paribus*, suggests that spells end more rapidly. In the case of the fishery, a higher hazard rate thus indicates a higher rate of attrition.

One can add generality to the basic duration model by allowing the hazard rate to vary across individuals. If individual fishers are in fact different from one another in ways that can be measured, then their dropout rates should vary in some deterministic ways. Parameterizing the hazard function parameter is a way to account for this heterogeneity. Let

$$\lambda_i = e^{-\beta'x_i}, \quad (3.4)$$

where i indexes individuals, x_i contains exogenous variables, and β is a parameter vector. This form can be used to estimate a Weibull model, which also nests the exponential model. The hazard function and survival function for Weibull are:

$$\lambda(t) = \lambda p(\lambda t)^{p-1} \quad \text{and} \quad S(t) = e^{-(\lambda t)^p} \quad (3.5)$$

Note that the exponential model results from restricting p to equal one. With the exponential distribution, the hazard function is constant across time, whereas the Weibull implies that the hazard function is monotonically decreasing. A decreasing hazard function for the fishery data implies that the instantaneous probability of exiting the fishery decreases over time. This may be the case, for instance, if the fishery naturally selects for highliners or full-time fishermen over time. Note also that with this specification:

$$\text{sign} \left\{ \frac{\partial \lambda_i}{\partial x_{ik}} \right\} = \text{sign} \left\{ e^{-\beta' x_i} (-\beta_k) \right\} = -\text{sign} \{ \beta_k \}. \quad (3.6)$$

Thus we can interpret the parameter signs as indicating the effect of a given exogenous variable on survival.

Again following Greene (1990), we can construct the log-likelihood of the Weibull model with covariates. We first make the following definitions:

$$\sigma = \frac{1}{p}, \quad \delta_i = \begin{cases} 1 & \text{if the individual exits} \\ 0 & \text{if not (i.e. is censored)} \end{cases} \quad (3.7)$$

and $w_i = p \ln(\lambda_i t_i) = \frac{\ln t_i - \beta' x_i}{\sigma}$

The log-likelihood then reduces to

$$\ln L = \sum_i \left[\delta_i (w_i - \ln \sigma) - e^{w_i} \right]. \quad (3.8)$$

To obtain estimates of β and σ , we simply maximize (3.8).

We estimate four Weibull duration models using GAUSS MAXLIK. Duration for each individual is their last decimal date fished minus their first decimal date fished, so the time is measured in decimal years. If the individual is still active as of the beginning

of 1998, the observation is considered censored and the maximum date is replaced with 98.0 for the duration calculation.¹⁰ Model 1 includes all divers who were active prior to 1998, the censoring point. It assumes that covariates do not affect survival and estimates σ and λ . Model 2 uses the same sample and estimates coefficients for four covariates: seasonal revenue, number of ports visited, share of southern California, and early dummy variable. The seasonal revenue is an individual-specific average revenue and is simply the person's total diving revenue divided by the person's length of participation in the fishery. For individuals active less than one full year, seasonal revenue is simply their total revenue in the fishery. Number of ports counts how many distinct ports at which the diver landed urchin. Share of southern California is the diver's total number of southern California diving trips divided by his total number of diving trips. Early is a dummy variable that indicates whether the diver was active in the urchin fishery prior to 1989. An important assumption is that all covariates are strictly exogenous. In that sense, we assume that the duration of activity does not affect the value of a regressor. This is problematic in the case of individuals who only participate once (or a small number of times) because the port variable, for instance, is necessarily equal to one if the duration is only one day. It also poses problems for the seasonal revenue variable because the measure of a diver's performance is pinned to a point in a particular season, and there is no interval over which this is measured.

Models 3 and 4 are the same as Models 1 and 2 but use a different sample. For 3 and 4, we restrict the sample to divers who were active for at least one full year. That is,

¹⁰ The last term in (3.8) accounts for the censoring. If the individual remains in the fishery, the term in parentheses is multiplied by zero and only this last term affects the probability. In the event that a diver exits and re-enters, the analysis counts the re-entry as a distinct spell if a new license code is assigned. If

we select only divers whose first dive in the sample and whose last dive in the sample were at least one year apart. This eliminates the ambiguity of how to define seasonal revenue (particularly for individuals who dove only once) and addresses the endogeneity problem of the port variable. However, it may introduce sample selection bias.

Table 3.6
Duration Model Maximum Likelihood Results

Variable	All divers active prior to 1998		Divers with at least one full season	
	Model 1 Estimate	Model 2 Estimate	Model 3 Estimate	Model 4 Estimate
σ (Equal to $1/p$)	3.9884 *** (0.1015)	2.8280 *** (0.0623)	0.7348 *** (0.0375)	0.6056 *** (0.0291)
Constant (Equal to $-\ln\lambda$ in Models 1 and 3)	1.0331 *** (0.1192)	-4.8382 *** (0.1987)	2.5178 *** (0.0493)	1.1453 *** (0.0812)
Seasonal Revenue (\$1,000s)		0.1348 *** (0.0143)		0.0168 *** (0.0036)
# of Ports Visited		1.7321 *** (0.0918)		0.2094 *** (0.0214)
Share southern Cal.		0.3718 ** (0.1801)		0.2684 *** (0.0741)
Early (Began before 1989)		0.8655 *** (0.3155)		0.1108 * (0.0850)
Log-likelihood	-3,880	-3,126	-768	-615
Observations	1583	1583	768	768
Pseudo R-squared		0.19		0.20

*** Indicates significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table 3.6 reports maximum likelihood estimates for the four models. All parameters are statistically significant with nearly all of them being significant at the 1%

the diver keeps the original license code, presumably because the individual was out of the fishery for less than two years, the analysis treats this diver as if there is just one long spell.

level. Based on the standard errors, in all four models restricting the Weibull model down to the exponential model is inappropriate. That is, σ is significantly different from one in all cases. These estimates also demonstrate that including covariates does help to explain exit behavior. The likelihood ratio test statistic for restricting the covariates is:

$-2[\ln(L_R)-\ln(L_U)]$ and is distributed χ^2 with four degrees of freedom. The critical value for a 95% confidence level is 9.49. The test statistic for restricting Model 2 is 1506.92, while the test statistic for restricting Model 4 is 305.53. Clearly, we reject the restrictions in both cases in favor of including covariates.

The signs of the parameters provide insight on why some fishers remain in the fishery and others exit. The positive signs on seasonal revenue indicates that high earning divers are more likely to survive than low earning divers. Similarly, the positive signs on ports visited suggests that more mobile divers are more likely to “survive.” This result, that more successful fishers are ones who are willing and able to explore multiple locations, is consistent with the findings of previous analyses of spatial choice in fisheries. Abrahams and Healey (1990) find that catch rates for vessels in the British Columbia salmon troll fleet are positively correlated with a measure of spatial mobility. Evans (1997) finds that mobile vessels in the California salmon fishery outperform sedentary vessels in terms of both catch per day and revenue per day.

The interpretations of the last two covariates are somewhat amorphous. The positive signs on share of southern California suggest simply that southern California participants are more likely to remain in the fishery. The question of why this would be the case is more complicated. Certainly, the southern California urchin fishery has been more stable in terms of aggregate catch than that in northern California. In that sense, this

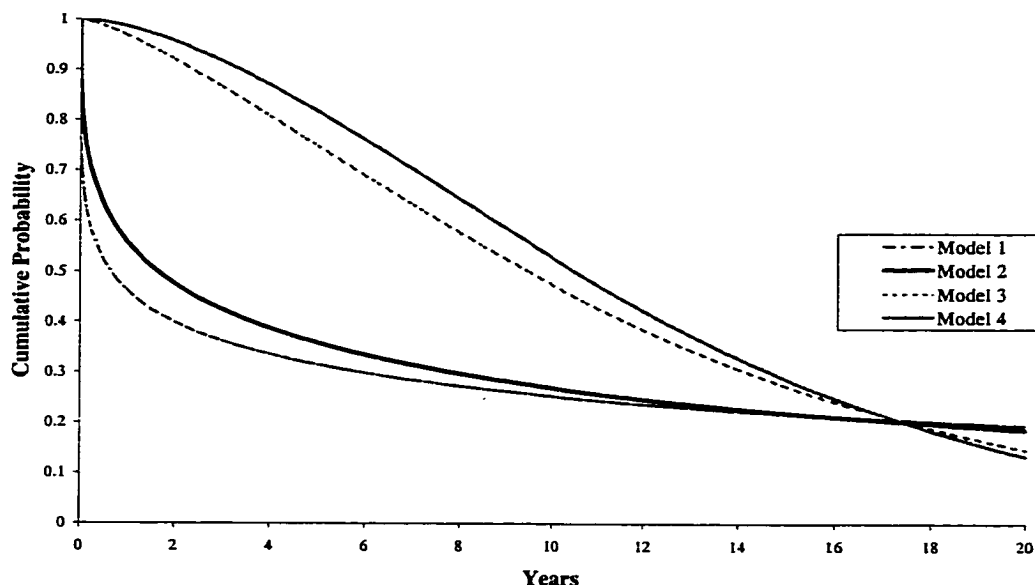
share measure may be related to mobility. Divers are more likely to remain in the fishery if they are willing to move to more productive areas, many of which are in southern California. Also, weather conditions in the south are milder. Thus individuals are more likely to exit the fishery if they are exposed more often to unsafe diving conditions. The positive sign on the early dummy variable indicates that fishers who were already harvesting urchins before the northern California fishery opened are the most likely participants to remain in the industry. Though seemingly tautological, this coefficient implies conversely that later entrants to the northern California fishery were less likely to survive. So, this variable may capture a degree of professionalization. Many early participants in the fishery were already involved in dive fisheries when the boom period approached and may have been former participants in the abalone fishery. Perhaps a number of non-professionals entered for the boom period but quickly exited because overall profitability of urchin diving declined.

Figure 3.9 plots the estimated survival functions for the four models. The plots of models 2 and 4 use the means of the independent variables in the corresponding sample. Model 2 is similar to Model 1 just as Model 3 is similar to Model 4. In both comparisons, the model with covariates declines more gradually in the early phase than the model without covariates. When we compare Model 2 to Model 4, it is important to recall that many divers exited after just one dive in the full sample, so naturally Model 2 is more steeply sloped at the beginning. This suggests that if divers make it through a full season, their survival probabilities are much higher. Conversely, including those who do not survive a full year biases the survival probabilities downward.

Figure 3.9

Estimated Survival Functions

Based on Means of Independent Variables for Models 2 and 4



The process of attrition raises the question of what is happening to the composition of active divers in the fishery. Is the fleet of harvesters becoming more or less heterogeneous? In other words, is performance inequality among urchin divers increasing or decreasing? One way to look at this issue is to calculate Gini coefficients and plot Lorenz curves across time. A Gini coefficient is the area between the 45 degree line (perfect equality) and the Lorenz curve, divided by the total area under the Lorenz curve. In contrast to the usual comparison of cumulative percent of individuals with cumulative income, this Lorenz curve analysis compares cumulative percent of individuals to cumulative percent of harvest. For purposes of sustainability, it is the harvest potential of the fleet that is critical. Figure 3.10 plots these Lorenz curves for even years beginning in 1988. All curves are severely bowed outward, suggesting that there is considerable heterogeneity in the composition of aggregate harvest. Even in the

most egalitarian year, 1996, 50% of the divers catch less than 20% of the total sea urchin harvest.

Clearly, most of this inequality is attributable to heterogeneity in participation rates. Full-time divers simply harvest more than part-time divers. Within each year, the correlation between a diver's pounds harvested and number of trips is 0.69. For every year in the sample, there are always some divers who make only one landing and others who are making the minimum landings necessary to renew their licenses. Table 3.7 summarizes the heterogeneity in number of trips across divers. As the standard deviations suggest, there is considerable variation across individuals in participation rates.

With the exception of 1998, the Lorenz curves flatten over time. That is, the distribution of catch in the harvester population becomes more uniform over the sample period. This trend is likely attributable to either the changing pool of sea urchin harvesters, the evolution of the underlying sea urchin stocks, or both. It is unclear whether the fact that the trend turns back at the end represents another structural change or is simply an aberration in the data.

Table 3.8 reports four different sets of Gini coefficients. Following the Lorenz curves, the first two report Gini coefficients for catch. The second two report Gini coefficients for revenues. Within each series pair, the distinction is whether all license codes are considered or license codes that have just one landing over the entire sample period are excluded. Single-trip individuals are excluded to check the robustness of trends to license code errors. All series exhibit the same patterns as the Lorenz curves. Inequality decreases over time but begins to increase again in the last two years. The

catch and revenue Ginis are remarkably similar at the beginning and end of the sample period. In between, however, there appears to be slightly more inequality in the revenue terms. This may be due to the evolution of quality-based pricing. In the late 1980s, processors had just begun to introduce quality premia on raw product purchases. Eventually, all processors began to offer quality premia, and perhaps more skilled divers responded by harvesting higher quality product. This would concentrate a larger share of revenues with the high-skilled divers. After several years of the limited entry program, some low-skilled divers may have exited the fishery, possibly dissipating the inequality differences between revenue and catch.

Figure 3.10

Lorenz Curves for Diver Catch

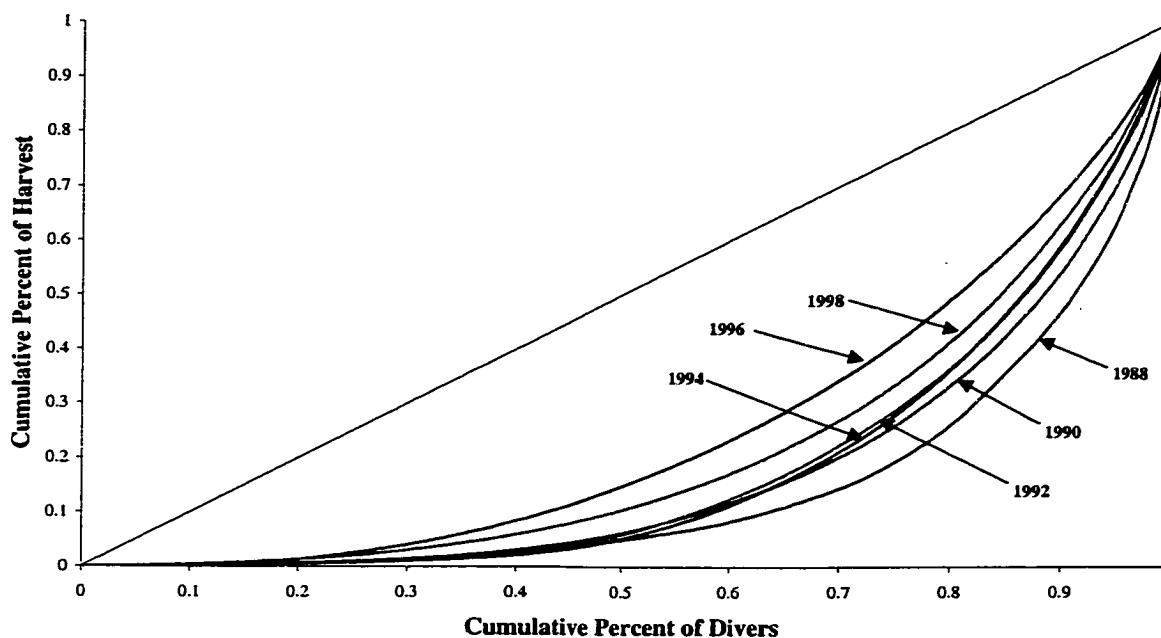


Table 3.7
Diver Number of Trip Heterogeneity

Year	Max. Dives	Average Dives	Std. Dives
1988	145	17.15	24.98
1989	159	16.94	22.70
1990	197	20.93	26.44
1991	179	22.84	25.87
1992	162	26.02	30.11
1993	133	25.84	27.87
1994	141	22.95	27.34
1995	151	31.75	27.88
1996	160	34.80	30.40
1997	175	34.03	29.16
1998	94	15.58	16.18

Table 3.8
Diver Gini Coefficients

Year	Catch Gini All Divers	Catch Gini Exclude < 2 Dives	Revenue Gini All Divers	Revenue Gini Exclude < 2 Dives
1988	0.7079	0.6800	0.7025	0.6853
1989	0.6457	0.6092	0.7042	0.6820
1990	0.6529	0.5998	0.6565	0.6128
1991	0.6314	0.5615	0.6450	0.5920
1992	0.6310	0.5685	0.6557	0.6063
1993	0.6185	0.5551	0.6323	0.5889
1994	0.6369	0.5281	0.6328	0.5241
1995	0.5219	0.5004	0.5285	0.5072
1996	0.5013	0.4783	0.5024	0.4885
1997	0.5126	0.4893	0.5229	0.5026
1998	0.5707	0.5464	0.5731	0.5490

Conclusions

Based on biological and oceanographic factors, red sea urchin, *Strongylcentrotus franciscanus*, is a prototypical candidate species for marine reserves. With this in mind and a concern for the fishery's sustainability, California regulators are explicitly

considering spatial management for the northern California urchin fishery. Thus, there is a need to understand the spatial behavior of sea urchin divers.

Fortunately, an extraordinary data set exists for this purpose. Preliminary spatial views of the data and analysis of diver behavior show spatial differences in catch, harvesting time, and trips, suggesting that sea urchin habitat is patchy and heterogeneous. Moreover, diving activity tends to concentrate near ports, again suggesting that spatial concerns are critical. In diving depth, once more we see spatial heterogeneity, and more importantly, behavioral patterns show that the Ricardian extensive margin shifts out over time. Differences across individual harvesters also appear to be important and, in part, manifest themselves in proclivity for spatial mobility. In particular, the duration analyses indicate that mobile divers are more likely to remain in the fishery than sedentary divers. Although the duration analyses are suggestive of the maximum harvest potential in the fishery, to predict actual harvest in a spatially explicit manner, it is necessary to model explicitly the magnitude and the spatial distribution of effort as well as the underlying spatial biological mechanisms. The following chapters undertake these analyses.

Chapter 4

A Discrete Choice Model of Participation and Location Choice

Harvesters in the California red sea urchin fishery clearly respond to economic incentives. Specifically, the empirical analysis in this chapter shows that urchin divers by no means distribute themselves evenly across space because opportunities are heterogeneous across space. In addition, this chapter shows that the aggregate participation of divers changes in response to economic conditions. The typical biological modeling assumption of uniform fishing effort across space thus does not accurately characterize this fishery. More importantly, we would expect that a structural change like the formation of a marine reserve would influence the total participation and spatial allocation of the pool of urchin divers. The empirical model of this chapter provides a framework for evaluating such responses to structural change.

Urchin divers make a series of discrete decisions that affect total fishing effort and its location over space. On each open season day, each diver chooses whether or not to participate based on prevailing weather conditions, expected prices, expected resource abundance, individual diver traits, and processor contractual arrangements with the Tokyo wholesale market. Among the potentially important individual traits are diver skill, attitudes towards risk, outside opportunities, and values of leisure time. Divers who have chosen to participate on any given day then choose diving locations based on expectations about spatially varying resource abundance and travel costs. Thus, on any given open season day there are two decision nodes or nests.

This chapter develops a micro-level behavioral model that treats individual harvester decisions as discrete choices among non-participation and participation in different spatial locations. These choices are functions of weather, expected revenues, and travel costs. A random utility model (RUM) provides the motivation for a Nested Logit specification. Predictions from the Nested Logit regression are aggregated across days and divers to arrive at monthly industry participation and location shares. The aggregate predictions are used to perform short-run policy simulations that assess the behavioral responses to marine reserves.¹

The work presented here contributes to the literature on discrete choice in commercial fisheries because it models participation and location choice simultaneously for a commercial fishery. Bockstael and Opaluch (1983) performed the first empirical analysis of discrete commercial fishing alternatives. Since then, a number of papers have

¹ These simulations are short-run because they track the instantaneous responses of harvesters without updating the state variables in the system. Over time, behavioral responses to policy would affect the underlying spatial abundances of the resource. In chapter 7, we will incorporate this behavioral framework

done discrete choice analysis of commercial fishing, including Eales (1983), Eales and Wilen (1986), Campbell (1991), Dupont (1993), Evans (1997), Holland and Sutinen (2000), Mistiaen and Strand (2000), and Curtis and Hicks (2000). Most of these papers have focused on location choice of commercial fishers. However, none of them model the magnitude of participation together with location choice.

A Random Utility Model (RUM) provides a useful motivation and framework for discrete daily participation and diving location decisions. A RUM is a method for modeling discrete decisions of individual economic agents. In contrast to most models of continuous decisions, a RUM treats individuals as heterogeneous. Like most models of choice behavior in economics, a RUM supposes that utility is the metric that drives individual choice. A RUM typically contains a systematic component of utility, which is common to all individuals in the data set, and a random component of utility, which varies across individuals. This approach often accounts for the empirical phenomenon that we as analysts see, namely that two individuals with the same observable characteristics and opportunities sometimes choose two different discrete alternatives.²

The distinction between commercial urchin divers maximizing utility or profits may be largely semantic. We do not observe profits directly nor do we observe costs directly, and there are unobservable characteristics that influence both of these metrics. So, the structure of a RUM is convenient even if our interest were only in random profits.

On a deeper level, there are several reasons to consider utility maximization in this commercial fishery context. First, divers are trading off work and leisure. A person's valuation of leisure time will influence the number of diving days that we

into a simulation model that does update the state variables and hence has the ability to simulate long-run impacts of reserves.

observe for that individual. Second, the non-transferability of licenses reinforces the influence of heterogeneous leisure values on participation rates. With transferable licenses, we would expect the capitalized value of a high participation rate to cause low-participation divers to sell, leading to a more homogenous population of harvesters. Finally, harsh weather makes urchin diving a dangerous profession. Individual tolerances of these weather risks are not purely a matter of profits.

Indexing individuals by i , diving locations by j , and days by t , diver i 's utility from diving in harvest zone j on day t is:

$$\begin{aligned} U_{ijt} &= v_{ijt} + \varepsilon_{ijt} \\ &= f(\mathbf{X}_{it}, \mathbf{Z}_{i1t}, \mathbf{Z}_{i2t}, \dots, \mathbf{Z}_{iMt}; \theta) + \varepsilon_{ijt}, \end{aligned} \quad (4.1)$$

where \mathbf{X} includes diver-specific and time-specific characteristics that are constant across choices, \mathbf{Z} denotes choice-specific characteristics such as travel costs and resource abundance, θ is a parameter vector, and ε_{ijt} is a random component that is unobservable to the analyst. Given M possible diving locations, the Random Utility Model posits that a diver chooses location k if the utility of choice k is higher than that of the $(M-1)$ other location choices as well as the choice of not to dive. For example:

$$\Pr[ikt] = \Pr[U_{ikt} = \max\{U_{i1t}, U_{i2t}, \dots, U_{iMt}, U_{i \text{ not } t}\}]. \quad (4.2)$$

There are numerous discrete choice formulations that capture the essence of spatial decision-making and are consistent with the above RUM. Many similar analyses that model participation and location choices have appeared in the literature on recreation demand.³ The general approaches fall into the following categories: Multinomial (and Conditional) Logit (MNL), Discrete Choice Dynamic Programming (DCDP), Random

² See McFadden (1974) for a more detailed discussion.

Parameters Logit (RPL), Multinomial Probit (MNP), and Nested Logit.⁴ The basic MNL is easy to estimate but inappropriate for spatial policy simulation because it imposes the Independence of Irrelevant Alternatives (IIA); the relative choice probabilities are unchanged by a change in the choice set. A spatial closure analysis with a model that imposes IIA at all levels of choice would, in essence, assume the answer to the policy question. In the case of a joint analysis of participation and location choice, MNL would impose a structure that determines the aggregate participation response to a closure. In particular, it would be like biological models that assume proportional increases in effort for non-reserve areas when a reserve is created.

Several alternatives to MNL pose different problems. DCDP is attractive to the analyst because it is an empirical model that is consistent with intertemporal optimizing behavior of individual agents and it avoids IIA. In the context of most commercial fisheries, however, it is unnecessary. The open access aspect of most fisheries truncates the relevant time horizon from the individual fisher's point of view. Moreover, DCDP is computationally burdensome. The RPL and MNP models can allow for heterogeneity of individual responses to independent variables and do not suffer from IIA problem, but they are also computationally cumbersome. Computational problems are especially important to this analysis due to the size of available data sets. More importantly, the

³ See, for instance, Morey, Shaw, and Rowe (1991), Morey, Rowe, and Watson (1993), McConnell, Strand, and Blake-Hedges (1995), Provencher and Bishop (1997), Morey and Waldman (1998), and Font (1999).

⁴ Ben-Akiva and Lerman (1985) provide a useful summary of multinomial techniques for discrete choice. The original MNL is due to Luce (1959). DCDP techniques were developed by Rust (1987). RPL originally dates back to Electric Power Research Institute (1977) but has become far more practical due to the work of McFadden and Train (2000). MNP also has a long history in the literature, but it too has become more practical in recent years with developments in simulation-based estimation (McFadden, 1989; Pakes and Pollard, 1989; Keane, 1994). A Nested Logit formulation for economic behavior was introduced by McFadden (1978).

goal of the discrete choice analysis is to obtain a useful representative diver model for policy simulation.

The method used in this chapter is Nested Logit. The approach closely follows the “Repeated Nested Logit” of Morey, Rowe, and Watson (1993) in which different decisions of the same individuals are treated as independent across time. Nested Logit does not impose IIA across branches of the decision tree, is easy to estimate, and is quite flexible.⁵ In addition, it allows for different variances at different decision nodes, and hence it can be used to construct a structural model of interdependent decisions of whether to go and where to go. Moreover, in contrast to DCDP, RPL, and MNP, the Nested Logit model is simple to use for policy simulation because it neither requires calculation of an individual agent’s entire optimal path nor integration over individual heterogeneity that is manifested in random parameters. Hence, the motivation for Nested Logit in this setting is similar to its original motivation; it is more flexible than MNL and, unlike more sophisticated approaches, has the quality of producing choice probabilities with closed-form expressions.⁶

There are two main drawbacks of Nested Logit worth mentioning. First, it is far less flexible in permitting individual heterogeneity than RPL and MNP. Thus, the gains in tractability, particularly for estimating over the large sea urchin data sets that are available, are somewhat offset by loss in generality. A second criticism of this Nested Logit framework is that it treats repeated choices by the same individuals as independent

⁵ Within each decision branch, Nested Logit does impose IIA. As such, in our analysis of reserves, the spatial redistribution of fishing effort is determined by the relative choice probabilities of the remaining alternatives.

⁶ In chapters 6, 7, and 8, we will see that having these closed-form expressions is useful for a bioeconomic model with many ecological complications.

across time.⁷ Clearly, this assumption is a simplification because divers undoubtedly use private information about recently visited locations to make their choices. Ultimately, the assumption here is that these types of microbehavioral effects are less important than structural changes in urchin abundance over the longer time horizon used in the policy simulations in later chapters. Thus, the proceeding analysis uses the Nested Logit in spite of these critiques in order to generate a tractable policy model, based on a representative diver, for studying marine reserves in the northern California sea urchin fishery.

In spite of its drawbacks, the Nested Logit is a useful model in this setting that it is consistent with utility maximizing behavior. As McFadden (1978) showed, if ϵ_{ijt} is independently and identically distributed Generalized Extreme Value, maximization of random utility gives rise to the Nested Logit model.⁸ If we assume further that indirect utility is linear in \mathbf{X} and in \mathbf{Z} , the following probabilistic model characterizes individual choices:

$$Pr(\text{Goto } j) = \frac{\exp\left\{\frac{\mathbf{z}_j' \boldsymbol{\gamma}}{(1-\sigma)} + \mathbf{x}_j' \boldsymbol{\beta} + (1-\sigma)I\right\}}{\sum_{k=0}^{10} \left[\exp\left\{\frac{\mathbf{z}_k' \boldsymbol{\gamma}}{(1-\sigma)}\right\} + \exp\left\{\frac{\mathbf{z}_k' \boldsymbol{\gamma}}{(1-\sigma)} + \mathbf{x}' \boldsymbol{\beta} + (1-\sigma)I\right\} \right]}, \quad (4.3)$$

and

⁷ These two criticisms are essentially questions of heterogeneity and state dependence, two issues that have a long history in the labor economics literature and are increasingly important in the marketing literature. Heckman (1981) outlines the distinction between state dependence and heterogeneity. In the marketing literature, Keane (1997) discusses a means to test for this distinction, and Erdem and Keane (1996) estimate a DCDP model that allows for heterogeneity. Recently, Breffle and Morey (2000) estimate a Nested Logit with a random inclusive value to allow for individual heterogeneity. Applications of such methods to the sea urchin data would be interesting analyses but would stray from the central goal of building a practical policy simulation model.

⁸ In the simpler model in which the ϵ 's are independently and identically distributed Type I Extreme Value, utility maximization gives rise to the familiar conditional logit model of McFadden (1974).

$$\begin{aligned}
 Pr(\text{Do not go}) &= 1 - \sum_{k=0}^{10} Pr(\text{Go to } k) \\
 &= \frac{1}{1 + \exp[\mathbf{x}_i' \boldsymbol{\beta} + (1 - \sigma)I]}
 \end{aligned} \tag{4.4}$$

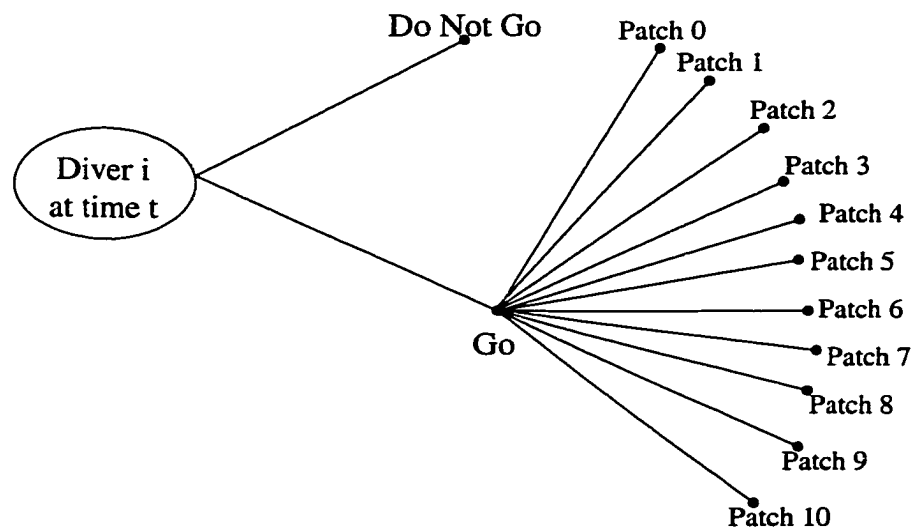
$$\text{where } I = \ln \left[\sum_{k=0}^{10} \exp \left\{ \frac{\mathbf{z}_{kt}' \boldsymbol{\gamma}}{(1 - \sigma)} \right\} \right]. \tag{4.5}$$

The i subscripts for individuals are suppressed because the form of the model is the same for each individual in the data set; only some \mathbf{X} characteristics could, in principle, vary across individuals. $\boldsymbol{\beta}$ denotes the parameter vector for characteristics that vary across individuals and/or choice occasions but not across choices. The parameter vector for characteristics that vary across choices is $\boldsymbol{\gamma}$. The coefficient on the Nested Logit inclusive value is $(1 - \sigma)$.

The nesting structure for this model is simple. Figure 4.1 depicts the decision structure for an individual on an open season day. Divers choose to go or not go fishing, and if they choose to go, they choose among the fishing locations. This decision repeats for each individual on each choice occasion. For identification, we have normalized the indirect utility of not diving to zero. Nevertheless, it is important to keep in mind that the indirect utility of not diving captures the value of leisure, work opportunities outside the fishery, and the value of not being exposed to unsafe diving conditions.

Figure 4.1

Daily Participation and Location Choice Decision



For empirical analysis, \mathbf{X} includes a constant (CONST), wave period (WP), wind speed (WS), wave height (WH), and a dummy (DWEEK) that indicates Friday, Saturday, or Sunday. *Ex ante*, there are strong expectations about parameter signs; we expect weather variables to have negative coefficients. Also, we expect a negative sign on DWEEK for several institutional reasons. First, the Tokyo wholesale market is closed on Sundays, so product landed and processed on Friday, shipped on Saturday, and arriving on Sunday would have to wait one day to be sold. Second, divers tend not to work on weekends, so processors tend to process lower quality or older product if they are open on Saturdays. Finally, processors are mainly closed on Sundays. If the data were available, \mathbf{X} would also include variables to control for individual diver heterogeneity

such as demographic indicators.⁹ For each location, Z contains expected revenues (ER) and travel distance from the diver's home port (DISTANCE). ER contains both price and abundance measures.¹⁰ The strong *ex ante* sign expectations are positive for ER and negative for DISTANCE.

The specification reported in this chapter is intentionally quite parsimonious. The ultimate intent of this behavioral modeling is to construct a simulation model that can be linked with a detailed biological metapopulation model and that only relies on one key variable, capturing all other effects as parameters. In this case, the only variable that will ultimately be used to link the economic model to the biological model is ER. By linking the biological and economic models through expected revenues, the bioeconomic model will be able to simulate dynamic responses to changes in abundance and economic conditions. Variation in factors such as weather can be simulated by changing constants in the model.¹¹

Results and Short-run Policy Simulations

Table 4.1 reports results from Nested Logit analysis on 401,151 observations. This constitutes all choice occasions for divers in northern California between 1988 and

⁹ Demographic information is simply unavailable. License codes allow us to track the same individual over time, but divers provided detailed logs to CDFG under the condition that their identities would remain confidential. Had we surveyed the divers, we would not have been able to connect their responses to the fishery data.

¹⁰ For the discrete choice model, expected revenues are calculated as the product of expected price and expected catch-per-trip. The former is a rolling one-month backward looking average across the entire northern California fishery. That is, for each day, the price calculation is based on the average price for the previous 30.4 days. The latter (expected catch) is a patch-specific rolling one-month backward looking average. The specification of one-month averages is also convenient for the simulation modeling in later chapters. For further discussion of the methodological issues involved in expected revenue calculations for discrete choice behavioral models, see Smith (2000).

¹¹ The estimation avoids non-structural factors that would change out-of-sample such as a time trend. Implicit trends are captured by the changing number of participants, the evolution of urchin abundance, changes in prices over time, and the changing number of open season days.

1996, excluding divers who had fewer than five total dives over the entire period.¹² All coefficients are statistically significant at the 1% level. The model fits well overall, as the high pseudo- R^2 value of 0.21 indicates. This goodness-of-fit measure is computed as $(1 - \mathcal{L}_U/\mathcal{L}_R)$, where \mathcal{L}_U is the log-likelihood for the model in Table 4.1 and \mathcal{L}_R is the log-likelihood for a model with choice-specific constants and no slope coefficients. It is worth noting that the unrestricted model does not contain choice-specific constants, so this high value is suggestive of how well the Nested Logit fits these data. One can also compute the pseudo- R^2 as if choices are selected at random in the restricted model, i.e. there are no choice-specific constants. Using this more generous method, the value is 0.81.

Although the coefficients of Nested Logit are not the marginal effects (because the model is nonlinear), the coefficient signs are interpretable as in a linear model. The negative coefficients on weather variables (WP, WS, and WV) all indicate that the probability of diving decreases when weather conditions are unfavorable. Wave period and height measure wave power, which increases the safety risk of diving, and wind speed is a general indicator of harsh weather. The variable DWEEK demonstrates the

¹² Divers with fewer than five dives were excluded to avoid the possibility of coding errors in the license field and to avoid fitting a model over individuals who simply tried out this profession. For purposes of policy simulation, we are interested in both full-time and part-time participants. However, we are not interested in the behavior of a handful of individuals who randomly dove on a trial basis and then exited the industry.

In preliminary analysis and specification testing, the data were sampled because the number of observations is so large, requiring enormous computing power and time given the highly nonlinear nature of Nested Logit. This preliminary sample was 30 divers followed over the entire period and led to a sample size of 27,822. The other specifications of the expected revenue term were tried on this sub-sample. Using these initial estimates as starting values, we estimated the model on the full choice set of 401,151 observations.

Note that the length of the data set used in estimation is not determined by the number of fishing observations but by the number of choice occasions. By modeling participation, the number of choice occasions inflates to nearly ten times the number of fishing observations because average participation among licensed divers is roughly ten percent of the available days for harvesting.

importance of urchin roe market institutions and the habits of individual fishers. As expected, diver participation is greatest in mid-week.

Table 4.1
Nested Logit Estimates

<u>Not Location-Specific</u>			
Variable	Coefficient	Standard Error	Z - statistic
Constant	1.06	0.048	22.21
WP	-0.18	0.005	-34.69
WS	-0.11	0.003	-36.69
WH	-0.74	0.011	-70.36
DWEEK	-0.74	0.012	-60.02
<u>Location-Specific</u>			
Variable	Coefficient	Standard Error	Z - statistic
DISTANCE	-7.27	0.036	-203.72
ER	0.08	0.001	65.17
σ	0.22	0.027	8.34
Log-likelihood	-189,878		
Observations	401151		
Pseudo R ² (1)	0.21		
Pseudo R ² (2)	0.81		

Pseudo R² (1) is based on the log-likelihood in a Conditional Logit Model with choice-specific constants.

Pseudo R² (2) is based on the log-likelihood of $n \cdot \ln(1/J)$, where $J = 12$ possible choices.

Patch-specific variables are also important explanatory variables. The positive sign on ER suggests that divers do indeed seek patches with high urchin abundance. The negative sign on DISTANCE suggests that travel costs deter divers from venturing far from their ports. The signs on ER and DISTANCE are also consistent with greater overall participation in the fishery when conditions are more profitable. Since the inclusive value coefficient $(1-\sigma)$ folds the lower branch utility back into the upper branch, the probability of participation increases when expected price or abundance increases.

Finally, since σ is statistically different from zero, the inclusive value coefficient is less than one. This has two implications: 1) the model estimated is consistent with stochastic utility maximization as demonstrated by Daly and Zachary (1979) and McFadden (1979), and 2) the variances of utility for participation and location choices are different. This second implication means that choices across branches of the decision tree are less similar than choices within each branch of the decision tree. Thus, choosing between going to patches 7 and 8 is more similar than choosing between going to patch 8 and not going fishing that day. This makes intuitive sense for our setting because we would expect that participation and location choices are qualitatively different.¹³

Using the fact that the underlying utility is linear in explanatory variables, we can calculate marginal rates of substitution (MRS) in terms of revenue. For travel distance, the MRS is (\$9,087.50). At the extensive margin, divers would need an extra \$9,087.50 to travel one more degree of latitude, which translates to \$151.46 for an extra nautical mile. At ten knots per hour and considering roundtrip travel times, the value of traveling one additional hour for sea urchins is a \$757.30 increase for the entire trip. This MRS seems high at first glance, but it is important to keep in mind two aspects of the diver decision problem. First, the statistical model averages across mobile and sedentary divers. Ultimately, there is a continuum of diver willingness to travel. The individuals who travel only short distances introduce considerable spatial rigidity into the problem. Second, additional travel involves not only the fuel costs and opportunity cost of time, but also more exposure to weather risk. The farther divers are from their ports, the longer it takes to return if there is a sudden change in weather conditions. The MRS of wave

¹³ Had the inclusive value coefficient been equal to one, then the model would still have been consistent with stochastic utility maximization. However, this would have implied that the participation and location

height and revenues confirms the importance of additional weather exposure. An additional reduction of a meter of wave height at the margin is worth \$925. Finally, we can calculate an incremental rate of substitution for the DWEEK variable. This value is also \$925 and indicates the tradeoff between diving on a Friday, Saturday, or Sunday and diving mid-week. Note that this value is less than the average revenue per trip in the sample but reasonably close to it. The reason is that diving on weekends is not profitable because the processing plants are not running. To dive for urchin in spite of this fact would sacrifice freshness, leading to a much lower value for the trip.

To help interpret the economic significance of effects, Table 4.2 reports variable means, minima, maxima, and a series of response elasticity estimates. Appendix A details the calculations for the Nested Logit elasticities. For **X** variables, the elasticity reported is the percent change in the probability of diving for a one percent increase in the variable. For **Z** variables, the elasticity indicates the percent change in probability of going to that location for a one percent increase in the **Z** variable at that location, holding other variables constant. The first set of estimates evaluates at the means. Evaluating at the means, however, is somewhat misleading because it assumes that all divers are coming from a fictive port in the middle of the coast rather than the actual ports from which they fish. The second estimate recognizes that mean distance across all locations tends to overstate actual distances traveled, so the mean distance is replaced with an average distance traveled across nodes chosen. The reason that mean distance for each patch overstates actual travel distances is that it calculates these distances from the fictive port in the center. In actuality, there are 11 travel distances for each of the four ports in our discrete choice model. Thus, by averaging across all of these actual distances for

choices were qualitatively similar.

each port, we capture a more realistic depiction of travel distances and do not bias the calculations in favor of ports located in the center of the coast. The third and fourth estimates evaluate for mid-week ($DWEEK=0$) and Friday or weekend ($DWEEK=1$) respectively. In all cases, the probability of participating is elastic with respect to either wave variable but inelastic with respect to wind speed. These results are plausible, since bigger waves likely increase the risks of being in the water more than high winds. In contrast, high winds increase the risks of being on deck. Some of the elasticities evaluated at the means are driven largely by the mean distances assumed. The overall sample mean probability of diving in a particular location is so low that responses to distance and increases in revenues are extremely elastic. When more realistic choice-specific distances are used, the elasticities settle down to less elastic levels. Setting $DWEEK=0$ or $DWEEK=1$ does not have much of an impact on the elasticities.

Table 4.2
Variable Summaries and Nested Logit Elasticities

	Minimum	Maximum	Mean	Elasticity at Means	Elasticity Distance Adjusted	Elasticity DWEEK=0	Elasticity DWEEK=1
<u>Not Patch-Specific</u>							
WP	4.57	13.97	7.70	-1.366	-1.157	-1.106	-1.237
WS	0.85	17.14	6.01	-0.629	-0.533	-0.509	-0.570
WH	0.62	8.85	2.41	-1.749	-1.481	-1.415	-1.583
DWEEK	0.00	1.00	0.33	-0.243	-0.206	0.000	-0.658
<u>Patch-Specific</u>							
DIST0	0.67	1.78	1.36	-53.14	-1.74	-1.72	-1.76
DIST1	0.83	1.94	1.52	-59.37	-1.76	-1.75	-1.78
DIST2	0.13	1.24	0.82	-32.09	-1.75	-1.73	-1.77
DIST3	0.19	0.93	0.61	-23.61	-1.75	-1.74	-1.77
DIST4	0.24	0.73	0.51	-20.00	-1.75	-1.73	-1.77
DIST5	0.06	0.56	0.43	-16.68	-1.75	-1.74	-1.77
DIST6	0.13	0.75	0.38	-14.90	-1.76	-1.74	-1.77
DIST7	0.03	0.93	0.37	-14.39	-1.76	-1.75	-1.78
DIST8	0.00	1.11	0.42	-16.23	-1.76	-1.75	-1.78
DIST9	0.22	1.33	0.64	-24.81	-1.76	-1.74	-1.77
DIST10	0.86	1.97	1.28	-49.76	-1.74	-1.72	-1.76
ER0	0.80	31.41	14.03	5.88	1.53	1.52	1.55
ER1	0.81	26.56	5.45	2.28	0.60	0.60	0.61
ER2	0.94	29.25	11.14	4.67	1.22	1.21	1.24
ER3	2.36	26.44	10.52	4.41	1.15	1.15	1.17
ER4	1.52	30.53	11.23	4.71	1.23	1.22	1.25
ER5	3.26	20.80	8.59	3.60	0.94	0.94	0.96
ER6	2.46	24.62	7.64	3.20	0.84	0.84	0.85
ER7	0.85	13.30	6.13	2.57	0.68	0.67	0.68
ER8	0.55	12.83	5.66	2.37	0.62	0.62	0.63
ER9	0.88	19.12	7.65	3.21	0.84	0.84	0.85
ER10	1.60	63.50	14.65	6.14	1.60	1.58	1.62

Because revenue changes affect both the magnitude and spatial pattern of participation, Table 4.3 reports cross-revenue elasticities for the mid-week (DWEEK=0) distance adjusted case. Although all cross-revenue elasticities are positive in this table, the sign in general depends on the relative magnitudes of two offsetting effects that are analogous to income and substitution effects. To distinguish between the technical term “income effect” and our meaning in this setting, we use the term magnitude effect. When expected revenue in patch j increases, the substitution effect draws fishing effort from other patches, and hence the probability of visiting patch j increases and the probability of visiting patch k decreases. However, the increase also creates a magnitude effect, which draws more total effort into the fishery. The increased effort distributes among all

possible patches, so all probabilities increase. If the substitution effect outweighs the magnitude effect, the cross-revenue elasticity between two patches is negative. In general, the sign will hinge on all of the variable values, and the substitution effects will be larger for patches that are visited more frequently, i.e. $Pr[k]$ is higher.¹⁴

Table 4.3

Nested Logit Cross-Revenue Elasticities
Mid-week distance adjusted

		1% Change in ER_j											
		j	0	1	2	3	4	5	6	7	8	9	10
%	k												
Change in P_k	0		1.515	0.042	0.085	0.080	0.086	0.065	0.058	0.047	0.043	0.058	0.112
	1		0.130	0.598	0.093	0.097	0.104	0.080	0.071	0.057	0.052	0.071	0.136
	2		0.117	0.045	1.212	0.088	0.094	0.072	0.064	0.051	0.047	0.064	0.122
	3		0.119	0.046	0.094	1.145	0.095	0.073	0.065	0.052	0.048	0.065	0.124
	4		0.117	0.045	0.093	0.088	1.221	0.071	0.064	0.051	0.047	0.064	0.122
	5		0.124	0.048	0.098	0.093	0.099	0.938	0.067	0.054	0.050	0.067	0.129
	6		0.126	0.049	0.100	0.094	0.101	0.077	0.836	0.055	0.051	0.069	0.131
	7		0.129	0.050	0.102	0.097	0.103	0.079	0.070	0.672	0.052	0.070	0.134
	8		0.130	0.050	0.103	0.097	0.104	0.079	0.071	0.057	0.620	0.071	0.135
	9		0.126	0.049	0.100	0.094	0.101	0.077	0.069	0.055	0.051	0.837	0.131
	10		0.104	0.041	0.083	0.078	0.084	0.064	0.057	0.046	0.042	0.057	1.580
Net Change in P_{GO}			2.736	1.063	2.163	2.051	2.190	1.675	1.491	1.196	1.103	1.492	2.857

There are at least two ways to generate predictions about participation and location choices. The easiest is simply to calculate the indirect utility of each choice (including the choice of not to dive) for each individual on each choice occasion. The prediction is then the choice with the highest indirect utility. This method ignores the probabilistic nature of a random utility framework but is the best if the analyst is truly interested in what a particular individual will do on a particular day. That is, this method is a best forecast for a single choice. In this dissertation, however, the interest lies in what the group of divers will do as a whole over some interval of time. As such, a

¹⁴ One reason for all positive cross-revenue elasticities in the table is that probabilities are evaluated at means. This has the effect of dampening intertemporal spatial variability. Thus, relative differences in probabilities across patches are small. As a simple experiment, we held all variables constant and evaluated the cross-revenue elasticities at the maximum expected revenue in patch 7. As expected, some negative cross-revenue elasticities did result in this situation.

second, more useful way to generate predictions is to calculate the probabilities of each choice for each individual on each choice occasion, and then add up all of the probabilities over the relevant interval to arrive at the predictions. This method is used in Table 4.4, which presents the actual and predicted number of diving trips at each location for 1996. For each day in 1996, probabilities for each outcome are calculated at each port. Then the probabilities are weighted by the number of active divers at each port. The predictions in Table 4.4 capture the magnitude of participation quite well. The predicted spatial distribution of effort is not as accurate, but it should be noted that the actual spatial variation in effort is very large and hence intrinsically difficult to predict. Some patches attract less than fifty divers whereas others attract nearly one thousand over the course of a year. The econometric results predict the basic spatial pattern reasonably well for such a parsimonious model.

Table 4.4 also presents predictions based on what would happen if one or more patches were closed during this time period. These predictions are derived from the Nested Logit model only. Thus they represent the “first round” or “impact effects” of a closure, before changes in effort cause subsequent changes in harvest, biomass, and egg production. We examine these subsequent, dynamic effects using an integrated bioeconomic model in later chapters. The method used in Table 4.4 is quite straightforward. One sets the indirect utility of the closed patch to a very negative number (-1000 was used here) and then proceeds to calculate the probabilities of all the choices.¹⁵ In theory there is still a positive probability of going to the closed patch using

¹⁵ The choice of the indirect utility for the patch closure only must be negative enough to drive the probability close enough to zero. But, if one chooses a number that is more negative than necessary, it does not matter because the functional form of logit always exponentiates this number, which, in turn, zeroes out the effect.

this method, but in practice this probability is zero out to many decimal places. This method can be extended easily to model multiple patch closures by substituting very negative numbers into the corresponding indirect utilities and performing the same calculations above. Appendix 4-B enumerates all of the single closures, several other pairs of closures, and several scenarios of multiple patch closures.

Table 4.4
Nested Logit Short Run Policy Simulations for 1996

Open Fishing Days = 247

Total Active Divers in Bodega, Point Arena, Albion, and Fort Bragg = 131

	<u>Based on Probabilistic Framework</u>					
	Actual	Baseline Predicted	Close Patch 2 Predicted	Close Patch 8 Predicted	Close Patch 10 Predicted	Close 7 & 8 Predicted
No Dive	28883	29078	29224	29814	29078	30518
Farallon Islands	32	2	2	2	2	2
Patch 1	0	0	0	0	0	0
Patch 2	32	183	0	183	183	183
Patch 3	267	120	149	120	120	121
Patch 4	270	135	141	137	135	142
Patch 5	903	515	516	521	515	547
Patch 6	345	467	468	491	467	591
Patch 7	953	779	780	884	779	0
Patch 8	501	934	934	0	934	0
Patch 9	166	143	143	206	143	252
Patch 10	5	0	0	1	0	1
Total Trips	3474	3279	3133	2543	3279	1839
Total Choice Occasions	32357	32357	32357	32357	32357	32357
Percent Reduction in Total Effort			4.45%	22.45%	0.01%	43.92%
Percent of Effort from Closed Patch Exiting			79.86%	78.81%	63.89%	84.06%

There several interesting results from patch closure simulations in Table 4.4. First, total fishing effort, i.e. number of trips, decreases when a diving location is eliminated.¹⁶ This is sensible because some divers who would be going to the closed area have outside opportunities (other employment or leisure) that are more valuable to them

than the remaining fishing location choices. Second, not all of the fishing effort in the closed patch leaves the fishery; some effort redistributes to the remaining open patches. For these individuals, the remaining locations in the choice set are still more valuable than outside opportunities. Third, there is an asymmetric redistribution of effort. The amount of effort that moves north is not the same as the amount that moves south. Fourth, the effort redistribution creates a spatially autocorrelated ripple effect. In other words, patches contiguous to the closed patch receive the largest effort inflows, and effort inflows die off as distances from the closed patch increase. This ripple effect occurs even when there are multiple closures as seen in the close 7 and 8 simulation. Finally, the exit of effort depends on which patch is closed. In particular, if more frequently visited patches are closed, a larger share of effort exits the fishery, measured both in terms of total effort in the fishery and in terms of share of effort from the closure. This result is consistent with the decomposition of cross-revenue elasticities discussed above. It also shows the importance of port location, transportation costs, local labor market conditions, and other land-based factors to the relative impacts of marine reserves. Moreover, this result suggests that closing very large or heavily exploited areas will lead to extreme exit behavior at least in the short-run because the overall profitability of fishing declines so much. The extent to which there are close spatial substitutes mitigates this impact. The analysis in Appendix 4-B provides further support for this result.

Conclusions

The Nested Logit results demonstrate that sea urchin harvesters respond to spatial differences in returns to fishing in both their spatial decision-making and in their levels of

¹⁶ Note that the patch 10 closure does not appear to affect overall fishing effort. This is an artifact of rounding in the table. In actuality, the predicted patch 10 effort is 0.3 trips, and after closure, the total

participation. Holding other expected revenues constant, an increase (decrease) in one patch's expected revenues makes fishing overall more (less) appealing. The results show that responses in aggregate participation are limited by weather conditions. Of the open season days, there are numerous occasions on which weather is prohibitively dangerous, and negative coefficients on weather variables confirm this. In the extreme case, the implied probability of not fishing at the maximum values for each weather variable is 0.999. Hence, with a limited entry program, nature also imposes some limits on the total amount of fishing effort that can exert itself in the system.

In terms of spatial responses, divers are ultimately limited in their abilities to respond to spatially explicit revenue differences by travel distances. These travel distances are determined by a diver's port of origin. However, we know from chapter 3 that divers occasionally switch fishing ports. Thus, the Nested Logit model estimated here puts a lower bound on spatial responsiveness. The next chapter will explore this added dimension of spatial behavior.

The short-run policy simulations provide insight on how marine reserves might perform in the real world. Closing areas with heavy fishing pressure will lead to larger declines in short-run aggregate participation. If there are close substitutes for the closed area, fewer divers will exit the fishery than if there are there are not close substitutes. In the long-run, results will hinge on the extent to which benefits from a closed area spill into remaining open areas and whether these benefits outweigh the opportunity cost of the closure.

fishing effort decreases by approximately 0.2 trips.

Appendix 4-A – Computation of the Nested Logit Elasticities

This appendix details the calculations for the Nested Logit elasticities that appear in Tables 4.2 and 4.3. There are two different elasticity types used in this analysis, participation and location. A participation elasticity is defined as follows for a given regressor x_m :

$$\eta_m^{Go} = \frac{\partial \tilde{p}^{Go}}{\partial \tilde{x}_m} \frac{\tilde{x}_m}{\tilde{p}^{Go}}, \quad (4-A1)$$

where tilde denotes a specific point at which to evaluate. Similarly, a location elasticity is defined for a given regressor in a particular location z_{mj} :

$$\eta_m^{Go,j} = \frac{\partial \tilde{p}^{Go,k}}{\partial \tilde{z}_{mj}} \frac{\tilde{z}_{mj}}{\tilde{p}^{Go,k}}, \quad (4-A2)$$

where $p^{Go,k}$ is the joint probability of participating and visiting patch k . Since the probability of participating in a particular location is the product of two marginal probabilities, 4-A2 can be rewritten as:

$$\eta_m^{Go,k} = \left(\frac{\partial \tilde{p}^{Go|k}}{\partial \tilde{z}_{mj}} \tilde{p}_k + \frac{\partial \tilde{p}^k}{\partial \tilde{z}_{mj}} \tilde{p}^{Go|k} \right) \frac{\tilde{z}_{mj}}{\tilde{p}^{Go,k}}. \quad (4-A3)$$

If $j=k$, then the elasticity in 4-A3 is an own- z_m elasticity. Otherwise, it is a cross- z_m elasticity. For the Nested Logit specification in (4.3) through (4.5), we have:

$$\begin{aligned} \eta_m^{Go} &= (1 - \tilde{p}^{Go}) \beta_m \tilde{x}_m, \\ \eta_m^{Go,k} &= \left(\frac{(1 - \tilde{p}^{Go|k})}{e^I} + \frac{(1 - \tilde{p}^k)}{(1 - \sigma)} \right) \gamma_m \tilde{z}_{mj}, \quad \text{for } j = k, \\ \text{and} \\ \eta_m^{Go,k} &= \left(\frac{(1 - \tilde{p}^{Go|k})}{e^I} + \frac{(-\tilde{p}^k)}{(1 - \sigma)} \right) \gamma_m \tilde{z}_{mj}, \quad \text{for } j \neq k. \end{aligned} \quad (4-A4)$$

Appendix 4-B – Additional Closure Scenarios

Table 4.5
Additional Closure Scenarios

	Baseline Predicted	Close Farallons Predicted	Close Patch 1 Predicted	Close Patch 2 Predicted	Close Patch 3 Predicted	Close Patch 4 Predicted	Close Patch 5 Predicted
No Dive	29078	29079	29078	29224	29165	29168	29461
Farallon Islands	2	0	2	2	2	2	2
Patch 1	0	0	0	0	0	0	0
Patch 2	183	183	183	0	206	186	184
Patch 3	120	120	120	149	0	123	125
Patch 4	135	135	135	141	138	0	165
Patch 5	515	515	515	516	519	537	0
Patch 6	467	467	467	468	469	480	539
Patch 7	779	779	779	780	780	783	799
Patch 8	934	934	934	934	934	935	939
Patch 9	143	143	143	143	143	143	144
Patch 10	0	0	0	0	0	0	0
% Total Reduction in Effort		0.04%	0.00%	4.45%	2.67%	2.76%	11.69%
% Effort from Closed Patch Exiting		69.5%	69.1%	79.9%	73.0%	66.9%	74.4%

	Baseline Predicted	Close Patch 6 Predicted	Close Patch 7 Predicted	Close Patch 8 Predicted	Close Patch 9 Predicted	Close Patch 10 Predicted
No Dive	29078	29399	29660	29814	29171	29078
Farallon Islands	2	2	2	2	2	2
Patch 1	0	0	0	0	0	0
Patch 2	183	183	183	183	183	183
Patch 3	120	122	121	120	120	120
Patch 4	135	149	140	137	135	135
Patch 5	515	574	536	521	516	515
Patch 6	467	0	542	491	470	467
Patch 7	779	832	0	884	790	779
Patch 8	934	951	1017	0	970	934
Patch 9	143	145	156	206	0	143
Patch 10	0	0	0	1	0	0
% Total Reduction in Effort		9.79%	17.76%	22.45%	2.85%	0.01%
% Effort from Closed Patch Exiting		68.7%	74.7%	78.8%	65.4%	63.9%

	Baseline Predicted	Close 7 & 8 Predicted	Close 5 & 6 Predicted	Close 5 & 8 Predicted	Close F + 1-5 Predicted	Close 6-10 Predicted	Close Odd Predicted
No Dive	29078	30518	29866	30203	29889	31236	30265
Farallon Islands	2	2	2	2	0	2	2
Patch 1	0	0	0	0	0	0	0
Patch 2	183	183	184	184	0	183	207
Patch 3	120	121	130	125	0	124	0
Patch 4	135	142	205	167	0	165	177
Patch 5	515	547	0	0	0	646	0
Patch 6	467	591	0	564	576	0	635
Patch 7	779	0	865	906	808	0	0
Patch 8	934	0	958	0	941	0	1070
Patch 9	143	252	147	207	144	0	0
Patch 10	0	1	0	1	0	0	0
% Total Reduction in Effort		43.92%	24.03%	34.30%	24.74%	65.82%	36.20%
% Effort from Closed Patch Exiting		84.1%	80.2%	77.6%	84.9%	92.9%	76.2%

Chapter 5

Port Switching Activity

The previous chapter estimates an econometric model of participation and location choice conditional on the port location of a diver. On any given choice occasion, a diver leaving from Fort Bragg may choose patch 8, while a second diver leaving from Albion may also choose patch 8. These events are not equally likely because the travel distances for these two divers are different. That is, the travel distances are conditional on the diver's port, and the profitability of patch 8 on a given day varies across individuals in the data set according to their ports. The discrete choice model captures these differences in profitability through the distance variable by using the data that denotes an individual's port. Yet, we know from Chapter 3 that individuals sometimes switch ports. Moreover, divers who are switching ports tend to persist longer in the fishery, making them an important subset of the population for performing long-run

simulations. Diver ports are known in-sample, but for simulating policies out-of-sample, we require a predictive model for ports. This chapter builds an empirical model of port location choices that, together with the discrete choice model, can be linked to a bioeconomic simulation of the fishery.

To understand regional concentrations of divers, it is essential that the port model predicts aggregate port shares. Ultimately, we need to know how many divers are in each port at any given time. Having the number of divers in each port allows us to construct the set of choice occasions for simulating out-of-sample with the discrete choice model. Fortunately, the problem is simplified somewhat because the limited entry program in the California red sea urchin fishery constrains the long-run number of divers to 300.¹ Thus understanding the port shares is sufficient to construct the number of choice occasions for each type of choice in the discrete choice model.

Port choice is a different type of discrete decision than the participation and location choices discussed in the previous chapter. For participation and location, the time step is naturally a daily one. Is it worth fishing today or not? If so, is it better to go to patch 1 or patch 2, etc.? Though port choices are also discrete decisions, it is not realistic to apply a daily time step to these decisions. First, it may be infeasible to switch ports every day, particularly if a diver switches from a port in southern California to one in northern California. In the data, port switches are fairly infrequent events. There were 57,550 dives reported in Northern California for which the diver was previously in a northern California port. Of these, only 2,796 were occasions on which the diver

¹ Recall that the program targets 300 divers by issuing only one new permit for each ten retired permits. Over time, attrition reduces the number of permit holders. When the number of permit holders (n) drops below 300, $(300-n)$ new permits are allowed to be issued. Of course, it is possible that there are fewer than $(300-n)$ permit applications when n is less than 300. For the bioeconomic simulations, the model assumes

switched ports from another northern California port (4.9%). We can also check the switching behavior of divers by including southern California and assigning all southern ports as "SOC." Under this definition, a switch occurs if someone moves from southern California to northern California, from northern California to southern California, or from one port in northern California to a different port in northern California. With this methodology, there are 167,042 total dives, and the diver switched ports 4,478 times (2.7%). Table 5.1 records the total number of switches from and to each port. Note the near symmetry of the switching matrix. This suggests that divers may switch on a short-term basis and return to a home port.

Table 5.1
Port Switches

From	To							Total
	ALB	BOD	CRC	FTB	HMB	PTA	SOC	
ALB		26	3	324	19	193	121	686
BOD	24		1	60	32	182	208	507
CRC	3	3		10		7	6	29
FTB	328	68	8		6	527	247	1184
HMB	14	31		9		7	9	70
PTA	194	175	11	525	6		203	1114
SOC	129	233	6	278	9	233		888
Total	692	536	29	1206	72	1149	794	4478

Second, switching ports entails lumpy costs. Not only are there the costs of moving the boat a potentially large distance, there may be long-term lease arrangements with marina owners. Perhaps more significantly is the lumpy cost of moving one's home and family. In general, we would expect an individual to switch ports if the discounted

that the participation component of the discrete choice model well approximates this effect through lower predicted fishing effort.

expected return differential (comparing the new location to the old location) exceeds the cost of switching. That is, a switch will occur if

$$\sum_{\tau=t}^T \delta^{(\tau-t)} E(\pi_{i\tau m} - \pi_{i\tau l}) \geq c_{i,m \rightarrow l}, \quad (5.1)$$

where m and l index ports, $m \rightarrow l$ indicates moving from m to l , δ is the discount factor, π is net rents in a location, and c is switching cost. Note that costs and revenues are subscripted by i to denote individual-specific values. One would expect that switching costs are heterogeneous across the population of harvesters for a variety of reasons. Some individuals have families, while others do not. Divers likely have heterogeneous economic opportunities outside the fishery. What we observe in the data actually requires that expected revenue streams are also heterogeneous across individuals. Specifically, there are days on which at least one individual switches from port A to port B while another individual switches from port B to port A. For instance, on 11/17/88 one diver switched from Albion to Fort Bragg, while another diver switched from Fort Bragg to Albion. Similarly, on 9/1/91 one diver switched from Bodega to Point Arena, while four divers switched from Point Arena to Bodega. Assuming that switching costs are positive, it must be that the expected revenue streams for these two individuals are different.²

Since individuals have heterogeneous switching thresholds and switching is costly, we would expect that port shares respond sluggishly to rent differentials across space. A contemporaneous rent differential is not necessarily enough for an individual to change ports. If the rent differential persists or widens over time, the expected rent

² The proof of this statement is simple. Since costs are non-negative, the revenue differential stream must be negative for the first individual and positive for the second individual.

differential stream would grow and eventually lead to a switch. A partial adjustment model is one way to model sluggish adjustment empirically. In this setting the equilibrium share s^* of divers in each port ($m = 1, \dots, M$) is a function of the expected net rents (Π) in each port and parameters (θ). Following the treatment in Greene (1993), we have

$$s_{mt}^* = f^m(\Pi_t, \dots, \Pi_t; \theta_{m1}, \dots, \theta_{mM}), \quad m = 1, \dots, M, \quad (5.2)$$

or in matrix form,

$$\mathbf{s}_t^* = \mathbf{f}(\Pi_t; \Theta). \quad (5.3)$$

Actual share adjusts to the difference between the current period's equilibrium share and the previous period's actual share. Assuming an additive error term, this leads to the following:

$$s_{mt} - s_{mt-1} = (1 - \lambda)(s_{mt}^* - s_{mt-1}) + \varepsilon_{mt}, \quad m = 1, \dots, M. \quad (5.4)$$

Substituting (5.2) into (5.4) produces the autoregressive form of the model:

$$s_{mt} = \lambda s_{mt-1} + (1 - \lambda)f^m(\Pi_t, \dots, \Pi_t; \theta_{m1}, \dots, \theta_{mM}) + \varepsilon_{mt}. \quad (5.5)$$

Implicitly, this model averages over the heterogeneity that exists across individuals in both their assessments of rent differentials and in their lumpy switching costs.

Modeling Rents and Revenues

Empirically, we do not observe rents across space and time. We assume that expected revenues adequately account for rents because the two measures are highly correlated. Fixed costs that vary across space do not vary across time because they partly involve features of the coastal geography, and variable costs that do change over time are likely to be correlated across space (e.g. fuel costs and wages in other fisheries). Thus changes in revenues likely capture changes in rents across space and time.

The important data for diver decision-making are the *ex ante* expected revenues in a given location, not the *ex post* actual revenues. As analysts, we only see revenue (or catch) histories and choices but do not know the way that these histories map into expectations about revenues (or catch). Various structural and *ad hoc* approaches are possible. Structural approaches, which explicitly model the underlying biological stock, typically are intractable without extremely simplifying assumptions. However, they can be useful when estimation of aggregate industry response and obtaining aggregate biological parameters are the goals. This is precisely what we need in this setting. The *ad hoc* approaches provide more flexibility and are likely to predict better the revenue data. They are also able to model explicitly the decay of information.³ Unfortunately, though the sea urchin data contain actual revenues in different ports at different times, divers do not land product at every port at every time. These gaps are not missing observations but rather limit the class of possible revenue models. For instance, if one uses an average of the last month's revenues in a port as the expected revenue model, then there are months with no data to use for computing expected revenue.

This section proposes a structural model of expected revenues that permits some persistence of information even after the underlying biological stock has changed. A structural model of fishing revenues must link prices, catch, and the evolution of biomass in each fishing port. Suppose that price (p) and hours per fishing trip (h) are constant, and suppose further that harvest is proportional to fishing effort times biomass as in the standard Schaefer (1957) model. Thus, revenues are:

$$R_{mt} = pqhX_{mt} \tag{5.6}$$

³ See Smith (2000) for a lengthy discussion of different expected revenue models.

where X_{mt} is unobservable biomass in location m at time t , q is a catchability coefficient, and h (hours) is the effort variable. Now suppose that biomass evolves according to the following simple process:

$$X_{mt} = X_{m,t-1} - H_{mt} + \bar{\rho}_m \quad (5.7)$$

where H is harvest and $\bar{\rho}_m$ is a mean recruitment parameter. By recursive substitution of (5.7) into itself, we obtain:

$$X_{mt} = X_{m0} - \sum_{\tau=0}^{t-1} H_{m\tau} + t\bar{\rho}_m. \quad (5.8)$$

Using (5.6), we obtain the following equation for catch per trip(y):

$$y_{mt} = qh \left[X_{m0} - \sum_{\tau=0}^{t-1} H_{m\tau} + t\bar{\rho}_m \right]. \quad (5.9)$$

This model is essentially a slight modification of the Leslie closed population model (see Hilborn and Walters, 1992). By adding an error term, one can construct a regression equation with three variables (an intercept, cumulative harvest, and a time trend) and three unknowns (qh , X_{m0} , and $\bar{\rho}_m$).

In reality, catch per trip might persist for some time beyond when the biological stock declines because divers possess information about patches of abundance with more spatial detail than at the aggregate port level. Moreover, the persistence of catch per trip may differ across ports because the amount of fishable area differs. Eventually, divers deplete such localized patches and the structural model accurately reflects the expected catch per trip in each port. The following regression equation captures the structural model with the possibility of catch per trip persistence:

$$\varphi(L)y_{mt} = \beta_0 + \beta_1 \left(\sum_{\tau=0}^{t-1} H_{m\tau} \right) + \beta_2 t + \varepsilon_{mt}. \quad (5.10)$$

That is, catch per trip is a linear function of a constant, cumulative catch and a time trend. Another benefit of this autoregressive specification is that it might purge residual autocorrelation. This is especially important because the cumulative catch variable includes data that are lagged values of the dependent variable, so in the presence of autocorrelation, the parameter estimates are biased and inconsistent.

To estimate the model above, the data were aggregated to a monthly level. The number of dives that generates the catch per trip variable differs across time. As such, we correct for heteroskedasticity, weighting each regression by the number of trips in the month.

Table 5.2 presents results from GLS catch per trip regressions with lags of catch per trip as additional regressors. To be consistent with the Leslie framework, we expect a positive constant, a negative slope on cumulative catch, and a positive coefficient on the time trend. Each specification is also tested for residual autocorrelation by regressing the residuals on the right-hand side variables and lagged residuals and performing a joint hypothesis test that the coefficients on the lagged residuals are zero (as suggested by Greene, 1993, p. 428). The corresponding F-statistics and critical values are also reported in the table. Note that the number of observations varies across regressions, reflecting the fact that some ports have months in which there are no dives. The recruitment parameter accounts for this, since it is the number of months from the beginning of the sample. The time series structure, on the other hand, is motivated by persistence in catch per trip. If no one fishes from a given port for several months, a diver can expect to find at least the same abundance in a local patch whether he returns

the next month or several months later. Thus, the cardinal period is less important than the ordinal period, and the time step for the autoregressive structure is simply the next month for which there is data.

Table 5.2
GLS Structural Model of Expected Catch Per Trip

Coefficient	SOC	HMB	BOD	PTA	ALB	FTB	CRC
Intercept	96.82 (1.06)	3607.34 (8.7)**	2455.42 (7.55)**	913.60 (3.57)**	426.29 (2.55)**	1021.66 (4.52)**	1869.89 (2.14)**
Cumulative Catch	-9.07E-06 (-1.99)**	-0.006142 (-3.81)**	-0.000213 (-6.31)**	-9.32E-05 (2.78)**	-8.05E-05 (-2.09)**	-0.000073 (-4.92)**	-0.010859 (-1.72)*
Time Trend	7.72 (1.86)*	15.27 (1.49)	12.90 (3.84)**	9.03 (2.21)**	4.71 (1.84)*	8.26 (4.67)**	28.32 (1.28)
Y_{mt-1}	0.61 (7.51)**		0.62 (7.85)**	0.66 (6.63)**	0.65 (10.91)**	0.87 (10.99)**	0.52 (4.16)**
Y_{mt-2}	0.21 (2.24)**		-0.23 (-2.97)**	0.04 (0.35)	0.09 (1.73)*	-0.11 (-1.51)	
Y_{mt-3}	0.09 (1.05)						
Observations	143	71	123	116	116	122	34
R-Square	0.916	0.414	0.871	0.888	0.856	0.943	0.838
F (for residual autocorrelation)	2.01	0.97	1.46	1.07	0.90	1.60	2.75
F Critical	2.44	2.52	2.45	2.46	2.46	2.45	2.74

t-statistics are in parentheses under the coefficients.

* indicates significant at the 10% level and ** at the 5% level.

All coefficients in Table 5.2 have their expected sign and nearly all are statistically significant. The test for residual autocorrelation is constructed such that H_0 is no autocorrelation. In all models except the CRC model, we fail to reject the null hypothesis of no autocorrelation. This CRC test statistic is extremely close to the critical value, and this regression is the one for which the most gaps exist.

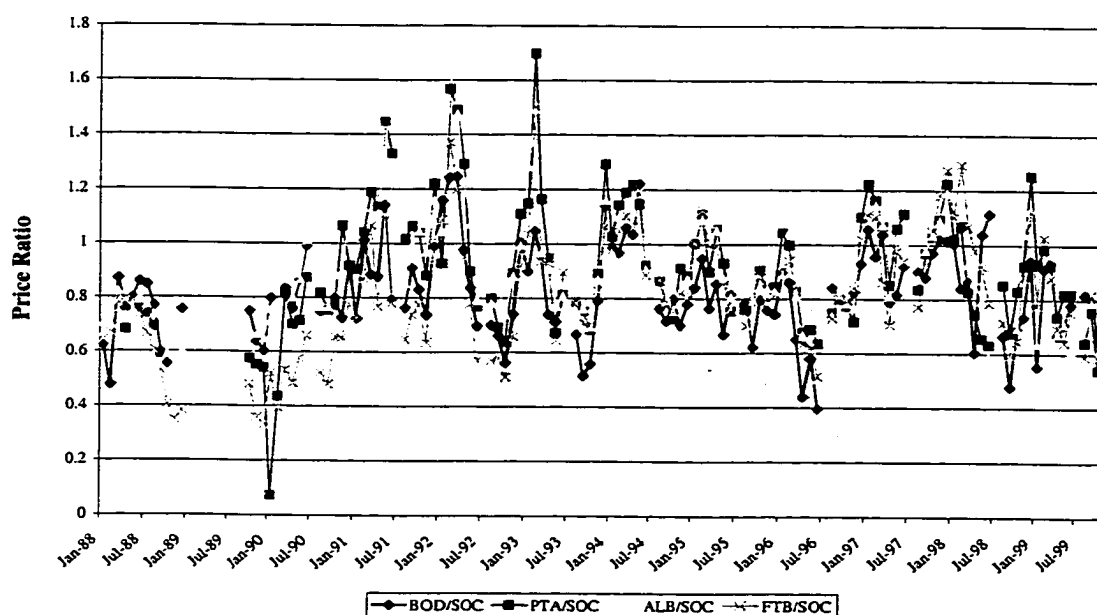
The coefficients in Table 5.2 are used to generate expected catch per trip in each port for each month, which in turn is used to generate expected revenue. On months for which there are no dives in a port, the value is interpolated linearly. Thus, the expected catch per trip in these periods accounts for additional recruitment.⁴ To complete the computation of expected revenues, we need a model for expected price in each location. These prices also have to be port-specific, since there is evidence that prices show some geographic variability. Figure 5.1 shows prices in each of the four main northern California ports relative to the average price in southern California on a monthly basis. The relative prices in different northern California ports tend to move together but do not coincide perfectly. Figure 5.2 plots the coefficient of variation in prices (measured across space) against time. Both figures demonstrate the spatial variability in prices for sea urchin. Over time, the price variability appears to dampen somewhat, suggesting a process of market integration.

⁴ Even though there urchin recruitment to a new cohort may be seasonal, it is reasonable to assume a mean recruitment parameter on a monthly time step because the relevant measure of recruitment is into the size class beyond the minimum size limit. Since urchins age continuously and there is some stochastic component of the process, it is sensible that members of a cohort arrive at minimum size continuously throughout the year.

The model of expected price is simply the previous period's actual average price in that port. When no data are available for a particular port and month, then the expected price is the previous period's expected price.⁵ Expected revenues then are the product of expected catch per trip and expected price.

Figure 5.1

Port-specific Relative Prices



⁵ For HMB and CRC, there are many months for which no price data are available. Regressions were run for these prices fill in these expected prices. The CRC price was regressed on the FTB price (the nearest port) with the following result:

$$P_{CRC} = 0.024458 + 0.696727 * P_{FTB}$$

(0.147) (3.615) $R^2 = .3836$

Note that t-statistics are in parentheses. For HMB, the nearest port (BOD) did not appear to explain variation in the HMB price. The following regression was estimated instead:

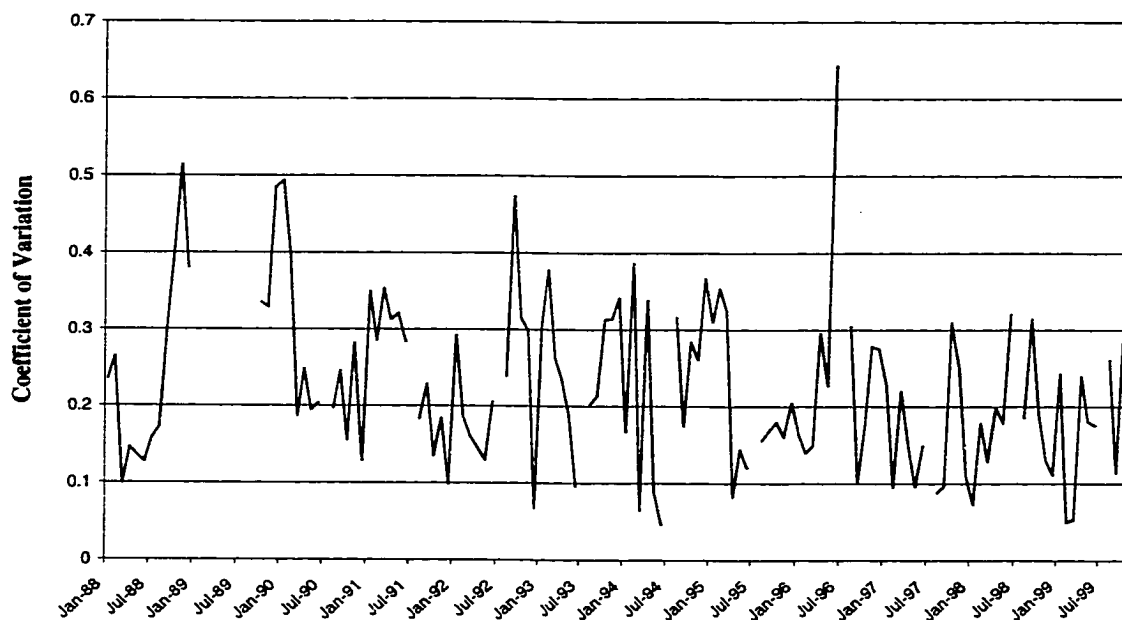
$$P_{HMB} = 0.421685 + 0.396799 * P_{SOC} - 0.243331 * P_{BOD} + 0.227510 * P_{PTA}$$

(3.815) (2.009) (-0.846) (0.827)

$$0.703999 * P_{ALB} + 0.337901 * P_{FTB}$$

(-2.041) (1.095) $R^2 = .1438$

Figure 5.2
Spatial Coefficient of Variation in Prices



Empirical Share Models

At least three different empirical approaches can be used to estimate a model of port shares. For convenience, I will denote these three models as the Logistic Model with Adding Up (LMWA), the Linear Model (LM), and the Logistic Transformation to the Linear Model (LTLM).

The LMWA uses the logistic cumulative distribution function to transform a linear function of exogenous regressors into the unit interval. The share model with the logistic cumulative distribution function is:

$$s_{mt} = \frac{\exp(\mathbf{X}_t \boldsymbol{\beta}_m)}{\sum_{k=1}^M \exp(\mathbf{X}_t \boldsymbol{\beta}_k)} \quad (5.11)$$

In our case, \mathbf{X} would include revenue terms as well as the lagged share interacted with a dummy. The LMWA has two virtues: by assumption the expected shares always sum to one and the expected shares are always in the unit interval. Miller and Plantinga (1999) use this approach to model land use shares. Specifically, they take the natural log of the ratio of the expected shares, restrict one set of parameters to zero, and estimate linear models with OLS. There are several problems with this approach. First, the model loses economic meaning after the parameter normalization. The parameters are defined relative to the normalized set.⁶ Second, the log transformation is problematic in the port data because there are occasions on which port shares are zero for some ports, particularly for HMB and CRC. As a result, the nonlinear form of the model must be estimated. Third, estimating the nonlinear form makes imposing restrictions intractable. In particular, theoretically motivated restrictions would be functions of the data and not just the parameters. This is especially problematic because there is no clear way to assess the effect of the lagged share globally in the model.

The LM is most similar to the partial adjustment model in (5.5). Here, we define the forcing equation as a linear function of revenues with a constant:

$$f^m(\Pi_1, \dots, \Pi_t; \theta_{m1}, \dots, \theta_{mM}) = \alpha_m + \sum_{k=1}^M \gamma_{mk} g(R_{kt}), \quad m = 1, \dots, M. \quad (5.12)$$

The α 's account for non-fishery benefits of being a particular port that do not change over time. Note that it is still possible to estimate the model as linear in the parameters but to nonlinearly transform the data. As such, a function $g(\cdot)$ is included in (5.12), since

⁶ Not surprisingly, none of the expected price parameters are statistically significant in Miller and Plantinga.

the relationship between shares and revenues does not have a definitive curvature a priori. The function $f^m(\cdot)$ in (5.12) leads to a system of equations with each equation defined by:

$$s_{mt} = (1-\lambda)\alpha_m + \lambda s_{mt-1} + (1-\lambda) \sum_{k=1}^M \gamma_{mk} g(R_{kt}) + \varepsilon_{mt}. \quad (5.13)$$

The virtues of this model are that the model can be estimated in a manner consistent with the partial adjustment model above and one can impose restrictions such that the long-run expected shares sum to one. Also, in contrast with LMWA, the economic content of the model is preserved in that shares respond unambiguously to revenue changes across space and time. The main drawback is that the model can predict individual shares outside the unit interval. Since we can impose that they sum to one in the long-run, the practical significance of this problem is that negative shares can be predicted. In the event of a negative share, one would have to make an *ad hoc* adjustment to the predicted shares used in the bioeconomic simulation model.

The LTLM is similar to the linear model, but estimates the share as a function of the inverse logistic transformation of the right-hand side with an additive error:

$$s_{mt} = \frac{1}{1 + \exp\left(-\left((1-\lambda)\alpha_m + \lambda s_{mt-1} + (1-\lambda) \sum_{k=1}^M \gamma_{mk} g(R_{kt})\right)\right)} + \varepsilon_{mt}. \quad (5.14)$$

In using the inverse logistic transformation, this method is similar to LMWA as well. It suffers from the same problem with the lagged share variable, but it preserves the economic meaning of revenue variables. It also has the virtue that all predicted shares are in the unit interval. Arguably the main drawback of this model is that these shares across ports do not necessarily sum to one either in the short-run or in the long-run. Moreover,

imposing that they sum to one is intractable because it requires nonlinear restrictions that are functions of the data.

Ultimately, all three models involve some *ad hoc* assumptions either before or after estimation, but LM is preferable for several reasons. Of course, all models involve an assumption about where the error enters into the problem, so this criterion is not useful for selecting among the models. The main advantage of LM is the ability to impose sensible restrictions. For instance, one can impose that the predicted long-run shares sum to one when there are no revenue differences across ports. One can also impose that the increased share in one equation due to an increase in revenues for that port exactly equals the sum of the decreased shares in other equations due to that revenue change. Neither of these restrictions are possible in LMWA or in LTLM. It is not possible to impose any adding up with LTLM. For LMWA, the adding up is imposed structurally but not in a way based on the economic meaning of the model. Instead, the adding up structure is simply a consequence of using a cumulative distribution function. A secondary advantage of LM is its ease of estimation relative to the nonlinear models.

Another argument against both LMWA and LTLM is that they have the potential to estimate non-stationary processes without a clear means to identify the problem, since the lagged share enters nonlinearly. Because the LM has a single lag, stationarity of the model simply requires that the eigenvalue is outside the unit interval which means that the coefficient on the lagged share is in the unit interval.⁷

⁷ There is not really any reason to expect a non-stationary process in this case because the shares cannot grow without bound. Thus, there is not a compelling reason to test for a unit root in each share series. The concern in the nonlinear models is that the model will estimate a coefficient that implies non-stationarity locally that is a function of the data.

A further argument against both LMWA and LTLM is that multicollinearity in the data make model estimation problematic. In general, all of the revenue variables are positively correlated with one another, which means that all of the regressors are positively correlated except the lagged share. Table 5.3 presents pair-wise correlations for the revenue variables.

Table 5.3

Expected Revenue Correlations

	SOC	HMB	BOD	PTA	ALB	FTB	CRC
SOC	1.000						
HMB	0.275	1.000					
BOD	0.566	0.514	1.000				
PTA	0.550	0.414	0.760	1.000			
ALB	0.636	0.463	0.771	0.832	1.000		
FTB	0.397	0.327	0.507	0.662	0.740	1.000	
CRC	0.573	0.361	0.762	0.747	0.776	0.460	1.000

Such high correlations are not surprising. By construction, the expected revenue terms include prices that we would expect to move together. And, indeed these prices do move together as shown in Figure 5.1. In addition, as harvesters exploit spatial arbitrage opportunities, they simultaneously lower the individual resource stocks across space, which induces correlation in the expected catch per trip variables. LM, of course, will still suffer from multicollinearity, but its presence will not inhibit estimation.

Share Model Estimation: Between northern and southern California

Because there is substantial geographic separation between the northern and southern California fishery, this section proposes to estimate port shares in a two-step process. First, divers are allocated between northern and southern California with one partial adjustment model. Then a separate set of equations is estimated to allocate northern California divers to the different northern California ports. This nesting permits

the speed of adjustment to differ for decisions about switching ports within northern California and decisions about switching from (to) northern to (from) southern California. For the south/north share equation, expected revenues are averaged across all northern ports.

Before turning to restrictions on the linear model, it is worthwhile to explore the functional form for the expected revenue terms. To this end, Box-Cox transformations are run on each port equation. Thus, for each equation in (5.13), a parameter η is estimated to define the $g(\cdot)$ such that:

$$g(R_{kt}) = \frac{(R_{kt})^\eta - 1}{\eta}. \quad (5.15)$$

One can then test η against different values. For instance, if the null hypothesis of $\eta=1$ is not rejected, then the model is linear in variables. Alternatively, if the null hypothesis of $\eta=0$ is not rejected, then the model is linear in the natural logs of the variables. There are seven total equations, one for the north/south share and six northern port share equations. Due to the multicollinearity combined with the highly nonlinear nature of the Box-Cox transform, one model does not converge and three models are singular. However, for the three models that do converge without singularities, we fail to reject the hypothesis of $\eta=1$. Thus, we proceed with the following functional form for the partial adjustment model:

$$s_{mt} = (1-\lambda)\alpha_m + \lambda s_{m,t-1} + (1-\lambda) \sum_{k=1}^M \gamma_{mk} \ln(R_{kt}) + \varepsilon_{mt}. \quad (5.16)$$

There are essentially two systems to estimate: one for the north/south switching and one for the switching within the north. One immediate restriction that we might impose is that the speed of adjustment is the same within each system (but not necessarily

across systems). This suggests that the inertia against switching ports is the same for similar decisions. In general, we would expect that north/south switching entails more inertia than switching within the north because the former decision is more costly in general. A second type of restriction is based on the idea that marginal effects of revenues must add up across equations. When revenues go up in one port, *ceteris paribus*, we expect an increase in that port's share. This increase must come from other ports. Thus, a share increase from a one percent increase in revenue must equal the total share losses from that increase in revenue. That is,

$$\sum_{m=1}^M \gamma_{mk} = 0, \quad (5.17)$$

where m indexes across ports and k is the index for each expected revenue term.

These restrictions identify the model such that one equation must be dropped from each system. For the north/south switching model, that means that there is just one equation to estimate. The reason is that there are six total parameters, three restrictions, and the dependent variables always sum to one. Hence, not dropping an equation creates a singularity in the covariance matrix. Table 5.4 summarizes the results of the north/south switch.

Table 5.4
South/North Switching OLS Model of Port Shares

Variable	Parameter	Coefficient	t-statistic
Constant	α	0.028061	0.151
Lagged SOC Share	λ	0.861212	17.242 **
$\ln(R_{SOC})$	γ_{SOC}	0.056192	1.6678 *
$\ln(R_{NOC})$	γ_{NOC}	-0.050767	-1.908 *

R^2 0.8231

n 111

** indicates significant at the 5% level and * indicates the 10% level.

All coefficients have their expected signs, and λ lies in the unit interval. The interpretation of the revenue coefficients is simply that the share of divers in southern California increases in response to expected revenues in that region and decreases in response to expected revenues in northern California. Interestingly, the expected revenue coefficients are very similar in magnitude. We can test that these coefficients are the same using an F test. The test statistic is 0.0446, the critical value (for 5% confidence) is 3.93. Thus, we fail to reject the hypothesis that the coefficients are the same. Combined with the cross-equation restrictions, this suggests that the southern California share increase from a one percent increase in R_{SOC} is the same as the northern California share increase from a one percent increase in R_{NOC} .

Another noteworthy aspect of these results is that the estimated λ —.86— is close to one. In a partial adjustment model, a λ of zero implies instantaneous adjustment. As λ approaches one, the speed of adjustment is slower. That is, in this model, the optimal shares of divers in northern and southern California respond slowly to structural

changes in the relative profitability of diving in these regions. This result is not surprising given the geographic separation of the regions.

Share Model Estimation: Within northern California

In northern California, there are six ports. The dependent variable is defined as share of northern California divers. There are six equations, forty-eight parameters, five restrictions on λ , and six restrictions on the γ 's. Now suppose that all revenues are the same across ports. We expect that the revenue terms within an equation might offset each other but that real differences in opportunities across ports persist. For the long-run expected shares to sum to one when revenue effects are offsetting, the following restriction must hold:

$$\frac{\sum_{m=1}^M \alpha_m}{(1-\lambda)} = 1, \quad (5.18)$$

which can be re-written as a linear restriction on the α 's and λ . By dropping one equation, we can estimate the parameters using Seemingly Unrelated Regression (SUR). The virtue of SUR in this setting is two-fold: it permits easy implementation of cross-equation restrictions and it is efficient relative to individual OLS estimations because it allows for contemporaneous correlation. The parameters for the dropped equation can be recovered from the restrictions on the γ 's, the λ 's, and the α 's. Table 5.5 contains the SUR results for HMB, BOD, PTA, ALB, and FTB along with the recovered parameters for CRC.

Table 5.5
SUR Results for Northern California Port Switching

Variable	Parameter	Coefficient	t-statistic
Diver share for:			
<u>Half Moon Bay</u>			
Constant	α_{HMB}	0.036008	0.71
Lagged HMB Share	λ	0.436385	10.37 **
$\ln(R_{HMB})$	$\gamma_{HMB,HMB}$	0.009295	2.29 **
$\ln(R_{BOD})$	$\gamma_{HMB,BOD}$	-0.011418	-1.13
$\ln(R_{PTA})$	$\gamma_{HMB,PTA}$	-0.001983	-0.24
$\ln(R_{ALB})$	$\gamma_{HMB,ALB}$	0.00211	0.16
$\ln(R_{FTB})$	$\gamma_{HMB,FTB}$	-0.006573	-0.57
$\ln(R_{CRC})$	$\gamma_{HMB,CRC}$	0.006441	1.40
<u>Bodega</u>			
Constant	α_{HMB}	-0.588058	-4.38 **
Lagged BOD Share	λ	0.436385	-- restricted --
$\ln(R_{HMB})$	$\gamma_{BOD,HMB}$	0.005392	0.50
$\ln(R_{BOD})$	$\gamma_{BOD,BOD}$	0.020226	0.76
$\ln(R_{PTA})$	$\gamma_{BOD,PTA}$	0.038562	1.79 *
$\ln(R_{ALB})$	$\gamma_{BOD,ALB}$	-0.093301	-2.71 **
$\ln(R_{FTB})$	$\gamma_{BOD,FTB}$	0.143569	4.69 **
$\ln(R_{CRC})$	$\gamma_{BOD,CRC}$	-0.00833	-0.69
<u>Point Arena</u>			
Constant	α_{PTA}	0.524777	2.60 **
Lagged PTA Share	λ	0.436385	-- restricted --
$\ln(R_{HMB})$	$\gamma_{PTA,HMB}$	-0.0183	-1.15
$\ln(R_{BOD})$	$\gamma_{PTA,BOD}$	-0.001566	-0.04
$\ln(R_{PTA})$	$\gamma_{PTA,PTA}$	0.068064	2.13 **
$\ln(R_{ALB})$	$\gamma_{PTA,ALB}$	-0.065888	-1.29
$\ln(R_{FTB})$	$\gamma_{PTA,FTB}$	-0.05216	-1.14
$\ln(R_{CRC})$	$\gamma_{PTA,CRC}$	0.000851	0.05

Table 5.5

SUR Results for Northern California Port Switching (cont'd)

Variable	Parameter	Coefficient	t-statistic
<u>Albion</u>			
Constant	α_{ALB}	0.424906	2.99 **
Lagged ALB Share	λ	0.436385	-- restricted --
$\ln(R_{HMB})$	$\gamma_{ALB,HMB}$	-0.013528	-1.19
$\ln(R_{BOD})$	$\gamma_{ALB,BOD}$	-0.056048	-2.00 **
$\ln(R_{PTA})$	$\gamma_{ALB,PTA}$	-0.043831	-1.93 *
$\ln(R_{ALB})$	$\gamma_{ALB,ALB}$	0.103488	2.86 **
$\ln(R_{FTB})$	$\gamma_{ALB,FTB}$	-0.067638	-2.10 **
$\ln(R_{CRC})$	$\gamma_{ALB,CRC}$	0.033086	2.56 **
<u>Fort Bragg</u>			
Constant	α_{FTB}	0.15705	0.77
Lagged FTB Share	λ	0.436385	-- restricted --
$\ln(R_{HMB})$	$\gamma_{FTB,HMB}$	0.019082	1.17
$\ln(R_{BOD})$	$\gamma_{FTB,BOD}$	0.048374	1.17
$\ln(R_{PTA})$	$\gamma_{FTB,PTA}$	-0.064931	-1.99 **
$\ln(R_{ALB})$	$\gamma_{FTB,ALB}$	0.047362	0.90
$\ln(R_{FTB})$	$\gamma_{FTB,FTB}$	-0.011484	-0.25
$\ln(R_{CRC})$	$\gamma_{FTB,CRC}$	-0.027462	-1.48
<u>Crescent City</u>			
Constant	α_{CRC}	0.008932	-- recovered --
Lagged CRC Share	λ	0.436385	-- recovered --
$\ln(R_{HMB})$	$\gamma_{CRC,HMB}$	-0.001941	-- recovered --
$\ln(R_{BOD})$	$\gamma_{CRC,BOD}$	0.000432	-- recovered --
$\ln(R_{PTA})$	$\gamma_{CRC,PTA}$	0.004119	-- recovered --
$\ln(R_{ALB})$	$\gamma_{CRC,ALB}$	0.006229	-- recovered --
$\ln(R_{FTB})$	$\gamma_{CRC,FTB}$	-0.005714	-- recovered --
$\ln(R_{CRC})$	$\gamma_{CRC,CRC}$	-0.004586	-- recovered --

R^2 (System Weighted) 0.357

n 555

** indicates significant at the 5% level and * indicates the 10% level.

Note first that the estimated λ is much smaller than the λ from the north/south system. As such, the speed of adjustment is much faster in the northern California system than in the cross-regional system. It is much less costly to switch from, say, Fort Bragg to Albion than to switch from Fort Bragg to southern California. Thus, the optimal port shares within northern California respond more quickly to structural changes in expected revenues.

For the most part, the expected revenue coefficients are in accordance with our prior beliefs. Of the five estimated own-revenue coefficients, three are positive and statistically significant, one is positive and not significant, and the other is negative and not significant. Many of the off-diagonal revenue coefficients are negative and some are statistically significant. Only two of the off-diagonal coefficients have the wrong (i.e. positive) sign and are statistically significant ($\gamma_{BOD,FTB}$ and $\gamma_{ALB,CRC}$). These aberrations are likely the result of multicollinearity in the expected revenue terms. Overall, in spite of the CRC expected revenue coefficient, the ALB model appears to work best. The intercept and own-revenue coefficients are positive and significant, two neighboring revenue coefficients are negative and significant, a revenue coefficient two ports away is also negative and significant, and a revenue coefficient three ports away is negative though not significant.

The SUR model for northern California also appears to work well for predicting shares. By construction, the shares sum to one. For BOD, PTA, ALB, and FTB, the predicted shares are always in the unit interval. The HMB predicted share is positive on 106 occasions out of 111. The CRC predicted share is positive on 94 occasions out of 111. The minimum predicted share for either port is -0.0048 , so there is little practical

significance in adjusting port shares in the simulation model when a negative prediction results.

Conclusions

An important spatial decision for commercial fishing is the choice of a fishing port. In the California sea urchin fishery, divers take single-day diving trips, and thus port-of-origin ultimately conditions their choices among fishing grounds. Analysis in Chapter 3 showed that individual harvesters sometimes change ports, and in this chapter we discover that such events are relatively rare. Although port switching does not occur as frequently as switching fishing locations, the SUR analysis in this chapter confirms that port choices are influenced by economic considerations. Specifically, aggregate revenue prospects for fishing grounds in close proximity to each port in part determine the share of divers in each port. Therefore, we have further evidence that the spatial distribution of total fishing effort responds to spatial rent differentials.

This chapter also demonstrates that port shares adjust sluggishly, perhaps reflecting the lumpy costs associated with changing one's port. Finally, port shares within northern California respond more rapidly than the aggregate shares of northern and southern California divers. This last result most likely reflects the fact that switching regions is more costly than switching to another port within the same region.

Chapter 6

A Metapopulation Model for Red Sea

Urchins, (*Strongylocentrotus franciscanus*)

The biological literature of Chapter 3 characterizes sea urchins as having patchy habitat, spatial heterogeneity in abundance, and larval transport in ocean currents. This chapter outlines a biological model of an exploited sea urchin population that is both spatially explicit and dynamic. An early version of this empirical spatial model for sea urchins is in Botsford et al. (1993), and the biological structure discussed in the next section matches that of Botsford et al. (1999). The aim of this chapter is to describe this empirical model and, as in Chapter 2, use the reasoning and pedagogical tools of production theory in economics to elucidate the impacts of behavioral assumptions on predictions about marine reserve formation.

The sea urchin population is described as a metapopulation of 11 discrete patches or subpopulations, which correspond to the patches in the behavioral models in previous chapters. Each subpopulation has its own natality/mortality, growth, and recruitment parameters. The subpopulations are linked with a dispersal matrix that can characterize any type of qualitative dispersal pattern. For evaluating likely outcomes in the steady-state, several comparative static results are presented and discussed. Then, using the structure of the biological model, the chapter presents a conceptual analysis of the distribution of fishing effort and its likely impacts on inferences about marine reserves. Finally, bioeconomic simulations are presented under different assumptions about fishing effort and recruitment.

The Biological Model

The metapopulation model based on Botsford et al. (1999) is developed to examine spatial management policies in the red sea urchin fishery, and it consists of 11 discrete size-structured populations (called subpopulations) linked by a dispersal matrix. Each separate subpopulation has a size structure described by a von Bertalanffy equation, so that the size of an individual of age a in patch j is given by:

$$Size_{j,a} = L_{\infty}^j (1 - e^{-k_j a}), \quad (6.1)$$

where j is indexed from 0 to 10 (to match the patch indexes in previous sections), a is indexed as a monthly time index from 1 to 360, and L_{∞}^j and k_j are patch-specific growth parameters. It is important to note that L_{∞}^j is a terminal size, which is a limit in this biological system. We will see below that this implies a maximum amount of biomass for an individual organism.

The model begins computations with a set of initial abundance matrices for each site. The initial abundance matrix in the first period is generally set with all zeros except for the month zero age class, which is read from an initial distribution file.¹ The populations are then aged by advancing the abundance values for each month to the next older month so that $A_{j,a} = A_{j,a-1}$, where A denotes the number of organisms in the cohort. After the populations are aged, the survival of the population along with the catch are computed. Survival is determined by a Beverton-Holt mortality relationship, which embeds both patch-specific natural mortality rates m_j as well as fishing mortality rates f_j if the size is above the minimum size limit L_{limit} . Thus survival of the number of individuals of age a is:

$$A_{j,a} = \begin{cases} A_{j,a} e^{-m_j} & \text{if } Size_{j,a} < L_{limit} \\ A_{j,a} e^{-m_j - f_j} & \text{if } Size_{j,a} > L_{limit} \end{cases}, \quad (6.2)$$

and total catch (C) consists of the sum of harvests of all sizes greater than the minimum size over all patches. That is,

$$C = \sum_{j=0}^{10} \sum_{a=0}^{360} (1 - e^{-f_j}) w Size_{j,a}^b A_{j,a}, \quad (6.3)$$

where w and b are allometric parameters relating weight and length. These parameters essentially convert number of organisms of each size to an aggregate measure of biomass. Note that for a given organism of terminal size, L_{∞}^j , there is a corresponding terminal biomass. This, in turn, implies a maximum possible catch for a given number of organisms. The allometric parameters give rise to the possibility of a non-convex production technology. That is, there are increasing returns to the size of an organism

¹ In the simulations performed in the next section, we begin with non-harvested steady-states. The fishery sample period essentially begins when the northern California resource is almost completely unexploited.

when $b > 1$.² This is the root of a fundamental argument in favor of reserves put forth by biologists. If an on/off harvesting policy, such as a reserve or a rotating spatial closure, is able to shift the size distribution of organisms towards larger ones, the resulting catch may be able to take advantage of these increasing returns. Thus, an on/off policy can improve on a harvesting policy based on spatially uniform effort policies.

The metapopulation model also computes egg production, larval dispersal, settlement, and survival. Egg production is computed after survival has been calculated for each month. If the month is a spawning month, then egg production in patch j is computed with:

$$e_j = \sum_{a=0}^{a=360} \alpha x^\beta A_{j,a} \quad \text{where} \quad x = \begin{cases} \text{Size}_{j,a} & \text{if } \text{Size}_{j,a} > L_{\text{maturity}} \\ 0 & \text{if } \text{Size}_{j,a} < L_{\text{maturity}} \end{cases} \quad (6.4)$$

This equation sums the egg production from each age and size class, where there is only positive production for sizes greater than the size at reproductive maturity. The exponent on the egg production parameter is greater than one, since egg production increases exponentially with size. Thus, we have another source of increasing returns to size of organisms. For a given organism, doubling its size more than doubles its production of eggs, so again this is a justification for moving the size distribution of organisms towards the larger end of the spectrum.³ As a practical matter, shifting the size distribution requires shifting the age distribution because size is a function of age.

After eggs are produced, they are distributed spatially over the system, using a dispersal matrix which can take on a number of different qualitative forms. During the

Beginning at a non-harvested steady-state matches the actual conditions of a virgin fishery.

² To be precise, what is meant here is that "size" is an input in the production of catch. "Increasing returns to size" means that there is increasing returns to the input size.

³ Here "increasing returns to size" indicates increasing returns of organism size in the production of eggs.

months in which larval dispersal is assumed to take place, settlement of larvae is calculated. For each month of the egg production period, a fraction of egg production is presumed to survive and this is distributed via the dispersal matrix from each of the patches to each individual patch according to:

$$\mathbf{s}^{in} = p\mathbf{D}\mathbf{e}. \quad (6.5)$$

This 11×1 vector gives the array of settlement associated with the array of egg production from the system, modified by the survival probability p , and distributed by the dispersal matrix \mathbf{D} . If all of the patches cover all possible dispersal sites, then the rows of \mathbf{D} sum to one. Beyond that possible restriction, \mathbf{D} is general and can characterize a variety of dispersal mechanisms. One particularly important dispersal mechanism is uniform dispersal. This means that the production of larvae in each location re-distribute uniformly over the entire system. As such, we can think of egg production as forming a common larval pool.

The number of larvae that actually end up settling successfully is then assumed to follow a stock-recruitment function, namely:

$$s_j^{out} = \frac{s_j^{in}}{a^{-1} + c^{-1}s_j^{in}}, \quad (6.6)$$

where a and c are parameters. This specification enables the model to simulate various density-dependent larval survival mechanisms in the system, all of which may be patch-specific. Once the settlement is calculated for any given site, the successful settlers become the next period's age zero entry and the growth process starts again. Thus, s_j^{out} is the number of organisms in a new cohort.

Table 6.1 contains baseline values of the biological, economic, and institutional parameters for the model described above. Initially, we set potential spatially varying parameters to be equal across space.⁴ The biological parameters in this table are based on Botsford et al. (1994), Smith et al. (1998), Morgan (1997), Morgan et al. (2000), and Botsford et al. (1999). Estimation of these parameters and biological modeling of the sea urchin population are part of a long-term research program at the University of California at Davis and its affiliated Bodega Marine Laboratory. Raw data on growth increments and size distributions were collected from marked sea urchins and transects at various locations along the northern California coast. Growth and natural mortality were estimated using maximum likelihood techniques. The size limit is the actual size limit for sea urchin harvesting in California. The fishing mortality parameter is a particular value used later in this chapter, but in general this parameter is unknown.⁵

⁴ For the simulations in this chapter, we use the lower value of the recruitment parameter c . In later chapters, we use the higher value so that the calibration of the model matches the actual path of northern California catch.

⁵ Under uniform dispersal, this particular fishing effort coefficient gives rise to a steady-state harvest that matches the steady-state harvest predicted by the bioeconomic model in later chapters that accounts for economic behavior.

Table 6.1
Baseline Parameter Values

Parameter	Description	Value
k	growth	0.24
m	natural mortality	0.09
Linf	terminal size (mm)	118
Llimit	min. size limit (mm)	89
Lmature	min. size of sexually mature organism	60
f	fishing mortality	0.29
w	1st allometric weighting parm.	0.001413
b	2nd allometric weighting parm.	2.68
α	1st egg production parm.	5.47E-06
β	2nd eggs production parm.	3.45
p	survival probability	1.0
a	resiliency settlement parm.	0.005 - 0.05
c	carrying capacity settlement parm.	1.2E+07 - 2.4E+07

Some comparative statics of (6.6) provide insight on when a system has a propensity to be overexploited and hence when a reserve is likely to pay off. For convenience, we drop the subscript j . The parameters a and c are strictly positive and s^{in} is always non-negative. Appendix 6-A summarizes the derivatives. First, s^{out} is increasing and concave in both a and s^{in} . The importance of the latter is that there are diminishing returns to larvae in terms of producing new members of the cohort. Given that new membership in a cohort within each patch is concave in s^{in} , ceteris paribus, uniform dispersal actually maximizes the aggregate new cohort. Second, s^{out} is increasing in c but whether the relationship is concave or convex depends on a and on s^{in} . In general, the relationship will be concave if a is low and c is low relative to s^{in} . Third, the change in the rate of settlement from incoming larvae from a change in a depends on magnitude of a , c , and s^{in} . Specifically, the rate of settlement increases with a if $s^{in}c^{-1} < a^{-1}$. Finally, $\lim_{a \rightarrow \infty} s^{out} = c$, so as a gets very large, the incoming larvae do not

affect the size of the new cohort. This is important because the biological productivity of the rest of the system, i.e. the other patches, becomes less important when a is big. So, a captures the resiliency of the system, or alternatively, the propensity of the system to be overexploited. At high levels of a , the system is highly resilient because new cohorts are replenished even at low levels of larval production.

Now let us combine these results and consider the effects of a marine reserve in the steady-state. If the parameter a is high, then additional larvae do not add much to the new cohort. Thus, we would expect a reserve not to pay off in terms of increased steady-state harvest. This is consistent with the findings of Botsford et al. (1999) using an earlier version of this metapopulation model. Similarly, if s^{in} is high, additional larvae do not add much to the new cohort and a reserve would not be likely to pay off in terms of increased steady-state harvest. There are many different situations that would lead to a high s^{in} for a given patch. If we consider the simple case of uniform dispersal, i.e. a common larval pool, s^{in} is high if steady-state aggregate spawning biomass is high for the system. This would be the case if the system were not heavily exploited and natural mortality were low.

Qualitatively, the size of the new cohort in the steady-state as a function of fishing effort does not have the same curvature over the domain of effort (f). At low levels of exploitation, the cohort function is decreasing and concave in f . Even though lower f corresponds to egg production characterized by increasing returns, the recruitment function is relatively flat. At high levels of exploitation, increasing returns have more of an impact on the new cohort because the recruitment function is relatively steep. Thus, the increasing returns argument that may favor on/off harvesting like a marine reserve is ultimately limited by the carrying capacity for a new cohort.

Distribution of Fishing Effort in the Metapopulation Model

The typical assumption of biological modeling of fisheries is that fishing effort is distributed uniformly over space. We have seen that both the magnitude and spatial distribution of fishing mortality ultimately affect system-wide harvest. This section focuses on the distribution of fishing effort and its effects on aggregate harvest, using the metapopulation model described above. We use a two-patch for analytical tractability and study how the steady-state production surface varies for different fishing mortality values. This analysis has important implications for various assumptions affect predictions about the effectiveness of reserves. In particular, assumptions about the distribution of effort affects conclusions about total harvest differently at different places on the production surface. As a consequence, if analysts assume uniform effort across space when it really is not uniform, they will overstate the productivity of the system in some instances and understate it in others. The conceptual implications of effort assumptions for the performance of marine reserves hinge on three conditions: 1) whether total fishing effort exceeds that associated with system-wide maximum sustainable yield, 2) whether the production set is convex at a particular effort allocation, and 3) whether the iso-effort line through a the allocation of interest intersects the “reserve” axis past the isoquant inflection.

Consider a two-patch version of the (6.1)-(6.6) in which all larvae disperse to the own-patch, so that the patches are only linked through harvest and not through biology. The metapopulation model essentially has Beverton-Holt models within each patch. We assume that fishing gear has knife-edge selectivity. This means that urchins below the size limit are never harvested but all urchins above the size limit are subject to

exploitation. It is certainly a reasonable approximation for sea urchins because divers are required to carry sizing forks. Clark (1990) explains how to obtain steady-state yield from a Beverton-Holt fishery with constant recruitment. The basic idea is that integrating over all age classes in the steady-state is the same as integrating over the life phases of an individual organism. Our model is somewhat more complicated because we need to compute the steady-state recruitment from egg production functions and we have both age and size classes. For analytical convenience, we allow the terminal age for the organisms to be infinite.⁶ Continuing to index patch by j , denoting recruits as R , and patch-specific steady-state harvest (yield) as y , we have:

$$y_j = R_j f_j e^{f_j t_\mu} \int_{t_\mu}^{\infty} e^{-t(m+f_j)t} w(t) dt, \quad (6.7)$$

where $w(t)$ is the weighting function and t_μ is the age at which an organism is first subjected to fishing mortality. From (6.2) and (6.1),

$$t_\mu = -k^{-1} \ln \left(1 - \frac{L_{limit}}{L_\infty} \right). \quad (6.8)$$

From (6.1) and (6.3),

$$w(t) = w [L_\infty (1 - e^{-kt})]^b. \quad (6.9)$$

In principle, biological and oceanographic parameters in the model could be patch-specific, but we set them equal to simplify matters and explore questions about effort distribution. Clearly, the integral in (6.9) will be problematic without the parameter b taking on an integer value. Typically, this parameter is assumed to be 3.0. See Clark (1990) for an example.

⁶ In the empirical model, this age is 360 months. As a practical matter, an infinite terminal age is nearly equivalent because very few organisms survive natural and fishing mortality beyond 360 months.

Finding steady-state recruits involves finding steady-state egg production. We note first that new recruits are simply settlers out, so:

$$R_j \equiv s_j^{out}. \quad (6.10)$$

In (6.6), we have an expression for settlers out as a function of settlers in. With own-patch dispersal, settlers in is simply a fraction of egg production in the patch, which we can assume for simplicity is one. Using the same logic as in (6.7) and substituting for settlers out, the following relationship must hold in the steady-state:

$$e_j^{ss} = \left[\frac{e_j^{ss}}{a^{-1} + c^{-1}e_j^{ss}} \right] * \left\{ \int_{t_{mature}}^{t_u} [L_\infty (1 - e^{-kt})]^\beta e^{-mt} dt + \int_{t_u}^{\infty} [L_\infty (1 - e^{-kt})]^\beta e^{-(m+f_j)t} dt \right\}, \quad (6.11)$$

where

$$t_{mature} = -k^{-1} \ln \left(1 - \frac{L_{mature}}{L_\infty} \right). \quad (6.12)$$

To continue with analytical expressions, suppose that $\beta=2$. We can then find an implicit expression for steady-state egg production as a function of effort and parameters:

$$e_j^{ss} - \left[\frac{e_j^{ss}}{a^{-1} + c^{-1}e_j^{ss}} \right] * \alpha\psi = 0, \quad (6.13)$$

where

$$\psi = (L_\infty)^2 \left\{ m^{-1} (e^{-t_{max}} - e^{-t_\mu}) + (m+k)^{-1} (2e^{-t_{max}} - 2e^{-t_{max}}) + (m+2k)^{-1} (e^{-t_{max}} - e^{-t_{max}}) + (m+f_j)^{-1} e^{-t_{max}} - 2(m+f_j+k)^{-1} e^{-t_{max}} + (m+f_j+2k)^{-1} e^{-t_{max}} \right\}. \quad (6.14)$$

Thus we have an analytical expression for R_j at different values of fishing mortality. Substituting the result into (6.7) and assuming $b = 3$, we can find an analytical expression for steady-state yield in each patch:

$$y_j = wR_j f_j (L_\infty)^3 e^{-m t_\mu} \Gamma, \quad (6.15)$$

where

$$\Gamma = (m+f_j)^{-1} - 3(m+f_j+k)^{-1} e^{-k t_\mu} + 3(m+f_j+2k)^{-1} e^{-2k t_\mu} + (m+f_j+3k)^{-1} e^{-3k t_\mu}. \quad (6.16)$$

In the two-patch system, total steady-state yield is simply the sum of patch-specific yields. So, we can depict the production surface in three dimensions. Throughout this section, we refer to the fishing mortality parameter f and fishing effort to be synonymous. In reality, the parameter is a scaled fishing effort.⁷

Figure 6.1 presents two different views of this production surface for f values ranging between 0 and 1, using the baseline parameters from Table 6.1, and setting $a=18$. The surface is strictly concave at low levels of effort, rising quickly from (0,0) to a maximum around (0.12, 0.12). The surface then drops off sharply and eventually enters a convex region. Viewing this surface as a production set, this suggests that the upper contour set is convex at low values of f and non-convex at higher values. Later we will see the importance of these production set non-convexities.

Figure 6.2 presents two views of the production surface for a higher value of the recruitment parameter, $a=40$. The surface is qualitatively similar to that in Figure 6.1, but the decline from the maximum is much more gradual. Moreover, we see that a maximum occurs at a point further from the origin, about (0.18, 0.18). The maximum is also higher than that depicted in Figure 6.1. This is expected because a higher recruitment parameter means, *ceteris paribus*, each new cohort is larger.

Figures 6.3 and 6.4 depict level sets for the two production surfaces. Thus, we can view these contours as isoquants. In both figures, we see not only the nonmonotonic relationship between f values and production but also the changing shapes of isoquants and how they reflect production set non-convexities. Here it is important to recall that the upper contour sets lie further from the origin for contours before the point of maximum production and closer to the origin for contours beyond the maximum sustainable yield. This figure also reinforces the importance of not assuming free disposal. If we permit free disposal of fishing effort, then the curve never turns down past the maximum sustainable yield.

⁷ The scaling of the recruitment parameter is different than in later simulation modeling because we permit infinite horizon organism life cycles and we are abstracting into a two-patch world. Total harvest is also re-scaled to avoid labels that are in scientific notation.

Figure 6.1

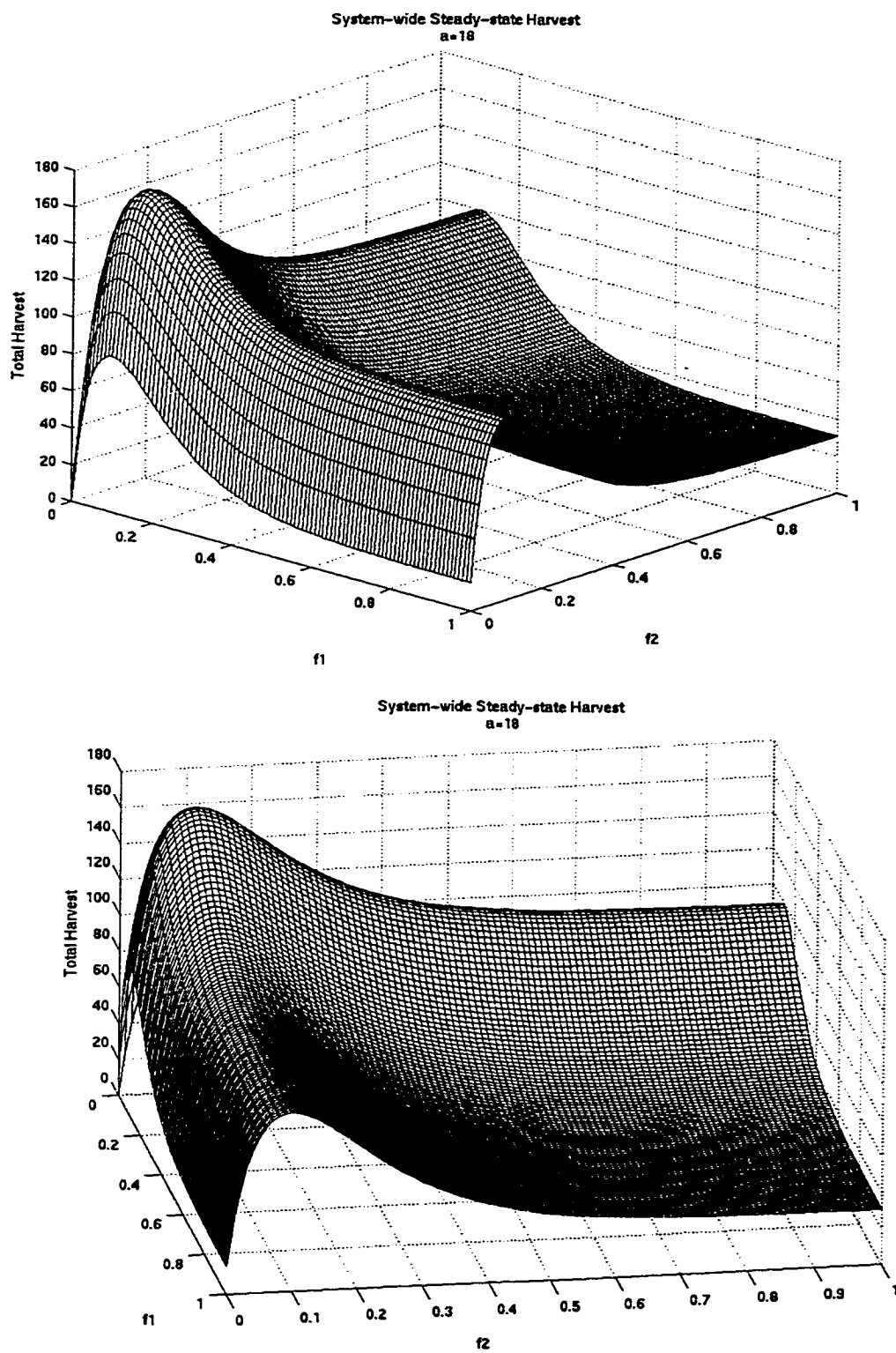


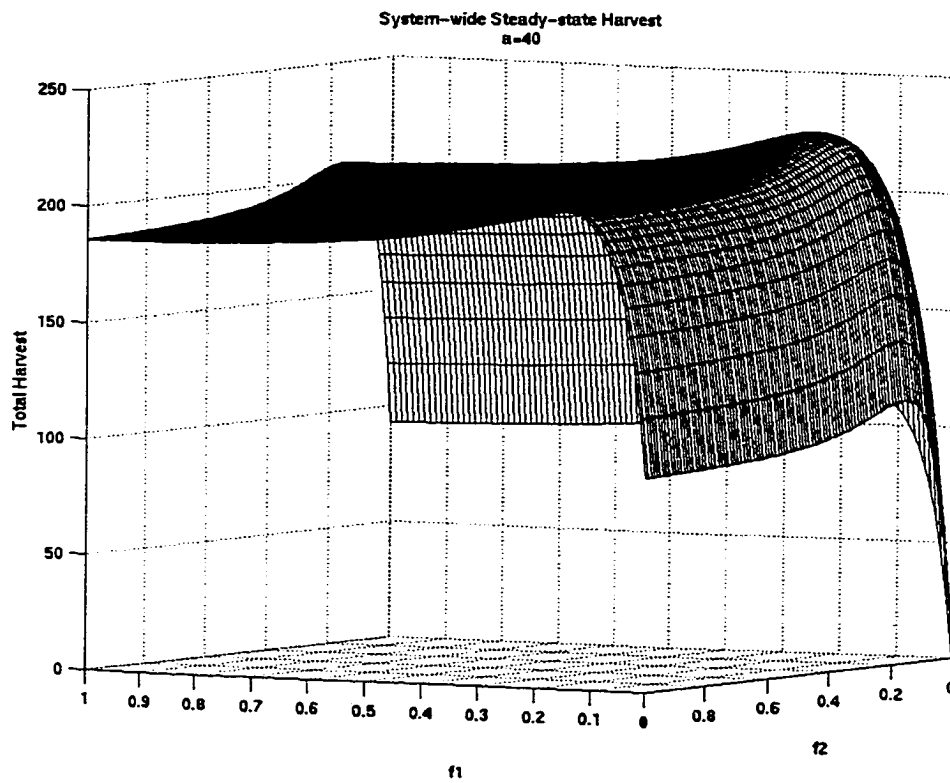
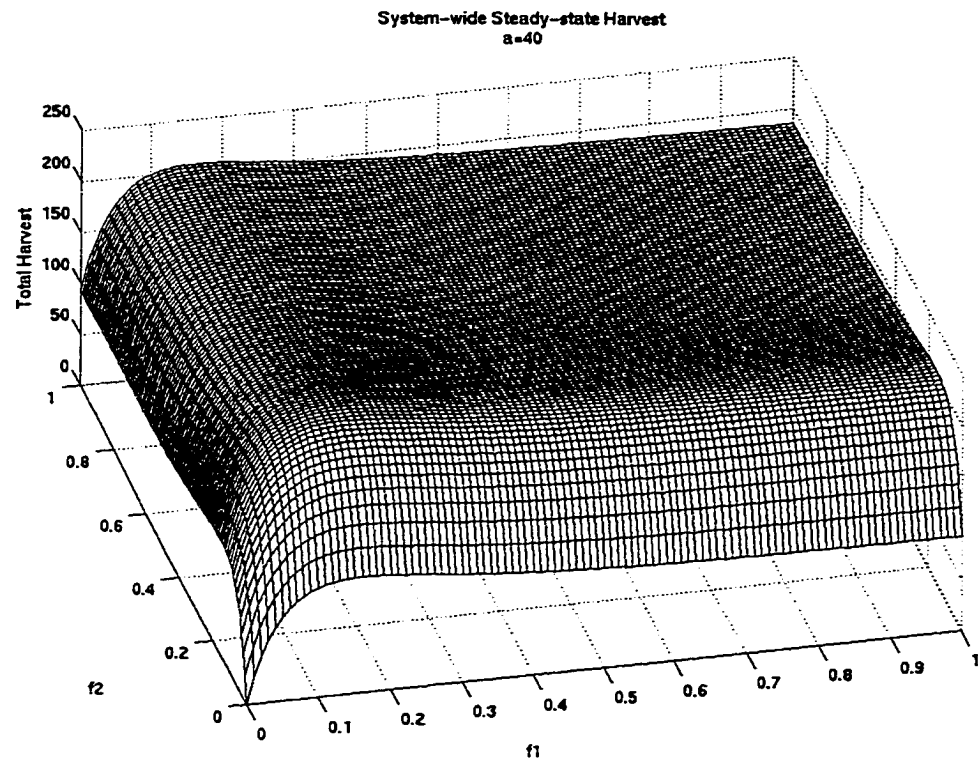
Figure 6.2

Figure 6.3

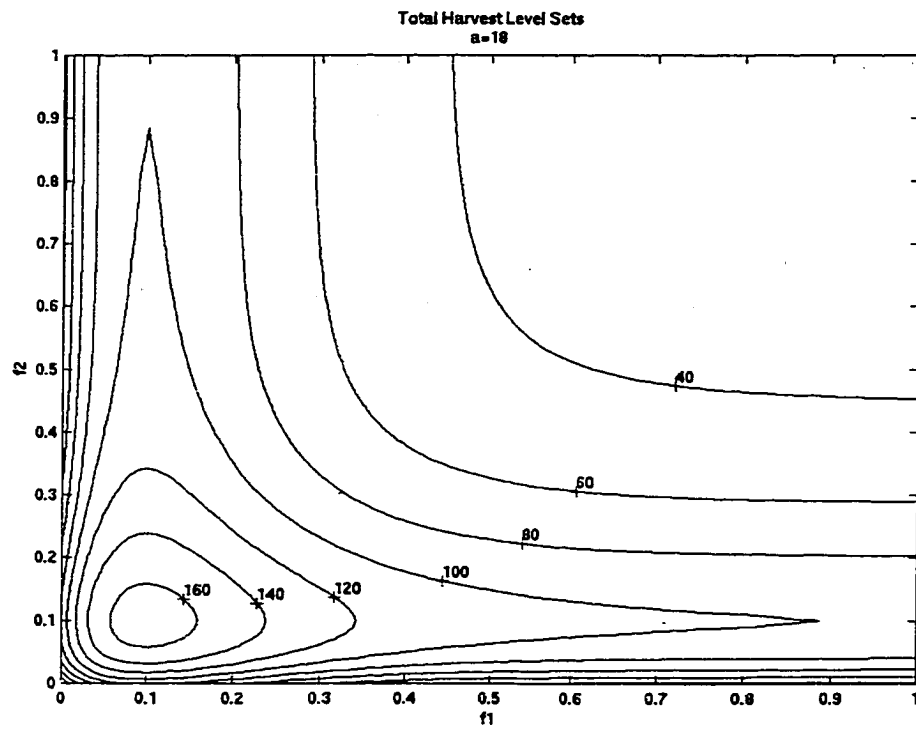


Figure 6.4

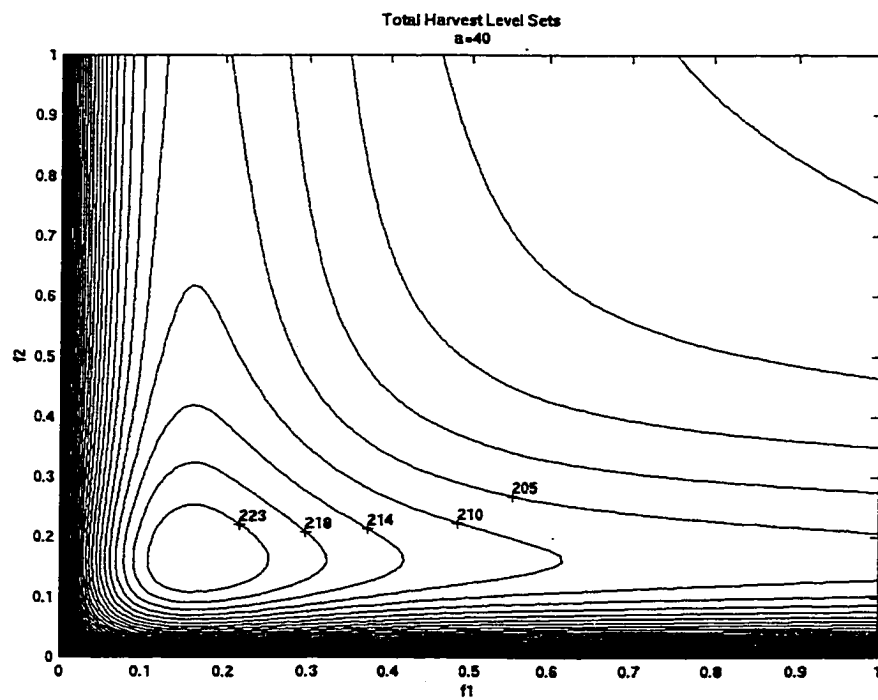


Figure 6.5 and 6.6 zoom in on the level sets, depict more of the contours, add several iso-effort lines (lines along which total system-wide effort is constant), and remove the contour labels for clarity. These figures use a gray scale so that lighter shades correspond to higher elevations on the production surface. We will use this figure to evaluate the importance of the distribution of fishing effort and not just the magnitude of effort. The iso-effort lines divide each figure into four regions. First we define these regions. All regions are bounded by the positive orthant. Next we apply Jensen's inequality to prove two simple lemmas. Finally, the results of the analysis are summarized in four propositions. Note that system-wide yield is $y(f_1, f_2)$, or more concisely, $y(\mathbf{f})$. The definitions of the production regions in Figures 6.5 and 6.6 are:

Region 1

Production is increasing and strictly concave in \mathbf{f} . The boundary is defined by $(f_1^*, 0)$ and $(f_2^*, 0)$ where $f_1^* = \operatorname{argmax}[y(f_1, 0)]$ and $f_2^* = \operatorname{argmax}[y(0, f_2)]$. That is, the boundary is the point on each axis that corresponds to each patch's maximum sustainable yield.

Region 2

Production is strictly concave in \mathbf{f} , increasing for part of the region, and decreasing for part of the region. Along the axes, production is decreasing in \mathbf{f} because \mathbf{f} 's are beyond patch-specific maximum sustainable yields. The boundary is defined by $(f_1^{**} + f_2^{**}, 0)$ and $(0, f_1^{**} + f_2^{**})$, where $[f_1^{**}, f_2^{**}] = \operatorname{argmax}[y(\mathbf{f})]$. That is, the boundary is the point on each axis that corresponds to the total amount of fishing effort at the system-wide maximum sustainable yield.

Region 3

Production is decreasing and strictly concave in \mathbf{f} . The boundary is defined by the plane of inflection between the convex and concave region of the production surface.⁸

Region 4

Production is decreasing and strictly convex in \mathbf{f} .

⁸ In Figures 6.5 and 6.6, the planes depicted are linear, but in general it does not have to be linear.

Figure 6.5
Contour Regions (a=18)

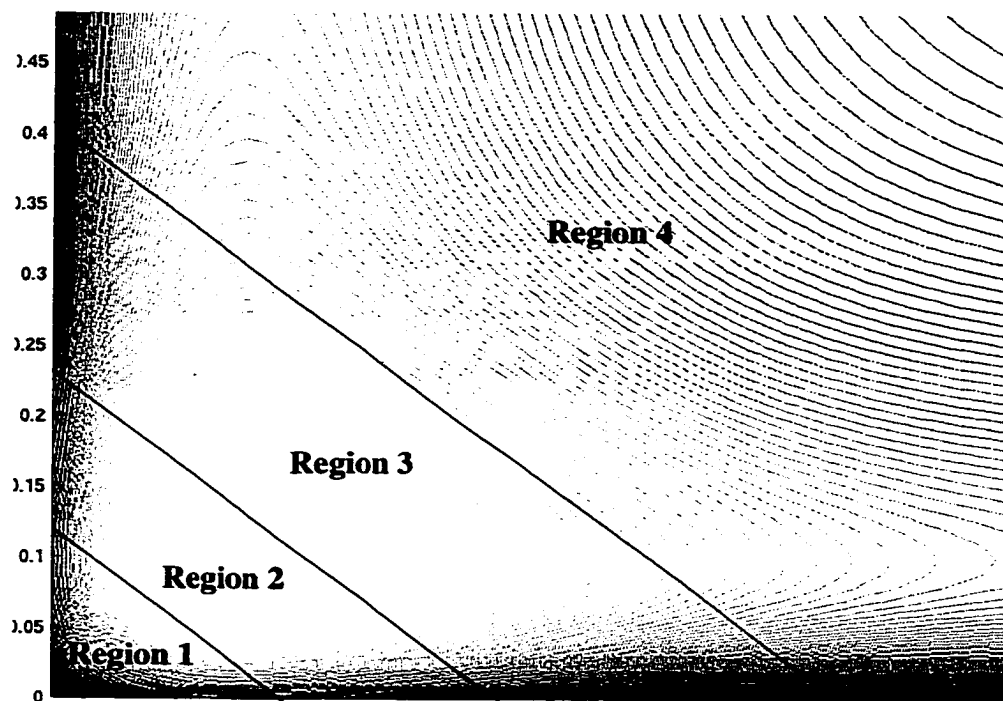
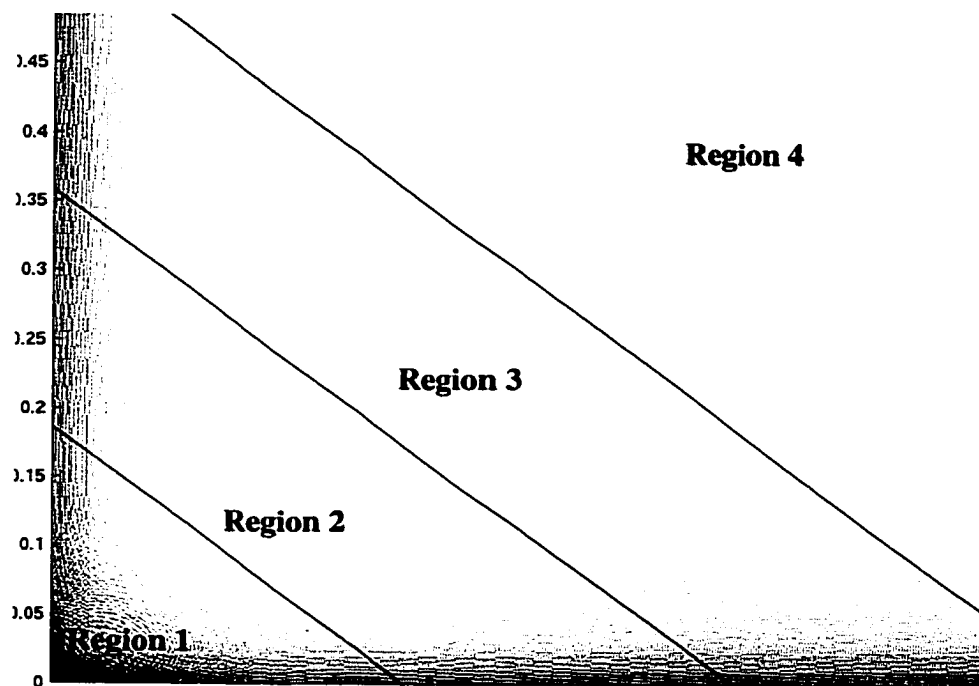


Figure 6.6
Contour Regions (a=40)



In the following two lemmas, we appeal to Jensen's Inequality rather than simply apply the definitions of concave and convex functions. The reason is to present results that are proved easily but generalize to more complicated settings including a larger number of patches and fishing distributions that are continuous across space.

Lemma 1

A uniform distribution of fishing effort maximizes system-wide production in regions 1, 2, and 3.

Proof: Suppose f is a random variable. $Y^{\text{tot}} = y(f_1) + y(f_2) = 2 \cdot E[y(f)]$. For a uniform distribution of effort, $Y^{\text{tot}} = y((f_1+f_2)/2) + y((f_1+f_2)/2) = 2y(E[f])$. By Jensen's Inequality, $y(E[f]) \geq E[y(f)]$. Q.E.D.

Lemma 2

A uniform distribution of fishing effort minimizes system-wide production in region 4.

Proof: Same as Lemma 1 except using the result from Jensen's Inequality for convex functions.

Proposition 1

For a given isoquant in region 1, a redistribution of uniform fishing effort into a reserve allocation decreases production **more** than the same redistribution of any other effort allocation along the same isoquant.

Proof: A reserve allocation corresponds to a point on either axis. By definition, yield is increasing in either f throughout region 1. Since uniform effort maximizes production for a given total effort (from Lemma 1), it has a dual interpretation as the minimum effort needed to obtain a given yield. Thus all other effort allocations for that yield correspond to a higher iso-effort line. The higher iso-effort line intersects the axes further from the origin, i.e. at a higher production level, than the iso-effort line corresponding to the uniform distribution of effort. Q.E.D.

The immediate implication of Proposition 1 is that at low levels of exploitation a reserve is likely to seem worse in terms of system-wide steady-state harvest than it really is. That

is, if analysts assume uniform fishing effort when, in fact, effort is heterogeneous across space, a reserve will appear to be a less favorable option than it really is under the correct effort distribution assumption.

Proposition 2

For a given isoquant in region 2, a redistribution of uniform fishing effort into a reserve allocation decreases production **less** than the same redistribution of any other effort allocation along the same isoquant.

Proof: The proof is the same as the proof for proposition 1, and we note simply that by definition of region 2, points along the axes correspond to lower levels of production as they move further from the origin.

The implication of Proposition 2 is just the opposite of Proposition 1. If managers falsely assume uniform effort, they will infer that reserves are less costly in terms of total yield than they actually are.

Proposition 3

For a given isoquant in region 3, a redistribution of uniform fishing effort into a reserve allocation decreases production **more** than the same redistribution of any other effort allocation along the same isoquant.

Proof: By Lemma 1, uniform effort maximizes production for that total amount of effort. Because production is strictly decreasing in effort within region 3, a non-uniform level of effort that lies on the same isoquant must be a lower level of total effort. Thus, the corresponding iso-effort intersects the axes closer to the origin, i.e. at a higher level of production. Q.E.D.

The implication of proposition 3 on the surface is essentially the same as that of proposition 1. However, on a deeper level, there is a key difference. In region 3, the fishery is heavily exploited. If a reserve seems more costly than it in fact will be, then analysts would be less likely to recommend one. Yet, in this region, the system is closer to being overexploited. So, choosing not to implement a reserve for allocations in region

3 could be more costly if there were an environmental shock to the system. Whereas in region 1, choosing not to put in a reserve is likely the best policy anyway.

Proposition 4

For a given isoquant in region 4, a redistribution of uniform fishing effort into a reserve allocation decreases production less (or increases production more) than the same redistribution of any other effort allocation along the same isoquant.

Proof: By Lemma 2, uniform effort minimizes production. So, any other point on the isoquant is on a higher iso-effort line, which intersects the axes further from the origin. Points further from the origin correspond to lower levels of production. Q.E.D.

The implication is that in a very heavily exploited fishery, falsely assuming that uniform effort produced the observed harvest gives rise to an overly optimistic evaluation of reserves.

To summarize the implications of Propositions 1-4, consider regions 1-4 as qualitatively representing regions of low, moderate, high, and extreme exploitation. Consider a management model that is calibrated to total fishing catch in the system. Then a naïve assumption that fishing effort is distributed uniformly over space has different implications at different levels of exploitation. At low levels, a marine reserve seems more costly than it really is, but there is little practical significance of this finding. The reason is that managers would be unlikely to consider a reserve in a lightly exploited system. At moderate levels of exploitation, a reserve seems less costly than it really is. If managers are extremely risk averse, falsely assuming a uniform effort distribution could lead to support for reserves when they are very costly in terms of total harvest. For high exploitation, the bias of assuming uniform effort goes against implementing a reserve. Finally, for extreme exploitation, the bias of assuming uniform effort favors

implementing reserves. The point, then, is that the typical effort distribution assumption embedded in most biological models of reserve formation, namely that effort is distributed uniformly, can bias the predicted impacts of marine reserve formation in significant ways and in a manner that depends upon the region in which the status quo is presumed to be located.

The Importance of the Spatial Distribution of Fishing Effort: Evidence from the Simulation Model

Without additional assumptions, the model in (6.1)-(6.6) is capable of simulating various policy scenarios and characterizing bioeconomic equilibria. These equilibria are not truly bioeconomic, however, because they are conditional on fixed and arbitrary values for fishing effort coefficients, f_j . That is, fishing effort is not endogenous in the model, nor does it relate to any economic variables that we would expect actually drive effort. The next chapter takes the extra step of endogenizing effort. To demonstrate first how Lemmas 1 and 2 affect outcomes, we run several simulations assuming that total fishing effort is exogenous. Throughout this dissertation, simulation models with exogenous effort will be called NOECON.

Comparing Figures 6.3 and 6.4, we see that the production surface reaches a maximum at higher effort levels for a higher value of the recruitment parameter a . Similarly, the region of non-convexity begins further away from the origin. To simulate the conceptual implications of the various effort distributions, we first run simulations for three different a parameters for a given total fishing effort that is distributed uniformly across the patches. Then we re-run the simulations such that effort in half of the patches is twice the level of effort in the other half of the patches but the total effort in the system is the same.

For all of these simulations, we introduce dispersal, which was not in the conceptual analysis of the effort distribution. To avoid biological heterogeneity across space, i.e. to isolate the effects of behavioral heterogeneity, we assume uniformly distributed dispersal.

Mathematically, this means that:

$$\mathbf{D} = \begin{bmatrix} 1/11 & \cdots & 1/11 \\ \vdots & \ddots & \vdots \\ 1/11 & \cdots & 1/11 \end{bmatrix}.$$

The implication is that all patches contribute to a common larval pool that is re-distributed evenly to the patches in each settlement period.

The results of these simple simulations are completely consistent with the analysis above. For $a=0.1$ (a high level), the uniform distribution of effort leads to a higher steady-state harvest level than heterogeneous effort (484,512 kg compared to 464,525 kg). For $a=0.005$ (a low level), the uniform distribution leads to a lower steady-state harvest level than heterogeneous effort (246,804 kg compared to 269,963 kg). For $a=0.01$ (an intermediate level), the steady-state harvest levels are very close (371,494 kg and 372,067 kg). At a low a , the system is exploited in the extreme region and uniform effort minimizes production. At high a , the system is in the high exploitation region and uniform effort maximizes production. The intermediate a falls near the inflection plane.

Success or Failure of Reserves Using NOECON

There are many ways to evaluate the success or failure of a reserve. One of the most interesting contentions coming from the economic research community is that reserves can lead to a net gain in system-wide steady-state harvest for the fishery (e.g. Holland and Brazee, 1996; Sanchirico and Wilen, 2000). That is, under some circumstances the steady-state harvest with a reserve summed across all open patches

may exceed the steady-state harvest without a reserve summed across all patches in the system. In this first set of numerical simulations, as above we use a uniform dispersal matrix such that there is a common larval pool and assume that effort is distributed uniformly across space, i.e. $f_j=f_k$ for all j,k . We simulate the total system-wide steady-state harvest under various combinations of fishing effort parameters (f) and recruitment parameters (a). These simulations also permit the terminal size of organisms to vary about L_∞ .⁹ Here and throughout the dissertation we use a standard deviation of 10 mm for the terminal size test diameter. In these simulations, we do not include a size limit; there is nothing to prevent a complete stock collapse in the presence of extreme exploitation. The goal is to assess whether a reserve will lead to a higher steady-state harvest than some benchmark allocation of fishing effort and to assess whether the reserve is close to a first best policy in these situations.

Figures 6.7 and 6.8 summarize the results for five values of a (0.001, 0.01, 0.1, 1.5, and 100). We denote one patch as the *reserve designate*, i.e. the experimental patch. We assumed that fishing effort is distributed uniformly across all other patches at a level of $f_j=0.29$. Within the experimental patch, we simulate a range of fishing effort values, including an actual reserve ($f=0$). Figure 6.7 depicts the total system-wide harvest in the steady-state against different values of f in the experimental patch. For clarity, the X-axis is $exp(-f)$. Thus, a reserve corresponds to the extreme right edge of the graph. The vertical line corresponds to an effort level in the experimental patch that equals effort in other patches. Thus, for each curve, we can draw a horizontal line through the intersection of this point and the curve to denote the benchmark system-wide harvest. As

⁹ Using a distribution for this parameter matches the empirical results in Morgan (1997).

we can see from Figure 6.7, a reserve leads to a lower steady-state harvest than the benchmark for high values of a . Also of importance, however, is that decreasing effort from the benchmark level in the experimental patch leads to an increase in total harvest and then a decrease. So, holding effort constant in other patches, total harvest is maximized at some effort level between zero and the benchmark in the experimental patch. As such, we can say that the system is at least in the “high” exploitation region because the level of exploitation is beyond the maximum sustainable yield, but it is not necessarily overexploited.

Figure 6.8 depicts the same simulations as 6.7 on a logarithmic scale. This allows us to resolve the results for low values of the a parameter. For both $a=0.01$ and $a=0.001$, a reserve improves on the uniform allocation. For the smaller a , stocks collapse to extinction at the uniform level of f . Thus, marine reserves can improve steady-state harvest in systems that are heavily exploited and prone to overexploitation. If there are no size limits, a reserve can prevent what otherwise would lead to extinction of the harvested species.

Figure 6.7

Total Harvest for Different Effort Levels in the Reserve Designate

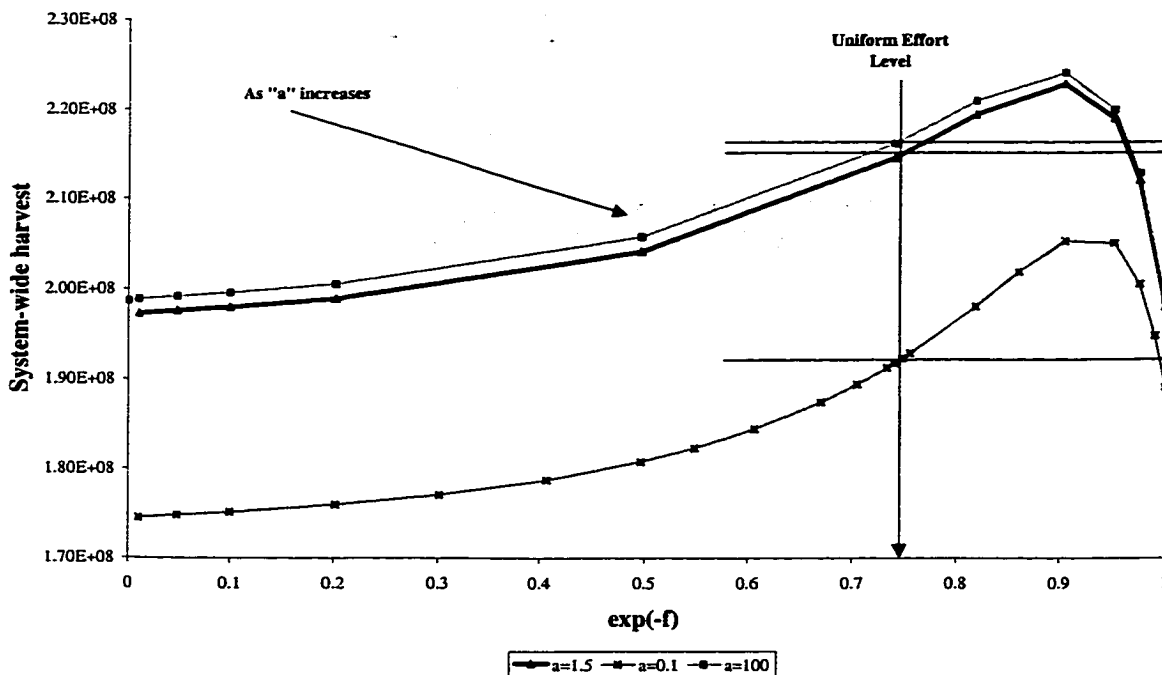
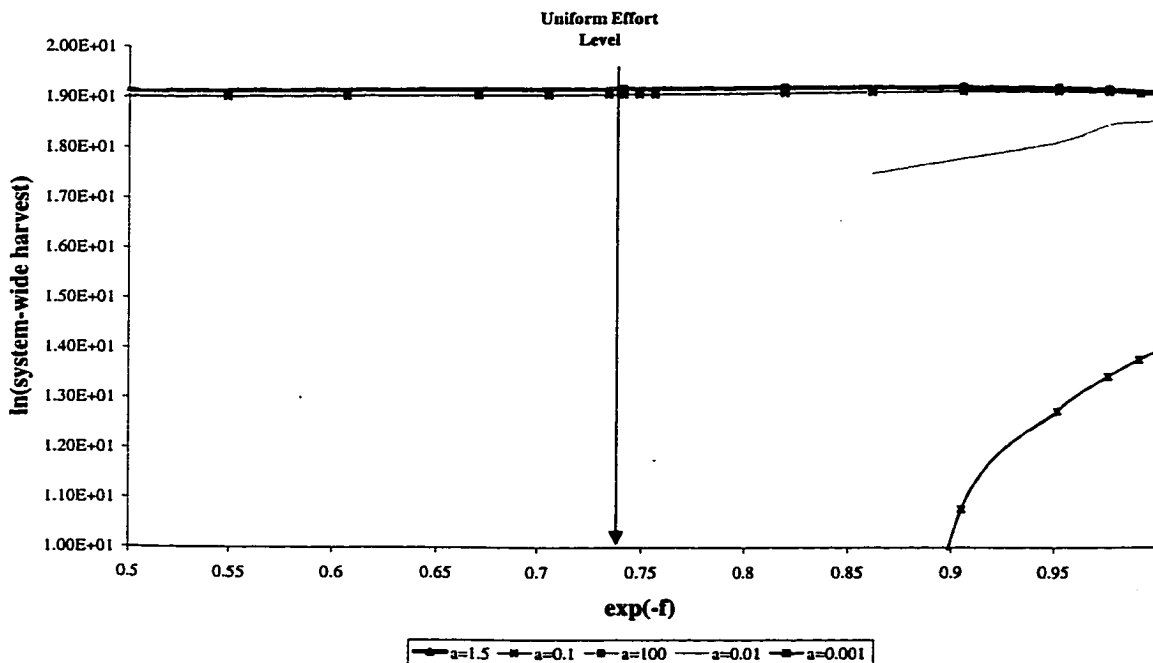


Figure 6.8

Total Harvest for Different Effort Levels in the Reserve Designate
Logarithmic Scale



Conclusions

This chapter has outlined a spatially explicit biological model of sea urchin population dynamics. When urchins are subjected to commercial exploitation, steady-state outcomes hinge on a combination of biological parameters, the intensity of harvest pressure, and the spatial distribution of harvest pressure.

As analysts continue to attempt to understand the implications of various spatial policy options including spatial closures, they will continue to make assumptions about effort, and implicitly about the economic motivations behind effort decisions. The analysis in this chapter demonstrates that the assumed spatial distribution of fishing effort profoundly affects one's inferences about spatial closures. Moreover, these effects vary both qualitatively and quantitatively for different levels of exploitation and for different values of biological parameters that capture the propensity of a system to be overexploited. We have shown that a reduction in fishing effort for one location without creating a reserve can enhance system-wide productivity in some circumstances. In other circumstances, the system is more productive with a reserve. Therefore, generalizations about marine reserves that are based on modeling efforts that do not incorporate sensible assumptions about spatial behavior are likely to be suspect.

Appendix 6-A - Comparative Statics for the Recruitment Equation

$$\frac{\partial s^{out}}{\partial a} = \frac{a^{-2} s^{in}}{(a^{-1} + c^{-1} s^{in})^2} > 0$$

$$\frac{\partial^2 s^{out}}{\partial a^2} = \frac{-2a^{-3} c^{-1} (s^{in})^2}{(a^{-1} + c^{-1} s^{in})^3} < 0$$
(6-A1)

$$\frac{\partial s^{out}}{\partial s^{in}} = \frac{a^{-1}}{(a^{-1} + c^{-1} s^{in})^2} > 0$$

$$\frac{\partial^2 s^{out}}{\partial (s^{in})^2} = \frac{-2a^{-1} c^{-1}}{(a^{-1} + c^{-1} s^{in})^3} < 0$$
(6-A2)

$$\frac{\partial s^{out}}{\partial c} = \frac{c^{-2} (s^{in})^2}{(a^{-1} + c^{-1} s^{in})^2} > 0$$

$$\frac{\partial^2 s^{out}}{\partial c^2} = \frac{-2c^{-2} s^{in} [(a^{-1} + c^{-1} s^{in}) c^{-1} s^{in} - 1]}{(a^{-1} + c^{-1} s^{in})^3}$$
(6-A3)

$$\frac{\partial^2 s^{out}}{\partial a \partial s^{in}} = \frac{a^{-2} (a^{-1} - c^{-1} s^{in})}{(a^{-1} + c^{-1} s^{in})^3}$$
(6-A4)

Chapter 7

A Fully Integrated Bioeconomic Metapopulation Model for Red Sea Urchins

In this chapter, the biological model in Chapter 6 is linked to the models of harvester behavior described in Chapters 4 and 5 by making fishing mortality a patch- and time-specific variable dependent upon the harvester model predictions of diver trips. The linked model is innovative in several respects. First, the model is truly bioeconomic, since it integrates a population model of the urchin with a behavioral model of the harvesting sector so that the equilibria generated are joint bioeconomic equilibria. Thus in any time period, effort distributes itself over space in response to anticipated profits, which depend upon expected catch per trip, price, day of the week, and distance (costs) to each patch from each port. Second, the economic model is also explicitly spatial and dynamic in that behavior responds to changes across space and time. The industry behavior is an aggregation of the individual choices made by divers. Finally, the

economic model of harvester behavior and the biological model are structural. This allows experimentation with spatially explicit and other management policies that have never been implemented without introducing what would amount to nonstationarities in a time series model. Moreover, the model can simulate economic and biological shocks and trace out both short-run impacts, steady-state impacts, and the dynamic and spatial adjustments that take place in transition to steady-states. In the economic model, economic variables determine both the distribution of a given amount of effort over space (as a function of relative profitability) and the total amount of effort associated with each port. Other things equal, as a given patch becomes more profitable, it attracts more effort from a given port, and in addition, the increase in port-wide profitability draws more divers into the fishery. Thus this model predicts not only the spatial distribution of effort, but also the absolute amount of effort. Importantly, effort is influenced by economic as well as biological variables so that, for example, the exchange rate between the U.S. and Japan (in this case the primary market for urchin) can affect effort distribution as much as some major change in abundance induced by biological events.

Following the analyses in Chapters 4 and 5, there are two layers to the economic model. The first layer accounts for individual spatial choice and participation. Similar to Table 4.4, this layer adds up all of the choice probabilities for each individual within each month, and then adds across individuals to arrive at a vector of predicted trips. To convert the daily time step of the nested logit model to the monthly time step of the simulation model, we assign monthly representative values for independent variables that are measured on a daily basis. Predicted trips are converted to time- and location-specific fishing coefficients, f_{jt} , by the following:

$$f_{jt} = (\text{Trips}_{jt})hq, \quad (7.1)$$

where h is hours per trip and q is a catchability coefficient (to be calibrated to the actual fishing data).¹ For purposes of simulation, we fix all independent variables in the discrete choice model except expected revenues. Expected revenues are endogenously determined by catch per trip, which is simply $C_{jt-1}/\text{Trips}_{jt-1}$.² As such, we use the previous month's catch per trip multiplied by exogenous price to determine spatially explicit revenues and hence predicted trips in each location.

In the parsimonious nested logit model, the only independent variable that varies across individuals in the sample is travel distance. Travel distances are not contingent on individuals, per se, but rather on port locations of individuals. The location choice probabilities account for these ports by assigning numbers of divers to each port that correspond to the numbers of active divers in these ports in the year 1996 (the baseline year for the nested logit simulations). Thus for each location and at each month in the simulation model, we compute four different probabilities, one each for Albion, Bodega, Point Arena, and Fort Bragg. Note that all other variables are the same across different individuals, so the stratification of choice probabilities is done only in one dimension. The total predicted trips in each location j in month t is the number of divers in each port

¹ The actual number of hours per trip exhibits considerable heterogeneity in sample, but attempts to explain it have not been successful. It appears to be random, and we assume that averaging across individuals is an appropriate proxy. One specific analysis that is undertaken is to see if hours per trip can be explained by travel distance. The idea is that larger travel distances allow less time for diving. The R^2 value is 0.0017. A statistically significant relationship is found, but it is quantitatively insignificant. The marginal decrease in hours per trip for a 69 mile travel distance was .013. That converts to about one second less diving for one mile of extra travel.

² Prices are exogenous, but the model is set up to simulate exogenous price shocks. Also, the model allows for seasonally varying exogenous prices.

(d_p) times the probability of visiting the patch from that port at t multiplied by the number of choice occasions in that month (o_t) ³:

$$Trips_{jt} = o_t \sum_{p=1}^4 d_p p_{pjt} . \quad (7.2)$$

Implicitly, this model assumes that the number of active divers and the distribution of these divers across ports will not change over the course of the simulation.

The second behavioral economic layer allows for port reallocation following the analysis in Chapter 5. In essence, this approach makes d_p in (7.2) endogenous. The first step is to assess the total number of divers in northern California. With the limited entry program, there are approximately 300 total divers in the fishery in the long-run. Though it is possible that the total active divers could drop below 300, the assumption is that decreases in profitability and the subsequent decreases in participation in the nested logit model would mimic this attrition. So, the key for the simulation model is to allocate the 300 divers between northern and southern California. This is done using the results of the regression in Table 5.4 from Chapter 5 and fixing southern California revenues.⁴ Since we fail to reject the hypothesis that $\gamma_{NOC} = -\gamma_{SOC}$, we use a single revenue parameter here.

The second step in diver port allocation is to allocate predicted northern California divers among the northern California ports. This is done using a stylized version of the regression results in Table 5.5. The reason that the model is stylized is

³ The choice occasions for a given month is determined by the season closure regulations. For northern California, all of July is closed. In June and August, the season is three days per week but closed one week each month. In May and September, the season is four days per week but closed one week each month. In April and October, the season is four days per week, and the rest of the year, all days are open.

⁴ This approach is evaluated over the sample period using the mean southern California revenue per trip and predicted and actual southern California shares in the lagged share variable. Both methods track the

twofold. First, although the port selection model is estimated over six ports and includes Half Moon Bay and Crescent City, the focus here is only on the four main ports of northern California. This is done for simplicity and to reduce the dimensionality of the model, but it is also justified because Half Moon Bay has limited activity and is separated from the rest of the fishery by most of the San Francisco Bay Area. Crescent City has even less fishing activity and is extremely far from the next nearest port. Moreover, activity in Crescent City, if linked to another fishing port for sea urchin may be linked more closely to the sea urchin fishery in Oregon. Second, the model is stylized because not all of the port selection regression results are economically sensible. In particular, some of the off-diagonal coefficient signs are opposite of what we expect. As discussed in Chapter 5, this is likely due in part to severe multicollinearity, since all port-specific revenues are positively correlated. The components of these revenues are correlated as well. Prices are highly correlated, presumably as a result of market integration, and catch per trip variables are correlated as a result of long-term downward pressures on the urchin stocks across the entire region.

The stylized model includes one speed of adjustment parameter (λ_{north}), one constant set equal across ports (α_{north}), and one diagonal or own-revenue adjustment parameter (γ_{north}) in conjunction with symmetric off-diagonals for the substitute ports. The northern California port shares are then:

$$s_{pt} = \alpha_{north} + \lambda_{north} s_{pt-1} + \gamma_{north} \left(\ln R_{pt} - \frac{1}{3} \sum_{p' \neq p} \ln R_{p't} \right) \quad (7.3)$$

We impose the following restriction to match the restrictions in Chapter 5:

share trends. Using actual shares rather than predicted does a better job, of course, but using predicted shares only misses the seasonality of the process.

$$4\alpha_{north} + \lambda_{north} = 1. \quad (7.4)$$

We can now combine the different layers and compute elasticities for trips to different patches with respect to changes in revenues. In Chapter 4, our elasticity calculations adjust distances but do not add across four separate port-specific calculations. Also, these calculations are in terms of probabilities. Here we calculate elasticities in terms of trips. Furthermore, adding the port allocation model permits us to distinguish between short-run and long-run elasticities. Table 7.1 summarizes the results of own-revenue elasticities at three different revenue levels. Appendix 7-A contains details of the calculations.

The first two columns of Table 7.1 contain, respectively, short- and long-run elasticities for the port switching model assuming that there is no adjustment at the patch level. That is, they take patch choice probabilities as given. All locations are inelastic with respect to own patch-specific revenues. This is not surprising given the infrequency of diver port switches. Moreover, trips are inevitably less elastic with respect to own patch revenues than with respect to port average revenues because port average revenues are comprised of multiple patches. The pattern of elasticities also suggests that edge patches are more elastic. The reason is that much of diver spatial adjustment in the interior patches can take place without moving from one port to another. On the outer patches, this is less true.

In the short-run and long-run, revenue increases within a patch draw more effort from other ports and draw effort from southern California. The long-run elasticities are composed of short-run effects modified by the two different adjustment parameters. Recall that adjustment is far more rapid within northern California than between northern

and southern California. The ratio of long-run to short-run elasticities reflects (7-A3) and (7-A4) in Appendix 7-A. This ratio is between $\frac{1}{(1-\lambda_{south})}$ and $\frac{1}{(1-\lambda_{north})}$. Neither set of elasticities changes in response to scaling revenues up or down because (7.3) is linear in logarithms, i.e. the revenue terms cancel from the elasticity calculations.

Columns 3 through 5 contain elasticities that do allow for discrete patch adjustment. Column 3 is the analog to own-revenue elasticities in Tables 4.2 and 4.3 from Chapter 4. It only allows for discrete patch adjustment, conditioning on ports. The reason that these are not exactly the same is simply that column 3 computes separate elasticities for each port and reports numbers that are weighted by the number of divers in each port. In contrast, the Chapter 4 results average the data to arrive at a single elasticity for each patch. Nevertheless, the magnitudes and pattern are essentially the same. Frequently visited patches are less elastic than infrequently visited patches. It is also worth noting that the elasticities become larger as mean revenues increase. Column 4 combines discrete adjustment with short-run port adjustment, and column 5 combines discrete adjustment with long-run port adjustment. Overall, the magnitudes from patch adjustment are greater than those from port adjustment.

Table 7.1

Elasticities With and Without Port Model Trips to Patch j with Respect to Revenues in Patch j

Patch	Elast. 1	Elast. 2	Elast. 3	Elast. 4	Elast. 5
<u>Mean Revenues</u>					
Farallons	0.251	0.508	2.076	2.328	2.584
1	0.098	0.197	0.807	0.904	1.004
2	0.207	0.457	1.607	1.814	2.064
3	0.017	0.068	1.520	1.537	1.588
4	0.126	0.301	1.483	1.608	1.784
5	0.119	0.271	1.066	1.186	1.337
6	0.057	0.127	0.974	1.031	1.101
7	0.111	0.239	0.775	0.886	1.014
8	0.090	0.178	0.699	0.788	0.876
9	0.122	0.241	0.983	1.104	1.223
10	0.233	0.461	1.895	2.127	2.355
<u>1.5 x Mean Revenues</u>					
Farallons	0.251	0.508	3.114	3.366	3.622
1	0.098	0.197	1.210	1.308	1.408
2	0.207	0.457	2.410	2.617	2.867
3	0.017	0.068	2.279	2.297	2.347
4	0.126	0.301	2.224	2.350	2.525
5	0.119	0.271	1.600	1.719	1.871
6	0.057	0.127	1.461	1.518	1.588
7	0.111	0.239	1.162	1.274	1.401
8	0.090	0.178	1.048	1.138	1.226
9	0.122	0.241	1.474	1.596	1.715
10	0.233	0.461	2.842	3.075	3.303
<u>0.5 x Mean Revenues</u>					
Farallons	0.251	0.508	1.038	1.290	1.546
1	0.098	0.197	0.403	0.501	0.601
2	0.207	0.457	0.803	1.011	1.260
3	0.017	0.068	0.760	0.777	0.828
4	0.126	0.301	0.741	0.867	1.042
5	0.119	0.271	0.533	0.653	0.804
6	0.057	0.127	0.487	0.544	0.614
7	0.111	0.239	0.387	0.499	0.626
8	0.090	0.178	0.349	0.439	0.527
9	0.122	0.241	0.491	0.613	0.732
10	0.233	0.461	0.947	1.180	1.408

Elasticity Definitions

- 1) Short-run elasticity with no discrete adjustment.
- 2) Long-run elasticity with no discrete adjustment.
- 3) Elasticity with no port adjustment (short- and long-run are the same).
- 4) Short-run elasticity with both port and discrete adjustment.
- 5) Long-run elasticity with both port and discrete adjustment.

Bioeconomic Simulations of Marine Reserves with Discrete Choice

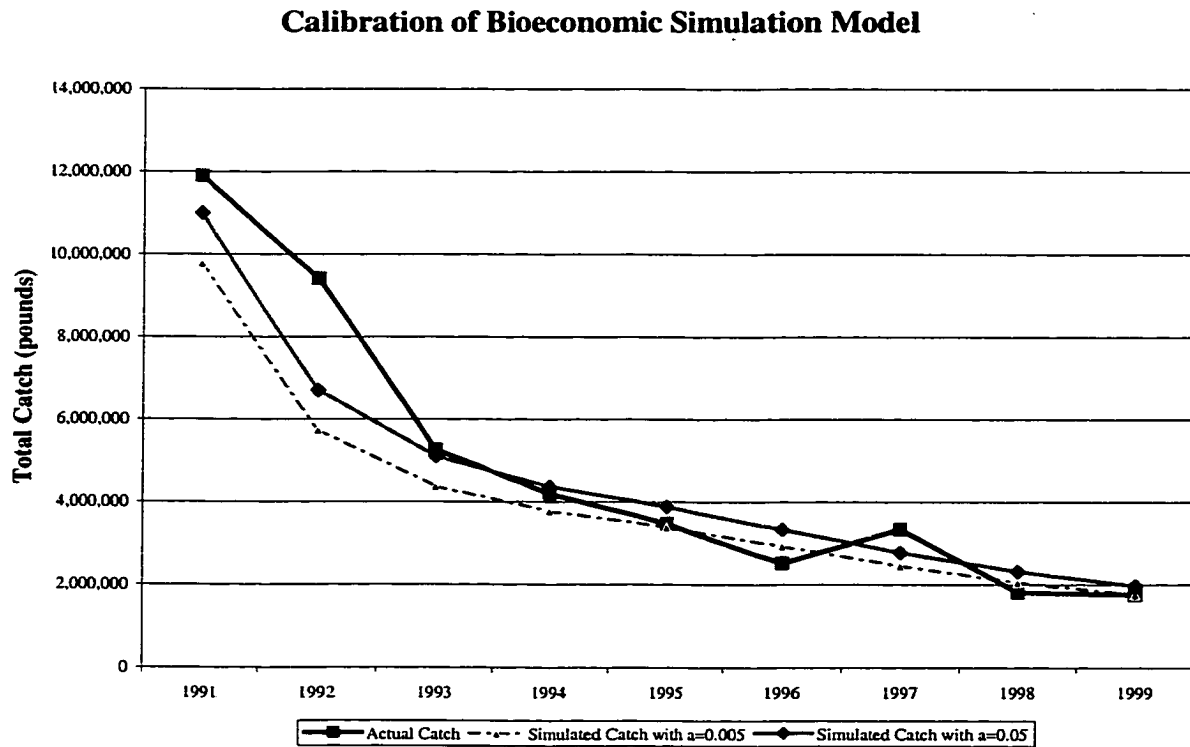
In this section, we consider the performance of marine reserves for the northern California sea urchin fishery using the metapopulation model of Chapter 6 integrated with the discrete choice behavioral model of Chapter 4 without port switching. The next section will add the port switching behavioral layer from Chapter 5. We calibrate the model with a combination of catch histories, urchin stock abundance transects, laboratory data on urchin growth rates, and samples of larval settlement from the Bodega Marine Laboratory.

An important source of ecological uncertainty is the qualitative form of sea urchin larval dispersal. For the dispersal matrix, \mathbf{D} , we use a gyre dispersal pattern that is consistent with the current thinking about California coastal oceanography. In particular, we specify that there are two principal larval pools off the coast of northern California. One is east of Point Arena and the other is east of Point Reyes (just south of Bodega). Urchin larvae are assumed to be swept into these pools through a general north-to-south movement. Then, as a result of upwelling and other oceanographic factors, larvae are spun out of these gyres in a general south-to-north direction, depositing more larvae close to the each gyre and fewer larvae as the distance increases. Botsford (1997) documents a combination of advection and upwelling mechanisms that could lead to a general north-to-south transport of planktonic larvae into such gyres similar to the dispersal pattern assumed here.

Figure 7.1 shows how the metapopulation model combined with the discrete choice behavioral model is calibrated to actual northern California catch. To bring simulated and actual catch together for each value of α , we manipulate the catchability

coefficient, q . The calibration is performed so that the simulations match recent catch histories but also to exhibit a fish-down period for the virgin fishery.

Figure 7.1



Before evaluating the fishery impacts of reserves and discussing different closures scenarios, it is important to reiterate why ecologists are such strong proponents of marine reserves. Biological metrics used to assess marine resource management typically include biomass and egg production. Biomass is commonly used to measure how close a system is to a potential collapse, and egg production is a measure of reproduction, which relates to a system's ability to recover from an environmental shock or other perturbation.

Looking at steady-state size distributions and egg production, Figures 7.2 and 7.3 clearly demonstrate how a spatial closure can promote ecosystem health. Here we analyze patch 8, a heavily fished area off of Fort Bragg. Figure 7.2 depicts the steady-

state size distribution and egg production for patch 8 when it is open to harvesting. When a marine reserve is created in patch 8, Figure 7.3 demonstrates the substantial fecundity of organisms that would be a part of the biomass in a patch protected from exploitation. The exponential increase in fecundity by size is shown by the fact that egg production peaks in a size class that is beyond the size class that has the most number of organisms. In contrast, Figure 7.2, which uses the same vertical axis scales, shows how the size distribution in a fished patch can be truncated back towards the minimum size limit. As a result, the egg production in an exploited patch is extremely low. Since organisms are caught shortly after they reach sexual maturity, they do not have a chance to grow large and produce large amounts of eggs. The total egg production for the patch is the area under the egg line, which we can see is substantially higher when the patch is set aside as a reserve.

Table 7.2 summarizes simulations of the long-run impacts of three different marine reserve locations on harvest and egg production for two different values of the recruitment parameter. In each simulation, the reserve is assumed to be implemented once a fished steady-state is reached.⁵ As we can see from the table, all reserve scenarios simulated lead to **decreases** in steady-state harvest and **increases** in steady-state egg production. This is a mixed performance outcome, and the important policy question is whether the gains in ecosystem health are sufficient to outweigh the economic losses from implementing reserves. Closing patch 8, for instance, leads to discounted revenue losses of between \$2.4 million and \$3.5 million.

⁵ In actuality, catch and egg production approach the steady-state asymptotically. As a practical matter, they get arbitrarily close to an equilibrium after approximately 80 years (960 simulation periods).

Figure 7.2

**Steady-State Size Distribution and Egg Production
Patch 8 when Fished**

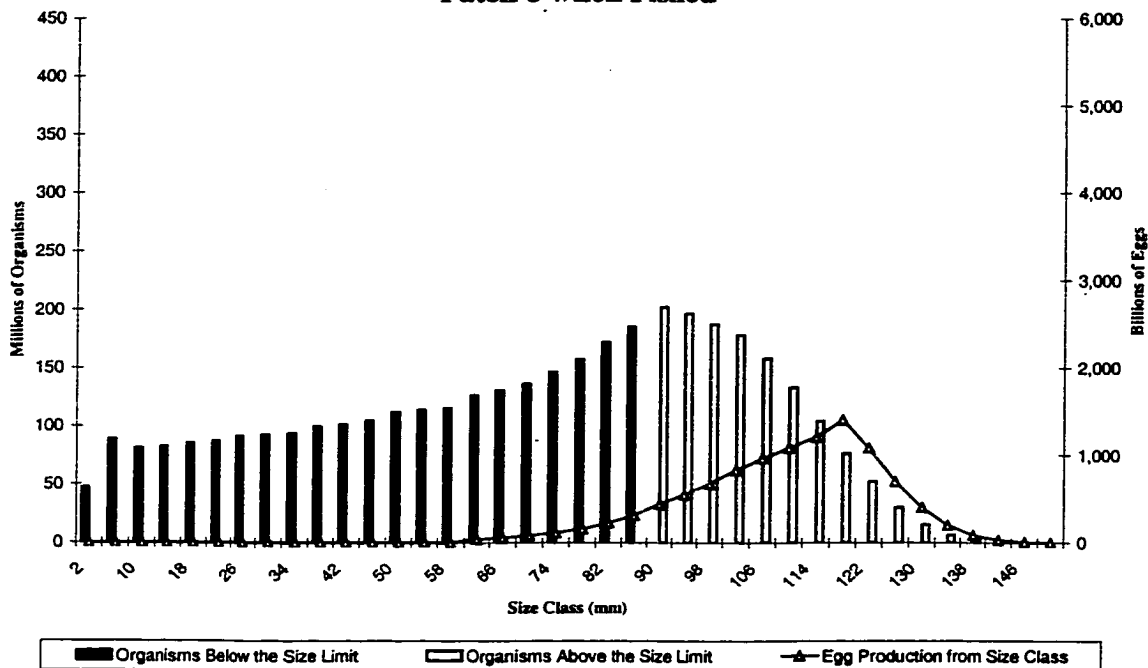


Figure 7.3

**Steady-State Size Distribution and Egg Production
Patch 8 when Closed**

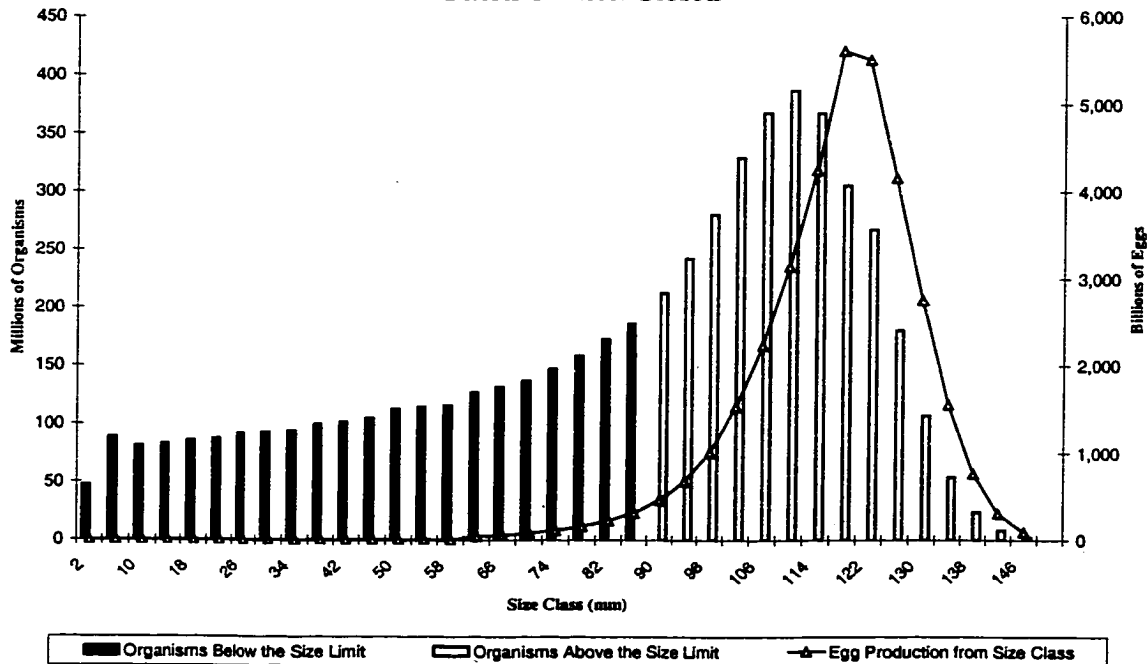


Table 7.2

Economics of Marine Reserves The Northern California Red Sea Urchin Fishery

	Steady-State Harvest (1,000 pounds)	Steady-State Egg Production (Billions)	Discounted* Revenues (\$1000)
<u>a = 0.005</u>			
No Closure	830	1,316	17,440
Close Patch 2	755	1,395	15,291
Close Patch 8	752	1,441	15,074
Close Patch 10	830	1,316	17,004
<u>a = 0.05</u>			
No Closure	1,049	1,770	22,035
Close Patch 2	954	1,840	19,546
Close Patch 8	903	1,893	18,537
Close Patch 10	1,046	1,772	21,438

* Uses a 5% constant discount rate and assumes \$1 per pound of sea urchin.

Figure 7.4

System-wide Harvest with Spatial Closures a=0.005

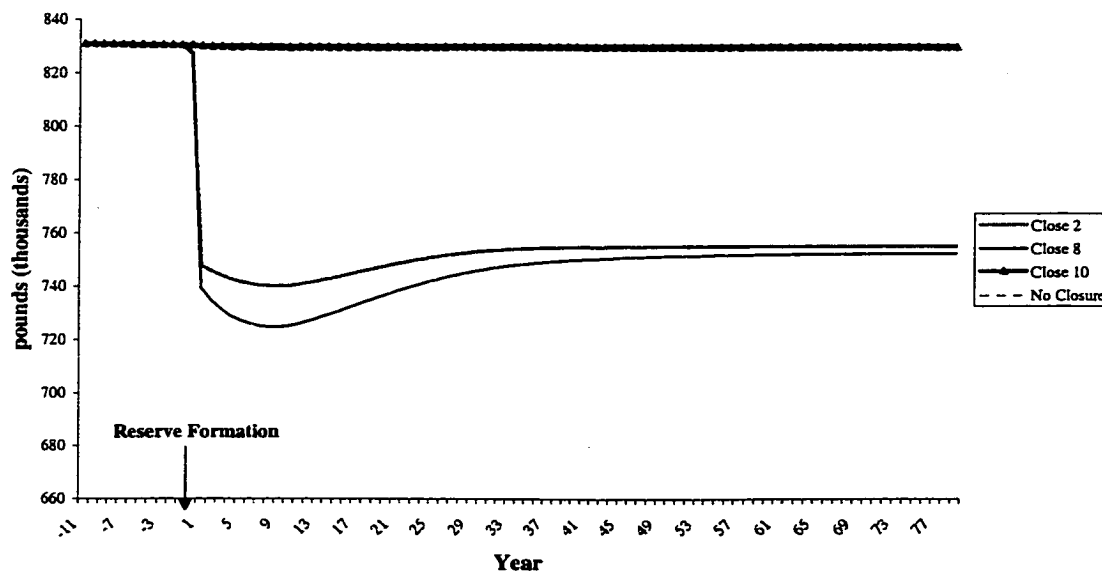
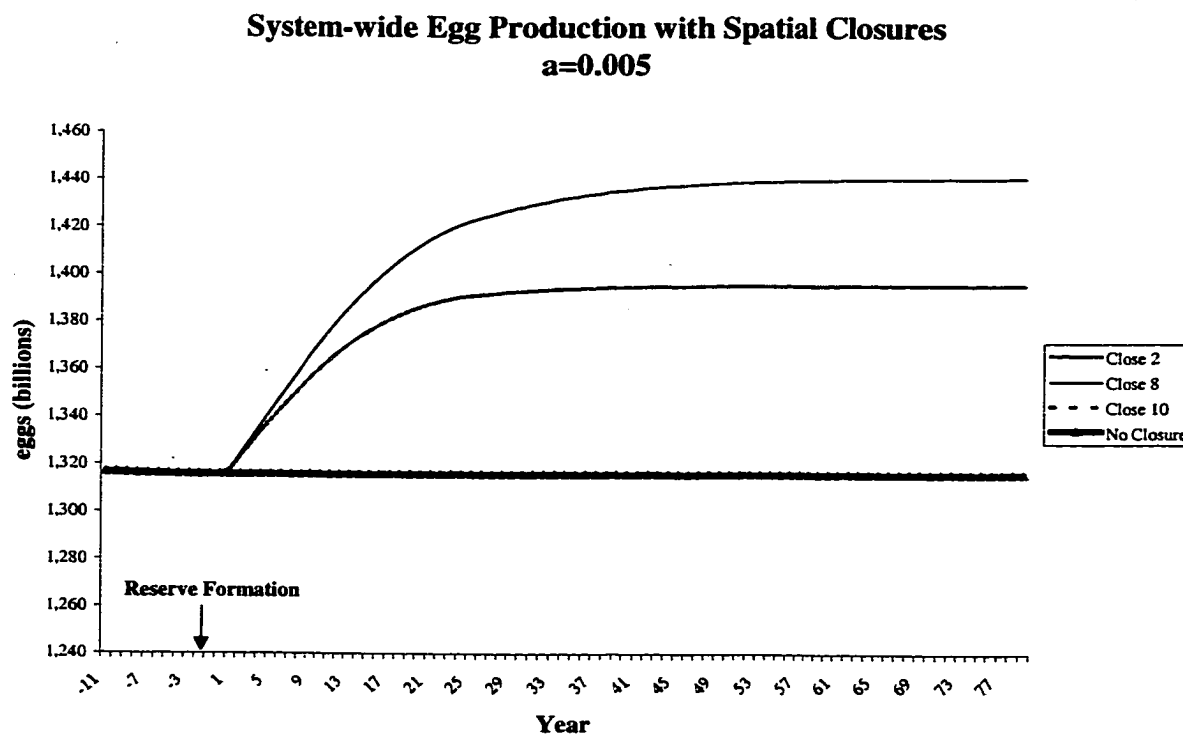


Figure 7.4 depicts the dynamic effects on total system-wide catch of different closures for $a=0.005$. While Table 7.2 shows that none of these closure scenarios give rise to a higher steady-state system-wide harvest, closing patch 2 or patch 8, there is some recovery of total harvest after the initial decline. This is attributable to the dynamics of rebuilding healthy stocks in the closed patch, which export larvae to the remaining open patches. Interestingly, a closure in patch 10 is virtually indistinguishable from the simulation without any closure. The reason is simple. Patch 10 is so lightly exploited that closing it has little impact on catch either initially or in the steady-state. The benefits from increased egg production are similarly small.

Figure 7.5 depicts the dynamic effects on total system-wide egg production of different closures with the value $a=0.005$ for the recruitment parameter. We can view the slopes of these curves as rates of recovery towards some healthier ecosystem. Recovery is more dramatic for a patch 8 closure and the curve remains steep longer in comparison to closing 2 or 10. The reason is that patch 8 is more heavily exploited in the pre-reserve system, so as we would expect, recovery takes longer in a heavily exploited area. As in the case of system-wide catch, we see that the impacts of closing patch 10 are indistinguishable from not closing any patch.

Figure 7.5



Figures 7.6, 7.7, and 7.8 depict steady-state catch comparisons between the baseline case (no reserve) and each closure experiment on a patch-specific basis ($a=0.005$). As expected, the largest changes mostly occur in close proximity to the closed patch. For example, behind the changes depicted in Figure 7.7 (closing patch 8), the largest catch changes in magnitude are in patches 9, 7, and 6, although in percentage terms, the largest change is in patch 10. Moreover, the spatial effects are asymmetric about a closure, reflecting differences in profitability of going to different contiguous areas. Increases in sustainable catch reflect a combination of redistributed effort and increased larval production due to implementing the reserve. However, as Table 7.2 demonstrates, over the whole system the gains in harvest from other patches are not

enough to compensate for the foregone harvest in the reserve patch. Figure 7.8 shows that closing patch 10 actually leads to decreases in steady-state harvests for other patches, albeit extremely small decreases. In essence, closing patch 10 has virtually no impact on the system because it is so lightly exploited. As such, the tiny increase in egg production for the rest of the system is outweighed by the tiny increase in fishing pressure on the rest of the system from reallocating patch 10 effort.

Figures 7.9, 7.10, and 7.11 depict steady-state egg production comparisons between the baseline case and each closure experiment. Again, the largest changes occur in close proximity to the closed patch. These figures also report the percent change in steady-state egg production in the closed patch compared to the baseline. The largest increases are associated with heavily exploited patches because (in the baseline case) steady-state biomass, and hence egg production, is lower in these locations. Again, the changes resulting from a patch 10 closure are insignificant.

The qualitative differences between Figures 7.9 and 7.10 result from the assumed gyre dispersal pattern of eggs. When we implement a closure, fishing effort increases in the nearby patches. This redistribution lowers biomass and hence egg production in the short-run. However, over time, a reserve creates a new infusion of eggs as the stock in the closed patch rebuilds. Now consider the differences between closing patch 2 and closing patch 8. For patch 2, the gyre off of Bodega lies north of the Farallon Islands and the San Francisco Peninsula (patch 1). As a result, the gyre redistributes in a south-to-north manner that does not benefit the Farallons and patch 1. Thus, the redistribution of effort to these locations leads to lower steady-state egg productions. In contrast, patches on both sides of patch 8 are fed by the same gyre off of Point Arena. Thus, these

locations do benefit from the reserve in terms of new settlers. The biomass declines due to increased fishing pressure are more than offset by the new settlers. Hence, egg production increases.

Figure 7.6

**Steady-State Catch Deviations
Close Patch 2 Compared to Baseline Economic Model**

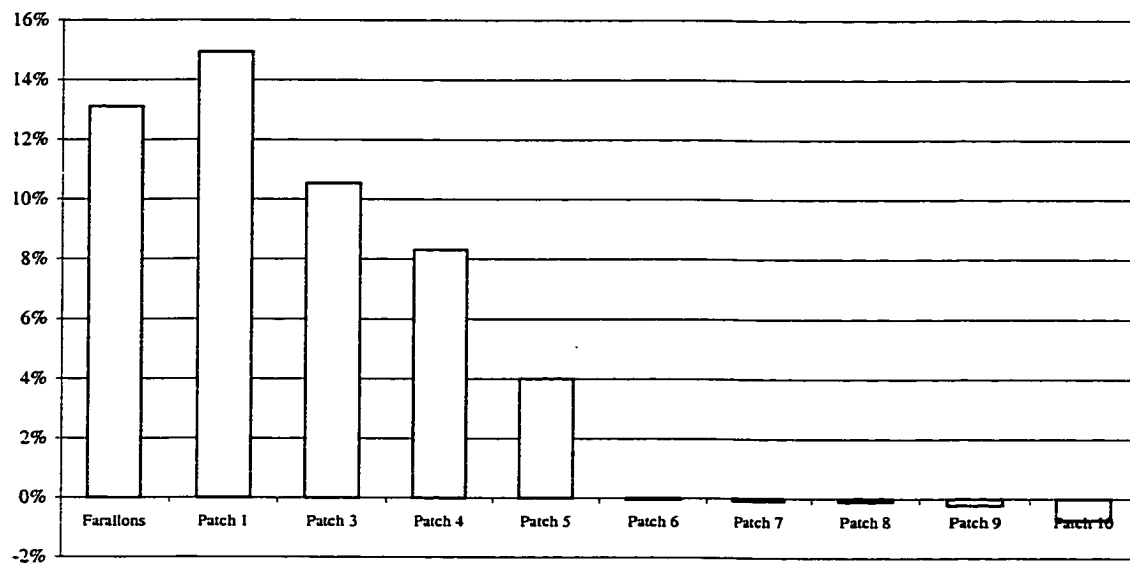


Figure 7.7

**Steady-State Catch Deviations
Close Patch 8 Compared to Baseline Economic Model**

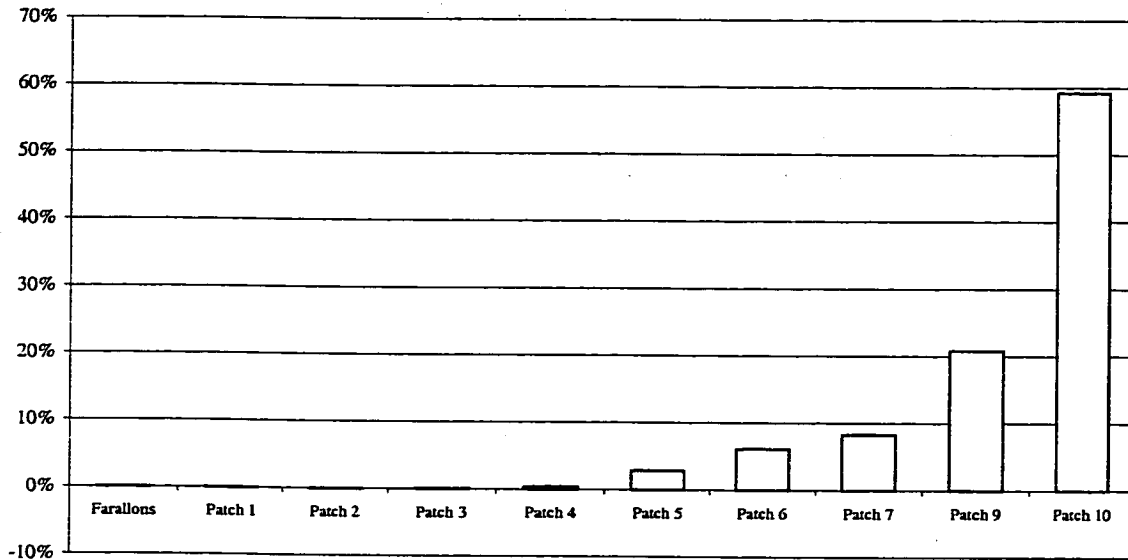


Figure 7.8

**Steady-State Catch Deviations
Close Patch 10 Compared to Baseline Economic Model**

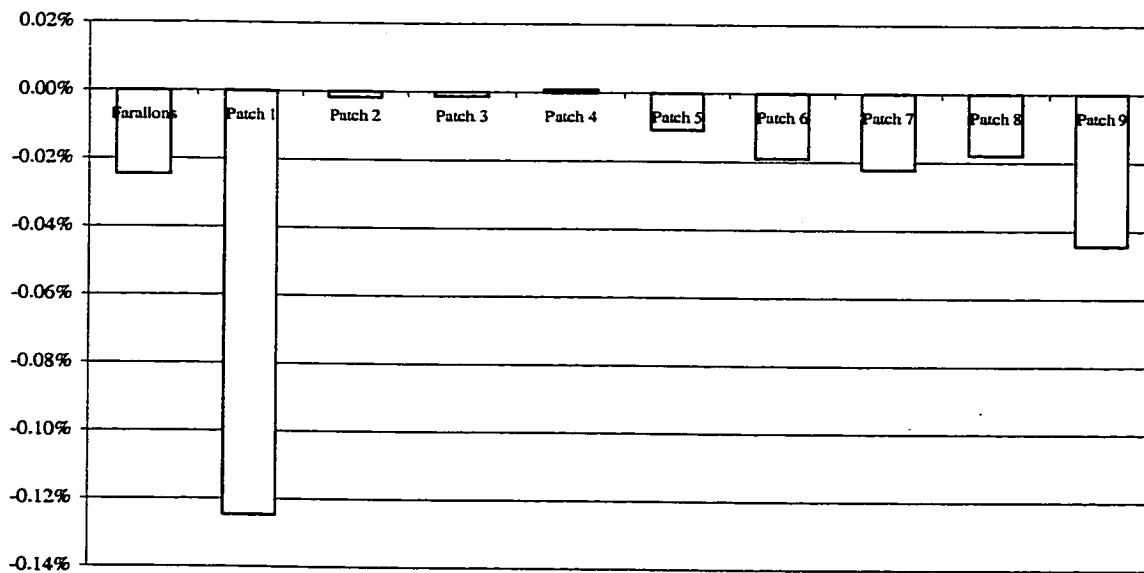


Figure 7.9

Steady-State Egg Deviations
Close Patch 2 Compared to Baseline Economic Model
70% Increase in Patch 2

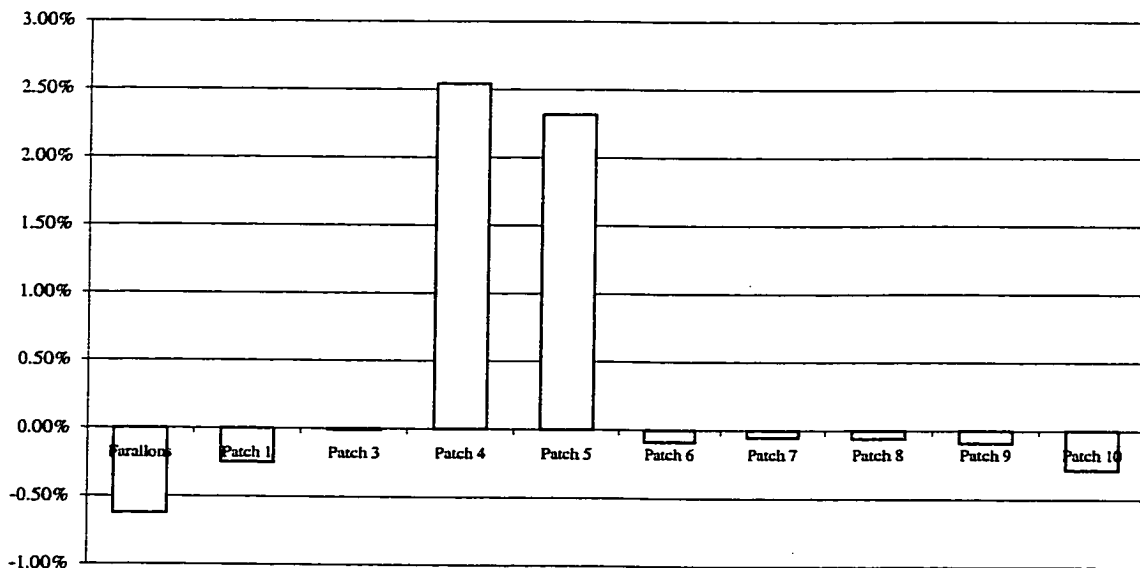


Figure 7.10

Steady-State Egg Deviations
Close Patch 8 Compared to Baseline Economic Model
184% Increase in Patch 8

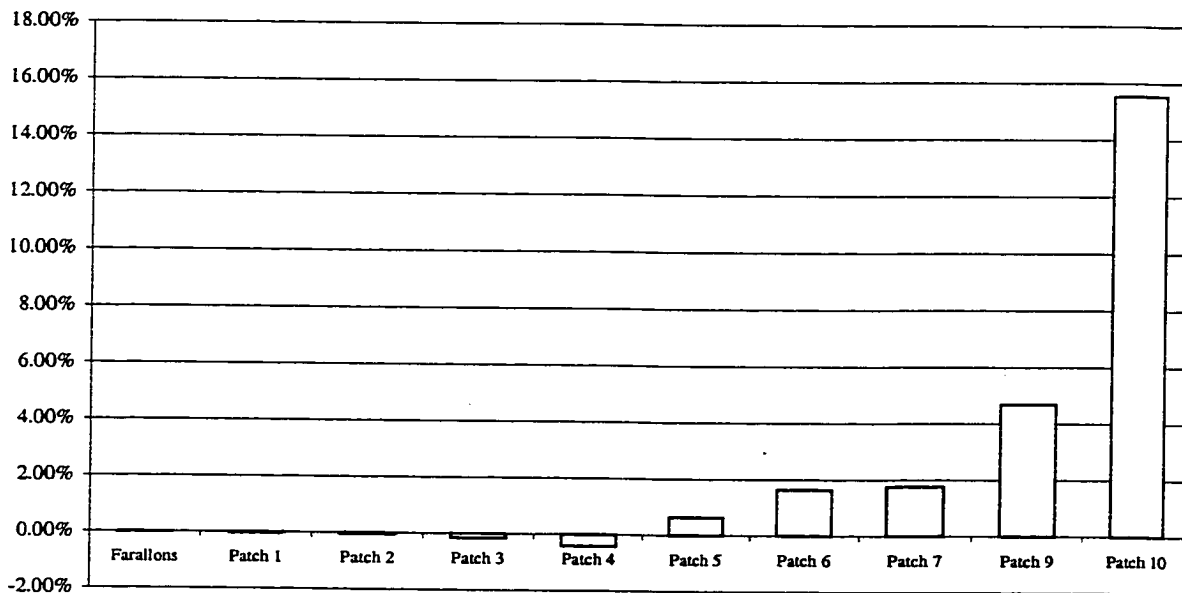
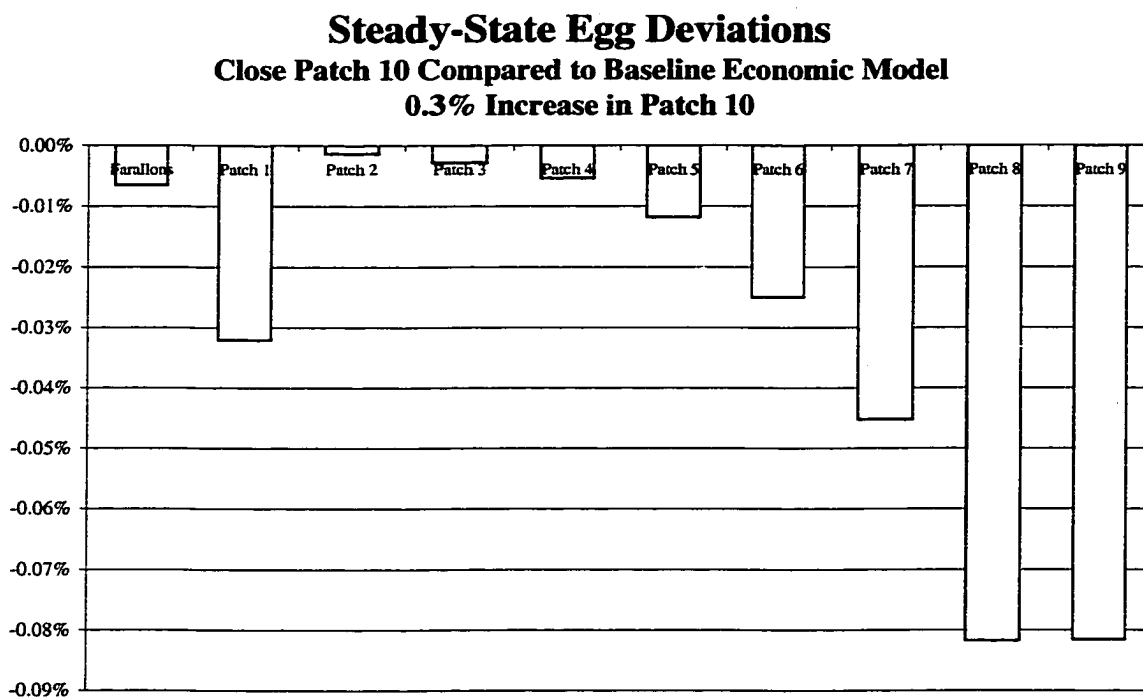


Figure 7.11



Bioeconomic Simulations of Marine Reserves with Discrete Choice and Port Switching

This section takes the bioeconomic model in the previous section and adds further spatial economic responsiveness by modeling the ability of harvesters to switch ports.⁶ In essence, it uses all of our information about spatial behavior combined with our knowledge of the sea urchin biology. The key difference between the simulation model with and without port switching is that the model with port switching computes the endogenous d_p 's in (7.2). We calibrate the model in a similar fashion to the previous section and focus on the lower recruitment parameter ($\alpha = 0.005$). Table 3.5 and the duration model of Chapter 3 both demonstrate the attrition of total active divers in the

fishery over the mid to late 1990s. Moreover, there was considerable entry into the fishery in the late 1980s before the limited entry program was instituted in 1989. Substantial entry and exit behavior thus takes place over the period during which we must calibrate the simulation model. To handle this changing total number of divers, we stop and restart the simulation model several times, changing the default total number of divers to match closely the actual number of participants in the fishery.

Figure 7.12 summarizes the results of the calibration. Once we are past the sample period, we do not know how many active divers will be in the fishery. However, the limited entry program includes a mechanism that will steer the long-run diver count to a target level of 300. Thus, to simulate out-of-sample, we assume that the long-run number of harvesters approaches the limited entry target of 300. Although by 1999 the diver count had not dropped to this level, as long as the limited entry program stays in place, this assumption is reasonable because natural attrition will eventually bring the count to 300.

⁶ Another behavioral layer, which is not considered in this thesis, is the ability of processing capacity to relocate over time. In essence, this would add still more behavioral responsiveness to the system.

Figure 7.12

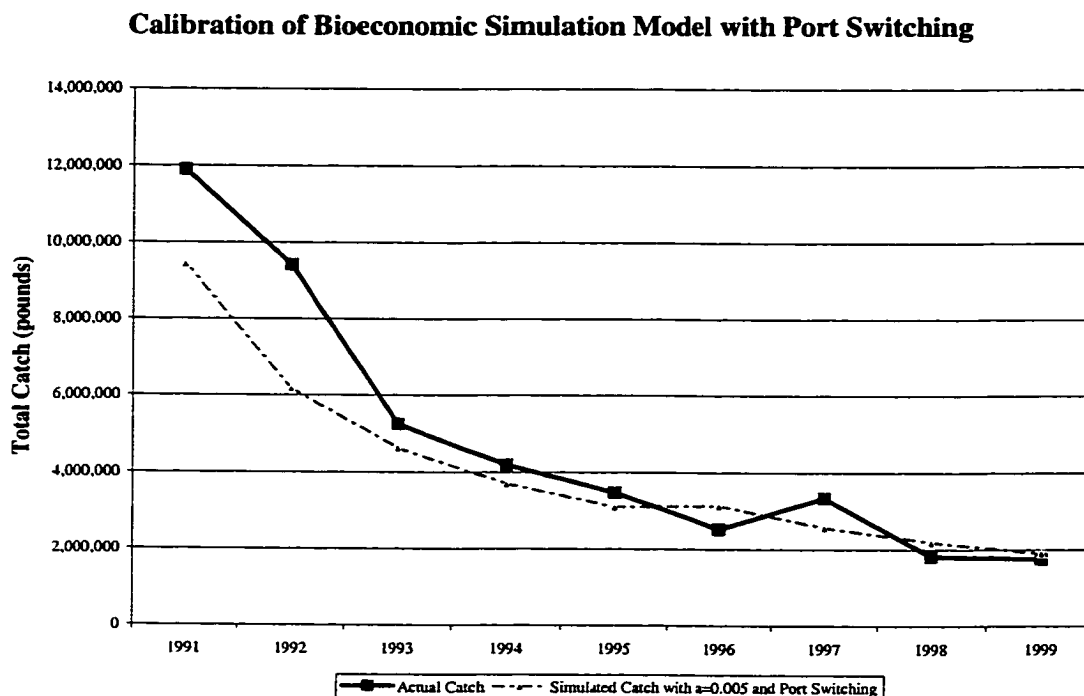


Table 7.3 compares results of the simulation model with and without port switching. The first two lines repeat the results from Table 7.2 for $a=0.005$ and add projected trips per year for each diver, i.e. a measure of per capita participation.⁷ These participation rates for the model without port switching approximately match actual participation of 26.52 per capita trips in 1996 for northern California.

By introducing port switching, the steady-state diver count in northern California declines dramatically from what we observe towards the end of our sample period. There are two driving forces of this predicted trend. The first is that the total number of divers decreases from approximately 400 at the end of the sample period to the limited entry

⁷ These simulations use $a=0.005$ because this corresponds to a less resilient system and would consequently be more likely to produce favorable outcomes for reserves. As such, we are testing whether the

target level of 300 in the steady-state. But this 25% reduction clearly cannot explain the entire difference between 131 and 33 divers. The second driving force is the evolution of state variables in northern California. As the simulation model proceeds beyond the sample period, continued fishing pressure reduces abundance and hence revenue per trip. By fixing catch per trip in southern California, increased pressure on the northern California resource ultimately leads to divers switching to southern California.

The switching behavior within northern California serves to reinforce the evolution of state variables and thus the prediction of a smaller number of total divers in the north. If some patches have high abundance but are difficult to reach from ports that have the most divers, in the model without port switching there is a limited amount of adjustment that will take advantage of these opportunities. High abundance patches might persist because there is a fixed small number of divers with reasonable access to these locations. In contrast, with port switching divers can relocate to ports near high abundance areas and put greater pressure on the resource in these areas. Eventually, this behavior lowers the average abundance in northern California and decreases the overall attractiveness of the region.

Across all three sets of simulations, the per capita trip count decreases when a reserve is introduced. The reason is straightforward. A reserve in patch 8, a heavily fished location, decreases the inclusive value in the nested logit model and hence decreases the overall attractiveness of participating. In the long-run, the benefits from reserve creation are not enough to offset the loss of this fishing alternative, so overall profitability of fishing is lower.

introduction of an additional layer of behavior changes our previous result that reserves do not pay off in terms of increased steady-state harvest.

Table 7.3

**Economics of Marine Reserves with Port Switching
The Northern California Red Sea Urchin Fishery**

	Steady-State N. California Divers	Trips Per Diver Per Year	Steady-State Harvest (1,000 pounds)	Steady-State Egg Production (Billions)	Discounted* Revenues (\$1000)
<u>Discrete Choice Only (a = 0.005)</u>					
No Closure	131	29.9	830	1,316	17,440
Close Patch 8	131	25.3	752	1,441	15,074
<u>Port Choice and Discrete Choice (a = 0.005)</u>					
No Closure	33	57.8	638	1,627	13,400
Close Patch 8	36	47.2	576	1,692	11,660
<u>Port Choice and Discrete Choice (a = 0.005) - 50% Decrease in S. Cal. Revenues</u>					
No Closure	83	37.9	802	1,399	16,846
Close Patch 8	89	31.2	728	1,495	14,683

* Uses a 5% constant discount rate and assumes \$1 per pound of sea urchin.

The long-run consequence of port switching in this model is reduced aggregate harvesting pressure on the northern California resource. As a result, egg production is considerably higher than in the simulations without port switching. However, the total harvest and discounted revenue predictions are also lower. This suggests that the system as a whole in the steady-state is more lightly exploited than the exploitation level corresponding to the system-wide maximum sustainable yield. If we return to Figure 6.1, the steady-state effort levels implied by both simulation models with behavior (discrete choice and both discrete choice and port switching) are close to the origin. That is, the system is in a region in which increased effort climbs the hill rather than slides down it.

The port switching model simply lands the system closer to the origin than without port switching.

The extreme predicted decline of northern California divers in the port switching model is partly an artifact of the assumption of fixed southern California revenues. At the outset, this assumption seemed reasonable because southern California catch per trip appears more stable in the sample period than northern California catch per trip, suggesting perhaps that southern California is already near a harvested steady-state.⁸ We would expect, however, that a major influx of northern California divers would decrease abundances in southern California. To assess this possibility, simulations are run with a 50% decrease in southern California catch per trip and hence revenues.

Clearly, the reduction in southern California revenues supports corresponding increased fishing pressure on the northern California resource, as indicated by the decreased egg production. There is also a dramatic increase in number of divers in the north, although the results of the 50% reduction still do not lead to a steady-state harvest that is as large as the model without port switching.

In all cases, with and without port switches, a marine reserve in patch 8 reduces discounted revenues and steady-state harvest but increases egg production. The discounted present value revenue cost of a reserve ranges from \$1.74 million to \$2.36 million, the largest cost being in the model without port switching. The key policy question is whether the gains in system-wide egg production and other ecological benefits outweigh foregone harvest and hence revenue. Although costs are largest for the model without port switching, the egg production benefits are also largest in this case. This

⁸ We would expect the price component of revenues to affect both southern and northern California revenues similarly, so the focus is on catch per trip.

suggests an essential tradeoff that exists for levels of exploitation below the system's maximum sustainable yield. Any marine reserve will increase egg production, but these increases will be larger for more heavily exploited systems.

Can a Marine Reserve in the Northern California Sea Urchin Fishery Pay Economically?

The simulations in Table 7.3 suggest that responsiveness to economic incentives may reduce the likelihood that marine reserves will pay off in terms of increased harvest. When we incorporate more behavioral flexibility, divers exit the northern California fishery because returns decline in the long-run. Even with a reduction in southern California returns, the predicted aggregate pressure on the northern California resource is not sufficient to give rise to a steady-state harvest increase.⁹

In Table 7.4, we consider more dramatic changes in the economic environment of sea urchin harvesters. Specifically, for each model, prices are doubled and the participation rate is manipulated exogenously to create conditions expected to be more favorable to a reserve.¹⁰ A price increase of this magnitude could result from a demand shift for sea urchin in Japan, a change in the U.S./Japanese exchange rate, or a combination of both.¹¹ A large exogenous increase in participation suggests that opportunities for urchin divers outside of the urchin fishery decline substantially,

⁹ A more extreme case would be a total collapse of the southern California fishery. We do not consider an exogenous collapse of southern California here, but the next paragraphs consider other extreme exogenous shocks and their impacts on the performance of a marine reserve.

¹⁰ Shocking the participation rate simply involves increasing (or decreasing) the constant parameter in the discrete choice model of Chapter 4. The baseline value is the estimated coefficient of 1.055. Several different shocks are attempted in search of a reserve scenario that increases steady-state harvest. The results in Table 7.4 use a value of 2.5 for the constant.

¹¹ Reynolds and Wilen (2000) discuss the importance of the U.S./Japanese exchange rate for the price of raw urchin in California. The authors also document demand-side conditions in Japan and general equilibrium supply forces that can combine to produce major changes in the market for urchin roe.

reflecting possibly a major recession, the collapse of other fisheries in which part-time divers participate, or both.

Table 7.4

**Economics of Marine Reserves with Macroeconomic Shocks
The Northern California Red Sea Urchin Fishery**

	Steady-State N. California Divers	Trips Per Diver Per Year	Participation Rate		Steady-State Harvest (1,000 pounds)	Steady-State Egg Production (Billions)	Discounted* Revenues (\$1000)
<i>Discrete Choice Only ($\alpha = 0.005$)</i>							
<i>Double prices and exogenous increase in participation rate</i>							
No Closure	131	107.1	46%	**	883	720	18,548
Close Patch 8	131	96.5	41%	**	921	879	17,362
<i>Port Choice and Discrete Choice ($\alpha = 0.005$)</i>							
<i>75% Decrease in S. Cal. Revenues, double prices, and exogenous increase in participation rate</i>							
No Closure	56	174.5	75%	**	972	796	20,402
Close Patch 8	68	143.1	61%	**	952	910	18,865

* Uses a 5% constant discount rate and assumes \$1 per pound of sea urchin.

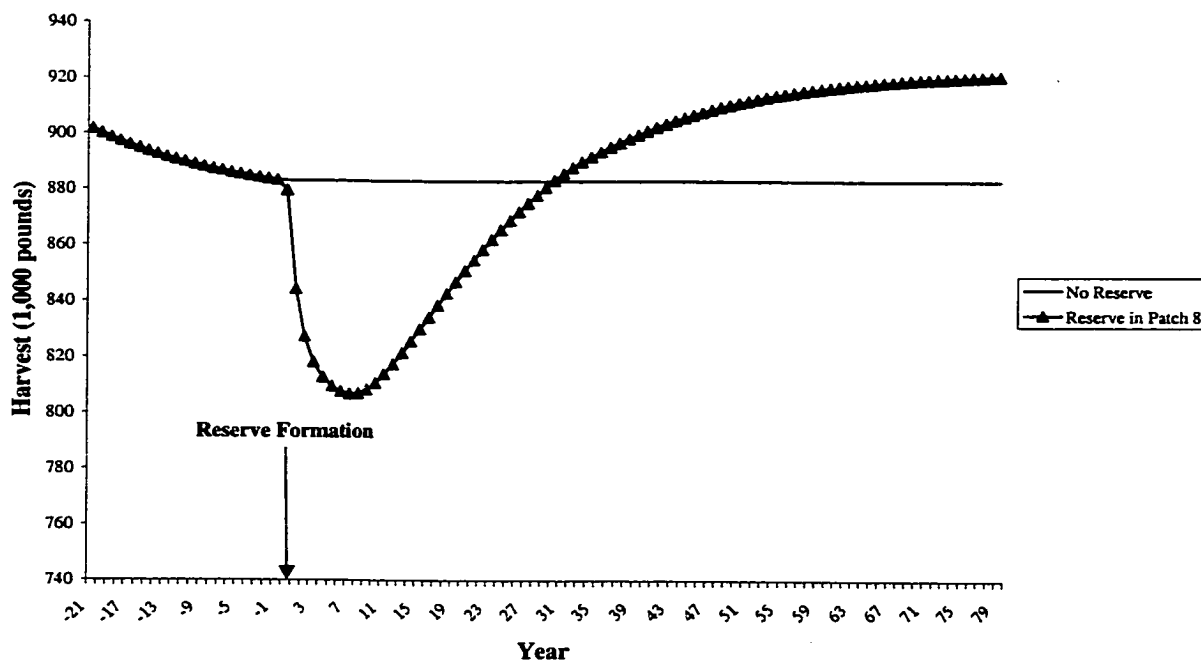
** Compare to participation rate of 11% using nested logit parameters and mean values of variables.

For these simulated re-parameterizations, the model without port switching predicts that an increase in steady-state harvest may be possible from creating a marine reserve in patch 8. At the same time, it is not just the change in steady-state harvest that is important; the whole time path after a reserve is created needs examination. Figure 7.13 depicts the harvest paths approaching the pre-reserve steady-state and the divergence of the reserve and non-reserve paths after implementing the closure. Because the system recovers slowly, in spite of the long-run increase in harvest, the discounted revenues for the closure are lower than for no closure. This reflects that fact that the biological consequences of a reserve are slow to take effect relative to the economic consequences

and the discount rate. Harvesters respond immediately to a closure by lowering their participation rates and redistributing some of their fishing effort across the remaining open areas. The short-run consequence is lower aggregate harvest. Over time, stocks in the reserve rebuild and export larvae to other areas. Eventually, when these urchins reach the minimum size limit, overall harvestable biomass is large enough to raise catch above the pre-reserve level. But, the time that it takes for this buildup leads to a negative net present value of the policy (in revenue terms).

Figure 7.13

A Marine Reserve with Macroeconomic Shocks



Because participation is much higher in the Table 7.4 scenarios compared to those in Table 7.3, egg production is much lower. As a result, the egg production increase from instituting a reserve is much higher. Egg production increases 159 billion in Table 7.4 but only 125 billion in Table 7.3

For the port switching model, we use the same exogenous increase in participation, double prices, and also decrease southern California catch per trip by 75%. Even under such extreme assumptions, a reserve does not lead to a steady-state harvest increase. Again, compared to the Table 7.3 scenarios, egg production is much lower with the increased participation rate.

Given the high participation rates in Table 7.4, we have to question whether the economic environment posited in these rather extreme simulations is even feasible. These simulations predict that the representative diver chooses to harvest between 40% and 75% of open fishing days. Given that the largest share of open fishing days occur in the winter months, this simply is unrealistic. We know from the discrete choice model that weather conditions profoundly affect the probability of harvesters going fishing. The simulation model incorporates estimates of diver sensitivity to bad weather, but when we exogenously shock participation rates, the marginal effects of bad weather are reduced. It seems unlikely that harvesters, even in the face of considerable macroeconomic shocks, would fish on extremely dangerous days. They may be willing to accept more physical risk from weather conditions when their economic circumstances are desperate, but it seems unlikely that they would accept such a dramatic increase in exposure to weather risk.

Another factor that impugns the reasonableness of these participation rates is the physical strain of diving. Diving is a physically taxing endeavor and can have a cumulative effect on the body over short time horizons. We observe very few divers participating repeatedly over many days in a row. Yet, we know that weather conditions can be autocorrelated, and thus favorable weather often occurs in spells of several

consecutive days. As such, we would expect the physical strain of diving to limit divers' abilities to select for favorable weather days. Hence, the realities of diving fatigue also cast doubt on the likelihood of extremely high participation rates.

Conclusions

Using the best available estimates of biological, oceanographic, and economic parameters to calibrate the simulation model to actual northern California harvest, marine reserves appear unlikely to increase steady-state catch for the northern California red sea urchin fishery and even less likely to increase discounted revenues. This result is significant because in many ways sea urchins seem ideal for spatial management, as Chapter 3 discusses. In particular, adult urchins are sedentary and live in patchy habitat, patches are connected by larval transport, and older and larger organisms tend to produce more gametes, which generates returns to organism size by extending urchin life cycles. Nevertheless, aggregate harvest benefits do not materialize in realistic models of marine reserve formation for northern California sea urchins, and egg production benefits are somewhat limited.

The key to these contradictory marine reserve predictions lies in the incorporation of economic behavior into the analysis. Simply put, in contrast to the biological models that ignore behavior, the behavioral responses of sea urchin divers make it doubtful that in the long run urchins would be exploited sufficiently to generate sustainable harvest gains from patch closures. Natural limits on harvest pressure, such as weather conditions and diving fatigue, combine with the economic costs of port-to-patch travel distances, declining economic benefits of harvesting a resource in the face of declining abundance, and institutional limits on harvest pressure—including the limited entry program,

seasonal restrictions, and the minimum size limit—together mitigate such extreme overexploitation.

Three important caveats are in order. First, there is considerable biological uncertainty about the recruitment parameters (a and c). In this chapter, we choose a value of c and two different values of a that can generate a catch path that approximately matches what we actually observe in the brief history of the northern California fishery. However, it is possible that these parameter values are off the mark. Perhaps a worst case scenario would be that the resiliency parameter is lower. The possibility of spatially differentiated recruitment parameters also confounds the situation. Second, there is substantial scientific uncertainty about Allee effects for sea urchins. If there is a threshold density of sea urchins below which patches enter into critical depensation, and if economic behavior drives some patches close to these thresholds, then spatial closures may be justified in spite of our deterministic model predicting lower steady-state harvests. This is essentially a form of the hedging argument in favor of marine reserves. Finally, there is considerable oceanographic uncertainty about larval dispersal. Costs and benefits of patch closures on the edges of the northern California fishery are small. If these locations are in fact closely linked to the rest of the system through larval transport, the biological benefits of closing these areas may be higher. The costs, nevertheless, are likely to remain low because distant patches lie on the extensive margin and thus significantly higher exploitation rates in the long-run are unlikely. Therefore, patch closures on the edge of the system may be worthwhile in the context of a qualitatively different larval dispersal matrix.

Appendix 7-A - Elasticities with the Port Allocation Model

For notational simplicity, denote trips as y , and the elasticity of trips to j at time t with respect to revenues in j at t as ζ_{jt} .

$$\begin{aligned}\zeta_{jt} &= \frac{\partial y_{jt}}{\partial R_{jt}} \frac{R_{jt}}{y_{jt}} \\ &= \sigma_t \sum_{p=1}^4 \left[\frac{\partial d_{pt}}{\partial R_{jt}} p_{pjt} + \frac{\partial p_{pjt}}{\partial R_{jt}} d_{pt} \right]\end{aligned}\tag{7-A1}$$

We can use Appendix 4-A to calculate $\frac{\partial p_{pjt}}{\partial R_{jt}}$ for each port. Note that the discrete choice model does not contain any lagged variables, so the short- and long-run derivatives are the same. Thus, we must only find short- and long-run expressions for $\frac{\partial d_{pt}}{\partial R_{jt}}$.

Denoting total divers as d_{tot} , northern California share as s_n , and port share as s_p , we note first that d_{pt} is defined as follows:

$$d_{pt} = (d_{tot}) s_n s_p.\tag{7-A2}$$

Hence, for the short-run, we have:

$$\frac{\partial d_{pt}}{\partial R_{jt}} = (d_{tot}) \left[\frac{\gamma_{SOC}}{R_{north,t}} \frac{\partial R_{north,t}}{\partial R_{jt}} s_p + s_n \frac{\gamma_{north}}{R_{pt}} \frac{\partial R_{pt}}{\partial R_{jt}} \right],\tag{7-A3}$$

and for the long-run we have:

$$\frac{\partial d_{pt}}{\partial R_{jt}} = (d_{tot}) \left[\frac{1}{(1-\lambda_{south})} \frac{\gamma_{SOC}}{R_{north,t}} \frac{\partial R_{north,t}}{\partial R_{jt}} s_p + s_n \frac{1}{(1-\lambda_{north})} \frac{\gamma_{north}}{R_{pt}} \frac{\partial R_{pt}}{\partial R_{jt}} \right].\tag{7-A4}$$

We can see from this expression that even though $\lambda_{south} < \lambda_{north}$, the long-run effects from within northern California switching are not necessarily lower because $\frac{\partial R_{north,t}}{\partial R_{jt}} < \frac{\partial R_{pt}}{\partial R_{jt}}$.

Chapter 8

Spatial Behavior and Biological Dispersal

Chapter 7 showed that with a realistic model of economic behavior, marine reserves are unlikely to increase steady-state harvest for the northern California red sea urchin fishery. Nevertheless, the question still remains: just how important are behavioral assumptions in this setting? As discussed and demonstrated in Chapters 4 and 5, we know that the typical assumptions made in the biological literature are unrealistic. Assuming uniform fishing effort over space is implicitly equivalent to assuming that harvesters do not respond to economic incentives that are spatially differentiated. In other words, it presumes that harvesters do not take advantage of spatial arbitrage opportunities. The typical assumptions about total fishing effort before and after a marine reserve are also unrealistic. At one end of the spectrum, the literature assumes that all effort in the closed area will exit the fishery. This suggests that not fishing is always preferable to relocating to the remaining fishing grounds. At the other end of the spectrum is the assumption that all effort in the closed area will redistribute uniformly.

This suggests that fishing in the remaining open areas is always preferable to not fishing. Both of these assumptions are extreme and unrealistic. The discrete choice model of Chapter 4 confirms this, predicting that some fishing effort would exit in response to a closure and some would redistribute.

We also know from Chapters 2 and 6 that the magnitude of fishing effort and its spatial distribution before and after reserve formation can have a profound impact on the predicted performance of that reserve. Moreover, Chapter 7 reinforces the importance of the magnitude of fishing effort, demonstrating that for the same biological and oceanographic conditions, a reserve may or may not increase steady-state harvest depending on the economic environment that harvesters face. This chapter further explores the empirical implications of fixing the total amount of fishing effort and assuming that it is distributed uniformly across space. We find that fixing total fishing effort also most likely overstates the long-run pressure on the resource. Furthermore, assuming a uniform distribution of fishing effort paints a more favorable portrait of marine reserves than is realistic.

As a basis for comparison, throughout this chapter we use the simulation model with the discrete choice behavioral component but without the port switching component. We refer to this model as ECON. We compare results from it to a model that assumes a constant total fishing effort before and after reserve formation and that distributes that effort uniformly across space. This is essentially the model at the end of Chapter 6 but with a size limit to match the actual institutional characteristics of the northern California sea urchin fishery. We refer to this latter model as NOECON.

Table 8.1 presents two different comparisons from closing patch 8, one ECON scenario compared to two different NOECON scenarios. The first NOECON model is based on uniformly distributed f values such that pre-reserve steady-state harvest is calibrated to the ECON steady-state harvest.¹ Immediately, we see the striking result that steady-state harvest is higher for NOECON after reserve formation but lower for ECON. That is, the NOECON model predicts an **increase** in harvest from implementing a reserve, while the ECON model predicts a **decrease** in harvest from implementing that same reserve policy. In spite of the steady-state harvest increase, a patch 8 closure decreases discounted revenues for the first NOECON scenario.

The second NOECON scenario calibrates to the actual harvest path (as in Chapter 7) rather than using a steady-state harvest calibration. As a result, this scenario implies more fishing effort and a lower pre-reserve steady-state harvest. For this simulation, instituting a reserve increases harvest even more than with the steady-state harvest calibration. In fact, the harvest increase is sufficient to actually lead to an increase in discounted revenues.

The conceptual analysis in Chapter 6 partly explains the divergence of ECON and NOECON results. Proposition 4 indicates that redistributing uniformly distributed effort either decreases production by a smaller amount or increases production by a larger amount than redistributing any other effort allocation along the same isoquant. At first glance, it seems ironic that true economic behavior produces a lower harvest than the fictional behavior assumed by biologists. The key is that economic behavior responds to revenue and costs in the system, including travel costs and opportunity costs in terms of

¹ The calibration is close but not exact because this system is enormously complex. Obtaining a steady-state can take up to two hours of computer time. For this calibration, approximately fifteen different f

foregone opportunities outside of the fishery. Thus, the uniform effort assumption produces an overly optimistic assessment of marine reserve performance.

Table 8.1

**Marine Reserves and Economic Behavior
The Northern California Red Sea Urchin Fishery**

	Steady-State Harvest (1,000 pounds)		Steady-State Egg Production (Billions)		Discounted* Revenues (\$1000)
<u>With Discrete Choice Behavioral Model (a=0.005)</u>					
No Closure	830		1,316		17,440
Close Patch 8	752		1,441		15,074
<u>With No Economic Model - NOECON (a=0.005) Steady-state Calibration</u>					
No Closure	829	**	434		17,400
Close Patch 8	868		553		16,423
<u>With No Economic Model - NOECON (a=0.005) Approach Path Calibration</u>					
No Closure	386	***	267		8,096
Close Patch 8	545		397		8,204

* Uses a 5% constant discount rate and assumes \$1 per pound of sea urchin.

** Calibrated steady-state harvest to behavioral model.

*** Calibrated approach path catch to actual catch.

The egg production totals provide another indication of the differences between ECON and NOECON. In both NOECON scenarios, egg production is much lower than in ECON, implying much greater pressure on the resource in the NOECON scenarios. In ECON, there is heavy pressure on the resource early on, but as abundance declines as a result of intensive harvesting, revenue per trip declines and so too does participation. Thus, harvest pressure on the resource declines out-of-sample, in contrast to the non-

values were tried.

structural approach of NOECON that maintains the same intensity of harvest pressure after the resource has been fished down to produce much lower catch rates. This leads the NOECON model to predict an extent of exploitation, or overexploitation in this case, that exceeds what would most likely occur in reality. The analysis in Table 7.4 reinforces this conclusion.

Another key to the dramatically different total egg production levels between ECON and NOECON is the spatial distribution of egg production. The steady-state spatial coefficient of variation for NOECON is 0.28 and for ECON is 0.43.² Whereas we know that spatial variability in egg production for NOECON is attributable to larval dispersal, for ECON it is attributable to larval dispersal and to spatially heterogeneous concentrations of fishing effort. Because actual fishing effort is so spatially heterogeneous, some patches in the ECON model remain lightly exploited even in the steady-state. These patches are thus de facto “reserves” in the sense that egg production from them is reasonably close to the level that would come about in a non-harvested steady-state. At the same time, the small number of divers who do visit these locations are able to harvest relatively large quantities for their efforts.

To verify this intuition, egg production minima and maxima across space are computed initially and at the steady-state for ECON and for the first NOECON model. Then the ratio of each initial extremum to the corresponding steady-state extremum is computed for each model. For ECON, the ratio of initial to steady-state minimum egg production is 5.56. The corresponding ratio for NOECON is 35.45. Even more striking

² Spatial coefficient of variation is simply the standard deviation of the egg production computed across space divided by the average egg production computed across space. Mechanically, these calculations are performed by treating each patch's egg production as an observation in the sample and computing the corresponding sample mean and standard deviation.

are the maximum ratios. The initial to steady-state maximum egg production ratio for ECON is 2.61, while the same ratio for NOECON is 15.54.

Larval Dispersal

Many analyses of marine reserves have focused on the importance of dispersal of the harvested organisms. The NOECON model provides a useful framework for analyzing the effects of biological dispersal alone. When economically motivated spatial behavior is introduced, however, results are quite different.

Table 8.2 contains the results of NOECON and ECON for simulated closures of each of the eleven patches in the northern California fishery. The table is divided into sections for patches in the southern part of the system, patches fed by each dispersal "gyre," and patch 5, which straddles the two dispersal gyres.

For NOECON, the egg production pre- and post-reserve essentially tells the story of larval dispersal. All reserve scenarios are predicted to lead to increased system-wide egg production. Within each gyre, egg production declines from south to north, as we close patches down. This reflects a combination of the NOECON system being heavily exploited and the south-to-north dispersal of organisms out of each common larval pool. For instance, because patch 2 receives a larger share of eggs than patch 4, patch 2 biomass has more to gain by instituting a reserve.

The impacts of reserves on steady-state harvest for NOECON are more complicated than on egg production. Here, the largest harvest increase comes from closing patch 5, the patch off of Point Arena that essentially straddles the two dispersal gyres. Because it receives few larvae from the lower gyre and only half of the patch is fed by the upper gyre, patch 5 acts primarily as a source. So, the fact that patch 5

generates the largest harvest gains is consistent with both the biological and economic literature on marine reserves. Interestingly, some of the NOECON closure scenarios lead to decreases in steady-state harvest. The worst cases appear to be reserves in the southernmost patches that are most decoupled from the system, namely Half Moon Bay on the San Francisco Peninsula and the Farallon Islands.

Table 8.2

Impacts of Dispersal and Spatial Behavior

	<u>System-wide Totals for the NOECON Model</u>		<u>System-wide Totals for the Discrete Choice Model</u>	
	SS Harvest (1,000 pounds)	SS Eggs (Billions)	SS Harvest (1,000 pounds)	SS Eggs (Billions)
No Closure	828.6	433.6	830.5	1316.0
<u>Separate Patches</u>				
Close Farralons	670.6	566.5	819.1	1322.5
Close Patch 1	749.4	580.3	827.1	1317.5
<u>First Gyre</u>				
Close Patch 2	807.5	584.1	755.2	1395.4
Close Patch 3	812.4	571.3	765.3	1382.3
Close Patch 4	816.3	559.3	761.2	1385.3
<u>Gyre Border</u>				
Close Patch 5	911.6	559.7	755.0	1425.6
<u>Second Gyre</u>				
Close Patch 6	868.3	594.7	743.6	1446.9
Close Patch 7	869.1	572.6	746.7	1447.5
Close Patch 8	868.0	553.3	752.4	1440.6
Close Patch 9	862.3	522.2	787.3	1374.3
Close Patch 10	839.5	470.8	829.6	1316.0

The other half of Table 8.2 demonstrates the importance of economic behavior to system-wide egg production. As in Chapter 7, the total pressure on the resource required to produce a comparable pre-reserve steady-state is much lower for ECON than for NOECON. The rankings for egg production are less clear in ECON because economic behavior confounds the oceanographic dispersal mechanisms. Moreover, economic behavior largely dominates the impacts of closures on total harvest. The patch closures

that are closest to equaling the pre-reserve harvest total are in patches 1 and 10, the most lightly exploited patches in the system. But, they also produce the smallest benefits in terms of egg production. The next closure in this ranking is the Farallon Islands, also an infrequently visited location. In contrast, closures in patches 2-8 are far more costly in terms of harvest because they are frequently visited and appear able to sustain high harvest levels in the absence of a reserve. Nevertheless, closing these areas are the policy scenarios that produce the largest egg production benefits.

Conclusions

This chapter empirically demonstrates that naïve behavioral assumptions can lead to overly optimistic predictions about the success of marine reserves. Specifically, by assuming a constant aggregate fishing effort before and after reserve formation and assuming effort is distributed uniformly across space, we predict that marine reserves enhance the aggregate steady-state harvest for northern California sea urchins. Yet, the model with more realistic behavioral assumptions that are estimated econometrically and calibrated to real catch reaches the opposite conclusion.

Consistent with much of the biological literature on reserves, this chapter also shows that the best location for a marine reserve hinges on the dispersal of organisms alone when economic behavior is simplified unreasonably. With a realistic behavioral model, in contrast, the question of marine reserve siting becomes far more complicated. Behavioral responses of harvesters can both reinforce and offset the impacts of oceanographic dispersal.

Chapter 9

Conclusions and the Future of Marine Reserves for Fishery Management

A marine reserve is a management tool that can have multiple objectives. As a means to preserve unique ecosystems, for instance, a spatial closure is arguably unparalleled as a policy instrument. A more controversial question is whether marine reserves can benefit commercial fisheries, and in some sense, improve on existing management tools. A long literature on this topic has emerged in marine biology and fisheries sciences that supports using reserves to manage commercial fishing. However, virtually all of this literature has ignored the importance of economic behavior. This thesis shows that the most optimistic results are a consequence of specialized assumptions. Incorporating a more realistic economic model into the analysis reduces the set of scenarios in which marine reserves generate favorable outcomes.

In Chapter 1, we note the one exception to biological models ignoring economically motivated behavior is Walters (2000). Walters' approach is a welcome departure from the bulk of the literature that ignores behavioral motivations behind effort decisions. At the same time, the Walters reduced-form approach raises some interesting questions about how to incorporate behavioral assumptions and data. Ultimately, the fisheries analyst wants to understand the spatial behavior of the fishery as a whole and predict how this behavior will respond to different policies. If microdata are available, should analysts statistically model the microbehavior of fishers and then aggregate the predictions of microbehavior to obtain a macroresult? Or, alternatively, should analysts aggregate the microdata and estimate a model that directly predicts the macroresults? If we consider the famous *Lucas critique* in economics (Lucas, 1976), we are led to conclude that the microbehavioral model is superior because unlike the aggregate model it has the potential to assess behavioral responses to policies that were never implemented within the sample period. Since the Walters approach calibrates behavioral responses in a non-structural way, its predictions about a reserve ultimately suffer from a spatial Lucas critique. Another potential problem with the ECOSPACE behavioral model is its inability to make total fishing effort endogenous. This dissertation thus contends that the behavioral modeling embodied herein provides a considerable improvement over even the most sophisticated existing management evaluation techniques because it posits a structural model of economic behavior.

Chapter 2 uses a two-patch lumped parameter model to highlight the importance of assumptions about the industry-wide aggregate level of fishing effort and its spatial distribution. The conceptual analysis demonstrates that while we can identify situations

in which marine reserves pay off relative to some benchmark allocation of fishing effort, there are few situations in which reserves globally maximize harvest. It is furthermore unclear whether these assumed benchmark allocations of effort accurately describe a real fishery.

Chapter 3 explains why the sea urchin fishery in northern California is an ideal test case for studying the impacts of marine reserves and analyzes spatial patterns of exploitation in the fishery. A duration model developed in this chapter shows that diver attrition is driven in part by lack of spatial mobility and lack of success in the fishery. The chapter also demonstrates that there is substantial participation heterogeneity within the urchin fishery.

Chapters 4 and 5 verify that sea urchin divers respond to economic incentives that vary across space. Though not surprising, these results clearly rebut the typical biological assumptions about fishing behavior. The analyses also provide a structural framework and parameter estimates for building a fully integrated bioeconomic simulation model of marine reserves that incorporates realistic harvester behavior. Moreover, Chapter 4 estimates the natural limitations on urchin diving participation that result explicitly from weather conditions and implicitly from diving fatigue and economic opportunities outside the urchin fishery.

Chapter 6 outlines a metapopulation model of sea urchin population dynamics and shows explicitly how assumptions about the spatial distribution of fishing effort can influence one's inferences about spatial management. It uses a two-patch version of the metapopulation model to show how modeling that does not incorporate spatial heterogeneity of harvesting effort can lead to spurious conclusions. Ironically, the typical

assumptions in the biological literature bias results in predictable ways that often favor instituting marine reserves.

Chapter 7 shows that marine reserves are unlikely to generate fishery benefits in the northern California red sea urchin fishery. A key factor in these conclusions is the fact that aggregate fishing effort in the long-run is expected to respond to the gradually declining resource abundance. In this fishery, limited entry and other forces, including harsh weather conditions, are predicted to relieve some harvest pressure on the urchin resource and make unsustainable levels of exploitation less likely to arise in the future. As a result, without severe overexploitation to begin with, most reserve scenarios do not increase steady-state harvests. The scenarios that do predict long-run harvest gains are based on extreme economic parameterizations that seem highly improbable.

Chapter 8 confirms the conceptual intuition of Chapter 6 by showing that assuming a uniform distribution of fishing effort leads to more favorable reserve predictions than depicting fishing behavior in a more realistic and spatially heterogeneous manner. In the specific examples considered, a marine reserve is predicted to increase steady-state harvest under naïve behavioral assumptions, but it will only decrease steady-state harvest using a realistic behavioral model with the same biological and oceanographic parameters.

It thus does not appear that a spatial closure in the northern California sea urchin fishery can reasonably generate a double benefit, i.e. an increase in biological productivity and an increase in long-run system-wide harvest. The end of Chapter 7 discusses several caveats based on scientific uncertainty about recruitment parameters, Allee effects, and oceanographic dispersal. We can add sources of economic uncertainty

to that list as well. Diver attrition, as suggested by the duration model, may change the average characteristics of urchin divers over time and hence the average propensity to participate. Major changes in the U.S./Japanese exchange rate or a collapse of the domestic Japanese urchin fishery could also have significant impacts on northern California's sea urchin resource. Nevertheless, the current institutional and economic setting of the urchin fishery has so many explicit and implicit limits on fishing intensity that the chances of a reserve scenario achieving the double benefit almost certainly would come only from major discrepancies between the true biological and oceanographic parameters and the ones used in this dissertation.

Considering the multi-objective context of marine policy, creating marine reserves will undoubtedly be an important policy tool for future management of marine fisheries throughout the world. Although it is not an indictment of spatial closures in general, the analysis in this dissertation weakens some of the conclusions that biological studies have drawn about the efficacy of marine reserves. Whether managers are surprised by the long-run consequences of reserves will hinge on their abilities to model accurately the behavioral responses of fishermen as well as the complexity of the biological and oceanographic system.

As this thesis demonstrates, constructing an empirical bioeconomic model of marine reserves requires extensive fishery data with spatial detail as well as knowledge about biological and oceanographic parameters. The data set on the California red sea urchin fishery exemplifies the type of data needed to engage in such an analysis. Nevertheless, the sea urchin data are not entirely unique; regulators in many commercial fisheries around the world have the ability to merge logbook and landings ticket data and

perform similar empirical analyses. Moreover, if not already required, regulators can insist that harvesters record detailed geographical information in their logbooks. The use of GPS technology for collecting these data and Geographic Information Systems for analyzing them will continue to foster analysis of spatial behavior and spatial management.

This thesis highlights the paramount importance of spatial behavior in exploited marine systems and provides the first example of a fully integrated spatially explicit bioeconomic model suitable for exploring the implications of spatial management options. In view of recent technological developments for monitoring spatial activity of fishermen, and in view of increased understanding of spatial processes in marine systems, it is likely that the future will bring more discussion of new spatial management options. These options will certainly include marine reserves, but they will also include yet unanalyzed policies such as rotating harvest zones, spatially explicit limited entry systems, spatially explicit transferable quotas, and spatial harvesting cooperatives. Models of the sort developed in this thesis will be essential for accurately forecasting the implications of these new policy instruments and necessary to avoid surprises that stem from naïve assumptions about economic behavior.

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