

## **A Bioeconomic Model of Spatial Policy Options**

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**Abstract:** This paper outlines an empirical bioeconomic model that is spatially explicit. It combines a metapopulation model of sea urchin biology with a discrete choice econometric analysis of harvester behavior. Discrete choice results are used to simulate short-term spatial closures in the fishery, and implications for long-term spatial management are discussed.

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## **A Bioeconomic Model of Spatial Policy Options**

### **I. Introduction**

Over the past several years there has been a steadily growing critique of conventional fisheries management methods. Beginning with several papers by prominent fisheries scientists including Ludwig, Hilborn, and Walters (1993) in highly visible outlets such as *Science* magazine, fisheries biologists and marine ecologists have begun to believe that current methods and institutions are predestined to failure in the long run. The standard argument supporting the critique is that fisheries populations are highly stochastic, the signal/noise ratio in commonly collected data is low, and hence measurement and modeling cannot hope to approach the stage whereby quantitative analysis can inform managers about best policies in any coherent manner. These preconditions set up the likelihood (indeed the certainty) that any given population managed by conventional methods will be driven to unacceptably low levels at least some time in the future. In the minds of the critics, a new paradigm is needed, one that acknowledges the fundamental and irreducible uncertainties in the task of management, and one that embeds some “safety first” assurance into management decisions and standard operating procedures.

This broad critique of conventional fisheries management science has emerged simultaneously with a major rethinking of marine ecology and marine population biology. The old view depicted populations as homogeneous, stable, predictable, and uniform over the marine environment, whereas the new view depicts populations as “metapopulations,” or collections of discrete and heterogeneous patches of biomass, linked through highly unpredictable oceanographic processes including upwelling, currents, wind, and advection.<sup>1</sup> Under this modern view, attempting to pursue anything like a maximum sustainable yield policy by

measuring and estimating stable yield functions and computing optimal harvests for such a complicated and inherently unpredictable system is simple folly.

Under the presumption that these criticisms and alternative depictions of marine ecosystems are correct, what kinds of policies and management strategies are appropriate? A consensus is beginning to emerge that new policies need to account explicitly for the **spatial** character of real marine ecosystems. In particular, new policies will have to recognize the patchiness of real systems, the heterogeneity of productivity and other life cycle factors over space, and the kinds and character of mechanisms that link together various elements of metapopulations. While it is not precisely clear what kinds of policies ought to replace old ones under these circumstances, one special subset of policy options that is receiving close to universal approval is the option of **marine reserves**. Marine reserves, or set-aside areas, are viewed by many as essential components of any strategy that is likely to emerge in the immediate future. The thinking is that protected zones can provide near fool-proof insurance against various measurement or management errors or other stochastic events by providing sources for repopulation of local populations temporarily depleted by management mistakes or by the inability to accurately set and enforce harvest targets.

While many tout the potential of marine reserves, all but the most ardent supporters agree that we really do not know how these spatial management options might work in practice. There are very few examples of set-aside areas in coastal zones around the world, and there are virtually no examples of reserves that have been created as a fisheries management tool and carefully monitored to gauge their impacts. In the absence of empirical information and carefully controlled experiments, ecologists have begun to explore the implications of setting aside fractions of spatial systems under various assumptions about growth, fishing mortality,

spatial dispersal, and other life history mechanisms with mathematical and simulation models. Most analytical exercises make simplifying assumptions about various aspects of real world complexity in order to keep the analysis tractable. For example, virtually all analysis of marine reserves and spatial management options ignores the fact that the harvesting sector will respond to closures. Most modelers assume constant fishing mortality and, after closure, some assume that the displaced effort simply disappears while others make various *ad hoc* assumptions about its reallocation. These simplifying assumptions are obviously false; what may not be appreciated is how different the conclusions might be when real behavioral assumptions are embedded in the harvesting component.

Despite the fact that most work on marine reserves is very recent, consensus is beginning to appear on several points. First, the kinds of dispersal processes and the magnitude of average spatial dispersal are critical to the question of whether reserves provide an effective safety valve under conventional management of remaining open areas. Second, we do not really know much about how spatial dispersal processes operate in real systems. In many marine ecosystems, larvae are transported from one patch to another, but the nature of the transport process is poorly understood. Third, the size of the areas required to be set aside for effective protection seems relatively large, on the order of 30% of the coastline. This suggests that the politics of marine reserve establishment will be contentious. Existing fishermen will clearly see areas this large as threats to conventional practices and they will have to be convinced that either the costs of these set-asides are low or that there are actual fishery benefits that seem tangible. All of these findings point to a need for serious empirical modeling of specific circumstances in order to learn which factors are critical to the overall effectiveness of reserves and other spatial management options.

This paper presents and discusses some preliminary analysis of spatial management options currently under consideration for California's red sea urchin fishery. In the next section we outline an empirical model of the red sea urchin fishery in California. We discuss how we are parameterizing and calibrating the model and show how the biological model is linked to the economic model. In the third section we discuss some empirical results associated with modeling harvester behavior using a Nested Logit specification. Our estimations are based on discrete daily observations drawn from fisheries logbooks, and we use the estimated model to predict some short run impacts of closures. In the final section we discuss future work and issues related to spatial management modeling.

## **II. A Dynamic Spatial Model of the Red Sea Urchin Fishery**

In this section we outline a spatially explicit and dynamic bioeconomic model of the sea urchin fishery that we are in the process of developing. The model is innovative in several respects. First, the model is a true bioeconomic model, integrating a population model of the urchin with a behavioral model of the harvesting sector so that the equilibria generated are joint bioeconomic equilibria. Second, the biological model is explicitly spatial and dynamic. We depict the sea urchin population as a metapopulation of 24 discrete patches, each with its own natality/mortality and growth parameters. The populations are linked with a dispersal matrix capable of characterizing any type of qualitative dispersal pattern. We parameterize the dispersal matrix with coefficients calibrated to mimic field observations of larval settlement along the Northern California coast. Third, the economic model is also explicitly spatial and dynamic. We model the industry behavior as an aggregation of individual choices made by divers, each of which is presumed responsive to the relative expected profitability of participation and location. Finally, the economic model of harvester behavior and the biological model are linked and

integrated over both time and space. This allows us to experiment with different spatially explicit policies, change economic and biological parameters, and trace out both short run impacts, long run steady state impacts, and the dynamic and spatial adjustments that take place in transition to steady states.

### A. The Metapopulation Model

The metapopulation model for spatial management policies in the red sea urchin fishery consists of 24 discrete size-structured populations 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  $i$  is given by:

$$\text{Size}_{i,a} = L_{\infty}^i (1 - e^{-k_i a}) \quad (1)$$

where  $i$  is indexed from 1 to 24,  $a$  is indexed as a monthly time index from 1 to 360, and  $L_{\infty}^i$  and  $k_i$  are patch specific growth parameters. 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. The populations are then aged by advancing the abundance values for each month to the next older month so that  $A_{i,a} = A_{i,a-1}$ . After the populations are aged, we compute the survival of the population along with the catch. Survival is determined by a Beverton-Holt mortality relationship, which embeds both patch-specific natural mortality rates  $m_i$  as well as fishing mortality if the size is above the minimum size limit  $L_{\text{limit}}$ . Thus survival of the number of individuals of age  $a$  is:

$$A_{i,a} = \begin{cases} A_{i,a} & \text{if } \text{Size}_{i,a} < L_{\text{limit}} \\ A_{i,a} & \text{if } \text{Size}_{i,a} < L_{\text{limit}} \end{cases} \quad (2)$$

and total catch from patch  $i$  consists of the sum of harvests of all sizes greater than the minimum size or

$$C = \sum_{i=1}^{i=24} \sum_{a=0}^{a=360} (1 - e^{-f_i}) w \text{Size}_{i,a}^b A_i \quad (3)$$

Where  $w$  and  $b$  are allometric parameters linking weight and length. The parameter  $f_i$  is the fishing mortality rate. In the fully bioeconomic version of the model,  $f_i$  will be determined by a behavioral equation.

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 presumed to be a spawning month, then egg production in patch  $i$  is computed with:

$$e_i = \sum_{a=0}^{a=360} \alpha x^\beta A_{i,a} \quad \text{where } x = \begin{cases} \text{Size}_{i,a} & \text{if } \text{Size}_{i,a} > L_{\text{maturity}} \\ 0 & \text{if } \text{Size}_{i,a} < L_{\text{maturity}} \end{cases} \quad (4)$$

This sums the egg production from each 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.

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 months in which larval dispersal is assumed to take place, settlement of larvae is first 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:

$$\vec{s}_{in} = pD\vec{e} \quad (5)$$

This 24x1 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  $D$ . The

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

$$\overline{s}_{out} = \frac{\overline{s}_{in}}{((1/a) + (\overline{s}_{in}/c))} \quad (6)$$

This allows us to embed various density dependent larval survival mechanisms into the system, all of which may be patch-specific. Once the settlement is calculated for any given site, they become the next period's age zero entry and the growth process starts again.

We currently have the model set up to produce two types of output displays. These are updated in real time as the model is run and the time counter moves through a monthly time step process. The graphical output includes graphs of egg production, catch, initial settlement and recruitment, as a function of time. We are now in the process of linking an economic model to the detailed biological model. This involves predicting the total amount of diver activity over the whole system, and the spatial pattern of diver activity, converting these into fishing mortalities for each patch, and then linking these to the biological model. In the next section we discuss the economic model we are developing, together with some preliminary (unlinked) predictions of reallocation after hypothetical closures.

## **B. An Econometric Model of Spatial Harvester Choice**

There are several ways one might model of the behavior of the harvesting sector that embody spatial structure. One method would be simply to estimate models of aggregate movement, say at the monthly level, using a specification matching the system in Sanchirico and Wilen (1999). Their structure is more realistic than most ecological spatial models because it includes a harvesting sector that is responsive over time and space to differential economic opportunities. When one closes a patch in this integrated bioeconomic structure, the harvesting



sector reallocates to remaining open areas according to relative profits. The model could be estimated as a Seemingly Unrelated Regression (SUR) system of share equations (or their rates of change), imposing various symmetry restrictions to conserve on parameters.<sup>2</sup> A second method would be to estimate models of individual daily choices, and then aggregate these up to higher levels of both spatial and temporal aggregations. We discuss preliminary uses of the latter method in this section.

In accord with the facts, we assume that urchin divers make a series of discrete and continuous decisions about fishing effort and participation on a daily basis. They also make a decision about home port on a longer time scale basis, say each year. The diver chooses a home port at the beginning of a season, which ultimately limits the choice set of fishing locations due to travel times. Then 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 individual traits are diver skill, attitudes towards risk, outside opportunities, and values of leisure time. Divers who have chosen to participate then choose diving locations based on expectations about spatially varying resource abundance, travel costs, and weather conditions. Finally, they may choose diving hours, a continuous variable, once they observe local weather and resource abundance. The sequence of daily decisions repeats for each day in the season without structural change, but available information changes as conditions change over time and as divers learn more about the spatial distribution of urchin abundance.

As a first step in analyzing urchin diver spatial behavior, we posit a Random Utility Model to study discrete daily participation decisions and diving location decisions. Index

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:

$$\begin{aligned}
 U_{ijt} &= v_{ijt} + \varepsilon_{ijt} \\
 &= f(\mathbf{X}_{it}, \mathbf{Z}_{i1t}, \mathbf{Z}_{i2t}, \dots, \mathbf{Z}_{iMt}; \boldsymbol{\theta}) + \varepsilon_{ijt}
 \end{aligned}
 \tag{7}$$

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,  $\boldsymbol{\theta}$  is a parameter vector, and  $\varepsilon_{ijt}$  is a mean-zero random component that is unobservable by the analyst. Given  $M$  possible diving locations, the Random Utility Model posits that a diver chooses location 1 if the utility of choice 1 is higher than that of the  $(M-1)$  other location choices as well as the choice of not to dive. For example:

$$\Pr[i \text{ chooses } 1 \text{ at } t] = \Pr[U_{i1t} > U_{i2t}, U_{i1t} > U_{i3t}, \dots, U_{i1t} > U_{iMt}, U_{i1t} > U_{i \text{ not } t}].$$

There are numerous discrete choice formulations that capture the essence of spatial decision-making and are consistent with the above Random Utility Model. Many similar analyses that model participation and location choices have appeared in the literature on recreation demand. The general approaches fall into the following categories: Multinomial (and Conditional) Logit, Discrete Choice Dynamic Programming, Random Parameters Logit, Multinomial Probit, and Nested Logit. The basic Multinomial (and Conditional) Logit is easy to estimate but inappropriate for spatial policy simulation because it imposes 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 would, in essence, assume the answer to the policy question. Discrete Choice Dynamic Programming 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 time horizon from the individual fisher's point of view. Moreover, it is computationally burdensome. The Random Parameters Logit and Multinomial Probit models can allow for heterogeneity of individual responses to independent variables and do not suffer from IIA problem, but they are also computationally cumbersome. Moreover, they would be difficult to integrate into the metapopulation model. The method used in this paper is Nested Logit. Nested Logit does not impose IIA, is easy to estimate, and allows for different variances at different decision nodes. So, Nested Logit is a behavioral model of the interdependent decisions of whether to go and where to go but is also quite flexible. Moreover, in contrast to Discrete Choice Dynamic Programming, random parameters logit, and multinomial probit, 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.

McFadden (1978) showed that if  $\epsilon_{ijt}$  is independently and identically distributed Generalized Extreme Value, maximization of random utility gives rise to the Nested Logit model.<sup>3</sup> If we assume further that indirect utility is linear in  $\mathbf{X}$  and in  $\mathbf{Z}$ , the following probabilistic model characterizes individual choices:

$$\Pr(\text{Go to } j) = \frac{\exp\{z_{jt}'\gamma + x_t'\beta + (1-\sigma)I\}}{\sum_{k=0}^{10} [\exp\{z_{kt}'\gamma\} + \exp\{z_{kt}'\gamma + x_t'\beta + (1-\sigma)I\}]} \quad (8)$$

$$\begin{aligned} \Pr(\text{Do not go}) &= 1 - \sum_{k=0}^{10} \Pr(\text{Go to } k) \\ &= \frac{1}{1 + \exp\{x_t'\beta + (1-\sigma)I\}} \end{aligned} \quad (9)$$

$$\text{where } I = \ln\left(\sum_{k=0}^{10} \exp\{z_{kt}'\gamma\}\right) \quad (10)$$

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 vary across individuals.

$\beta$  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  $\gamma$ . The coefficient on the Nested Logit inclusive value is  $(1 - \sigma)$ . For identification, we have normalized the indirect utility 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.

The fishery data we use to estimate this model is collected by the California Department of Fish and Game for management purposes and it include 257,000 observations on California urchin dives over the period 1988-1997. Each observation combines location-specific log book information about dive duration, depth, number of divers, and pounds caught with landings ticket information about price, quantity sold, landing site, and diver license. We divided Northern California into eleven geographically distinct harvest zones that roughly correspond to proposed spatial management zones. We also have collected locations-specific weather data from the National Buoy Data Center. These data contain hourly observations on variables that affect diving conditions including wave height, wave period, and wind speed. We aggregated these data into daily observations and linked them to the urchin databases.

For empirical analysis,  $\mathbf{X}$  includes price (PRICE), wave period (WP), wind speed (WS), wave height (WH), diver tenure (TENURE), diver past catch per unit effort (DCPUE), diver cumulative number of dives (CUMDIV), number of divers on the boat (DIVERS), and day-of-week dummies (SUN, ..., SAT).<sup>4</sup> *Ex ante*, there are several strong expectations about parameter

signs; we expect PRICE to have a positive coefficient and weather variables to have negative coefficients. For each location,  $\mathbf{Z}$  contains patch-specific constants (D0, ..., D10), patch-specific catch per unit effort (a measure of urchin abundance in each location) (CPUE), travel distance from the diver's home port (DISTANCE), and a variable that interacts DISTANCE with DIVERS (DIS\*DIV). The strong *ex ante* sign expectations are positive for CPUE and negative for DISTANCE. Daily decisions are made on each open-season day, of which there are approximately 200 per year. To construct the subset of data used for the analysis presented here, we randomly selected thirty divers, followed them over the entire sample period of ten years, and truncated daily decisions before a diver's first dive and after the diver's last dive.

### **III. Behavioral Results: Location and Participation Choice**

Table 1 reports results from Nested Logit analysis on the 27,822 observations.<sup>5</sup> Except the coefficient on divers per boat (DIVERS) and one of the patch-specific constants, all coefficients are statistically significant at the 10% level and most are highly significant. 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 positive sign on PRICE suggests that divers are more likely to dive when prices are high. 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 signs on TENURE, DCPUE, and CUMDIV have less obvious interpretations. One explanation for the sign on TENURE is that more experienced divers only participate when

conditions are good (e.g. urchin roe content is high due to spawning cycles). An alternative explanation is that TENURE picks up an age effect; more experienced divers are older and cannot participate as often in physically strenuous activities like urchin diving. An explanation for the negative sign on DCPUE is based on the idea that individual diver catch per unit effort measures diver skill. In contrast to CPUE, DCPUE is not a measure of urchin abundance. Similar to the first interpretation of TENURE, highly skilled divers are more professionalized and participate only when diving conditions are good. CUMDIV appears to indicate an individual diver's propensity to dive. Divers who have gone many times in the past are more likely to go again. More interestingly, this variable may partially reflect diver outside opportunities. Frequent divers may have lower outside employment opportunities, may attach a lower value to leisure throughout the sample period, or may be less risk averse towards unsafe diving conditions.

The day-of-week dummies demonstrate the importance of urchin roe market institutions. The pattern of the effects is what is relevant as well as the coefficients being significantly different from each other. Most California urchin roe processors are closed on Sundays, so there is less diving activity on weekends. Urchin landings on late Thursday or early Friday may be shipped to Japan Friday night and arrive in Japan Sunday. Since the Tokyo wholesale market is closed on Sundays, this decreases fishing effort at the end of each week. Thus, diver participation is greatest in mid-week.

Patch-specific variables are also important explanatory variables. The sign of CPUE is positive and indicates 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. Finally, the positive sign on DIS\*DIV has an interesting spatial economies of scale

interpretation. It suggests that when there are multiple divers on a boat, the fixed costs of travel are spread over multiple individuals, which partly offsets the DISTANCE variable.<sup>6</sup>

The model fits well overall, as the high pseudo- $R^2$  value of .28 indicates. Likelihood ratio tests were performed to evaluate the specification. First, the Nested Logit model was tested against a model that restricts the inclusive value coefficient ( $1-\sigma$ ) to 1. The test statistic, distributed  $\chi^2$  with one degree of freedom, was 145.9. Clearly, we reject this restriction in favor of the model in Table 1. The model was also tested against one in which the choice-specific constants are restricted to 0. The test statistic, distributed  $\chi^2$  with nine degrees of freedom, was 1076.89, which implies that we strongly reject the restrictions.

To help interpret the economic significance of effects, Table 2 reports variable means, minima, and maxima, and Table 3 includes response elasticity estimates. For **X** variables, the elasticity reported is the percent change in the probability of diving for a one percent increase in the variable, evaluated at the means of all variables in the model. For **Z** variables, there is a separate elasticity for each choice that 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 and evaluating at the means. Note that the distance variables are extremely important; i.e. their elasticities are large. 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. Nevertheless, the high elasticities in the middle patches confirm the importance of travel distance. It is also worth noting that the CPUE elasticities are all greater in magnitude than the DCPUE elasticity, which somewhat mitigates the curious sign result on DCPUE.

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. In this paper, however, the interest lies in what the group of divers will do as a whole over some interval of time. As such, a second, more useful way to generate predictions is to calculate the probabilities of each choice for each individual on each choice occasion. Then add up all of the probabilities over the relevant interval to arrive at the predictions. This method is used in Table 4, which presents the actual and predicted number of diving trips at each location for October and November 1996. The Nested Logit model with this prediction method performs quite well.

Table 4 also presents predictions based on what would happen if one patch were closed during this time period. The method used 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.<sup>7</sup> In theory there is still a positive probability of going to the closed patch using 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.

There several interesting results from patch closure simulation in Table 4. First, total fishing effort, i.e. number of trips, decreases when a diving location is eliminated. 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. Finally, 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.

The model was also used to generate aggregate predictions for the year of 1996. Table 5 reports the results. As the table indicates, the model does extremely well at predicting aggregate participation summed across all patches. At the individual patch level, it performs similarly to the way it performs in Table 4. The key difference is that for these predictions, actual values of explanatory variables are not used. Instead, representative values for each port in each month are chosen. The idea here is to move towards a simulation model that can be linked with the metapopulation model and that only relies on two key variables, capturing all other effects as parameters. In this case, the only variables are CPUE and PRICE. As such, the bioeconomic model will be able to simulate changes in abundance and changes in economic conditions over time. Variation in factors such as weather can be simulated by changing constants in the model.

#### **IV. The Work Plan**

Our work plan is proceeding on several fronts. First, we are in the process of calibrating the biological model using both fishery dependent and fishery independent data. Colleagues in the UC Davis Biology Department are sampling and measuring urchin in various sites along the

northern California coast, including some areas that have not been harvested. We will be using these size and abundance measurements to calibrate natural and fishing mortality parameters as well as growth functions. The difficult part of the calibration involves determining how to parameterize the dispersal matrix. Dispersal is a mechanism about which very little is known. We are sampling larval settlement along the coast and correlating it to changes in oceanographic patterns, including wind, current, and sea surface height. Our main hypotheses focus on the possibility that larval dispersal in the northern California system involves larvae being transported southward into a gyre off Point Reyes, at which point they are transported back and distributed during relaxation phases. We will be calibrating the dispersal matrix to mimic this structure, and then simulating the consequences and checking the “fit” against what we know about the population.

The second part of current work is to improve the econometric model of diver choice. A cursory examination of the data suggests that individual divers exhibit considerable heterogeneity in their behavior. However, we have very few diver-specific attributes and no demographic information on which to condition diver responses. One future direction is to estimate models with random parameters (e.g. Random Parameters Logit or Multinomial Probit with random coefficients) to account for unobserved diver heterogeneity. A second area of work is a refinement of the behavioral model such that divers respond to revenues across space and the uncertainty about these revenues. The spatial aspect of uncertainty derives from unknown and heterogeneous quality and abundance across space. Finally, as mentioned above, we are in the process of estimating the discrete choice models with a larger share of the data set.

The last step will be to couple explicitly the biological and economic models. We are in the process of doing this now with simplified structures, linking predicted diver hours to fishing

mortality coefficients in the biological model. At present, the metapopulation model can only explore spatial closures through *ad hoc* restrictions on fishing effort. The behavioral model, on the other hand, can only simulate spatial closures over a short time horizon and does not allow for biological feedback. Once the models are linked, we will calibrate actual and predicted harvest using the patch-specific catchability coefficients. Then we can explore via simulation many spatial management options as well as conventional options over short and long time horizons. The goal is to simulate steady state equilibria under different policy scenarios as well as the transition paths to those equilibria. We intend to look at permanent closures relatively intensively, focusing on whether closures can increase aggregate harvests in the long run, what kinds of biological protection is provided (eg. increased egg production), and how the transition to the long run plays out in both bioeconomic system, over space and over time. We will also look at various temporary closures, including rotating harvest zones under our hypothesized dispersal matrix and alternatives. Finally, we will be able to look at other conventional but spatially explicit policies, such as area licensing, spatially explicit ITQs, spatially explicit landings taxes, and participation fees.

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**Table 1**  
**Nested Logit Estimates**

**Not Location-Specific**

<b>Variable</b>	<b>Coefficient</b>	<b>Standard Error</b>	<b>Z - statistic</b>
PRICE	0.1348	0.0806	1.67
WP	-0.1474	0.0233	-6.33
WS	-0.08	0.0129	-6.20
WH	-0.7414	0.0465	-15.94
TENURE	-0.4853	0.0239	-20.31
DCPUE	-0.0313	0.0136	-2.30
CUMDIV	0.1385	0.0047	29.47
DIVERS	-0.0257	0.0376	-0.68
SUN	1.5108	0.289	5.23
MON	2.1867	0.2769	7.90
TUE	2.3032	0.2776	8.30
WED	2.2145	0.277	7.99
THU	2.1198	0.2796	7.58
FRI	1.6493	0.2863	5.76
SAT	1.5859	0.2856	5.55

**Location-Specific**

<b>Variable</b>	<b>Coefficient</b>	<b>Standard Error</b>	<b>Z - statistic</b>
CPUE	0.0791	0.0475	1.67
DISTANCE	-14.2648	0.6981	-20.43
DIS*DIV	0.9037	0.2436	3.71
D0	1.3598	0.4385	3.10
D1	0.8945	0.6064	1.48
D2	-4.4589	0.5111	-8.72
D3	-2.5582	0.4994	-5.12
D4	-2.1186	0.4529	-4.68
D5	-3.1119	0.4841	-6.43
D6	-4.1525	0.4903	-8.47
D7	-5.2753	0.5314	-9.93
D8	-7.1331	0.5884	-12.12
D9	-4.5808	0.5184	-8.84
D10	0	- restricted for identification -	
sigma	0.7552	0.0318	23.75

Log-likelihood	-9696.77
Observations	27822
Pseudo R-square	0.27985

The Pseudo R-squared is based on the log-likelihood in a Conditional Logit Model with choice-specific constants.

Table 2

**Variable Summaries for Nested Logit Model**

		<u>Not Location-Specific</u>		
Variable		Mean	Min	Max
PRICE		0.79	0.05	2.27
WP		7.70	4.57	13.97
WS		6.01	0.85	17.14
WH		2.41	0.62	8.85
TENURE		2.84	0.00	8.90
DCPUE		3.57	0.31	15.12
CUMDIV		7.39	0.10	46.40
DIVERS		2.01	1.00	4.00

  

		<u>Location-Specific</u>		
Location	Variable	Mean	Min	Max
Farallons	CPUE	4.54	2.04	7.40
	DISTANCE	1.36	0.67	1.78
	DIS*DIV	2.70	0.67	6.28
1	CPUE	2.22	0.86	5.18
	DISTANCE	1.52	0.83	1.94
	DIS*DIV	3.02	0.83	6.92
2	CPUE	4.09	2.21	7.01
	DISTANCE	0.82	0.13	1.24
	DIS*DIV	1.62	0.13	4.12
3	CPUE	3.14	0.98	9.73
	DISTANCE	0.61	0.19	0.93
	DIS*DIV	1.19	0.19	2.86
4	CPUE	3.17	1.30	10.43
	DISTANCE	0.51	0.24	0.73
	DIS*DIV	1.02	0.24	2.19
5	CPUE	2.77	1.21	9.76
	DISTANCE	0.43	0.06	0.56
	DIS*DIV	0.87	0.06	2.24
6	CPUE	2.79	1.32	7.62
	DISTANCE	0.38	0.13	0.75
	DIS*DIV	0.79	0.13	2.98
7	CPUE	2.44	1.27	7.22
	DISTANCE	0.37	0.03	0.93
	DIS*DIV	0.78	0.03	3.72
8	CPUE	2.20	1.05	8.98
	DISTANCE	0.42	0.00	1.11
	DIS*DIV	0.87	0.00	4.44
9	CPUE	2.62	1.09	9.48
	DISTANCE	0.64	0.22	1.33
	DIS*DIV	1.31	0.22	5.32
10	CPUE	4.93	2.29	9.17
	DISTANCE	1.28	0.86	1.97
	DIS*DIV	2.59	0.86	7.88

Table 3

**Elasticities from the Nested Logit Model**

		<u>Not Location-Specific</u>		
Variable		Elasticity		
PRICE		0.103		
WP		-1.103		
WS		-0.467		
WH		-1.734		
TENURE		-1.339		
DCPUE		-0.109		
CUMDIV		0.995		
DIVERS		-0.050		
SUN		0.164		
MON		0.363		
TUE		0.384		
WED		0.368		
THU		0.313		
FRI		0.180		
SAT		0.172		

  

		<u>Location-Specific</u>		
Location		CPUE	DISTANCE	DIS*DIV
		Elasticity	Elasticity	Elasticity
Farallons		0.359	-19.448	2.440
	1	0.176	-21.730	2.730
	2	0.323	-11.745	1.461
3	0.248	-8.626	1.078	
4	0.248	-7.260	0.918	
5	0.217	-6.052	0.776	
6	0.219	-5.428	0.711	
7	0.193	-5.260	0.702	
8	0.174	-5.942	0.785	
9	0.207	-9.080	1.184	
10	0.390	-18.211	2.344	

Table 4

**Nested Logit Policy Simulations for October/November 1996**  
**Open Fishing Days = 49**  
**Total Active Divers in Bodega, Point Arena, Albion, and Fort Bragg = 93**

Decision	Actual Choices	Nested Logit Predictions	
		No Closure	Close Patch 8
<b><u>Based on Probabalistic Framework</u></b>			
No Dive	2891	2760	2774
Farallon Islands	10	11	11
Patch 1	0	1	1
Patch 2	12	26	26
Patch 3	95	81	81
Patch 4	68	82	83
Patch 5	116	255	258
Patch 6	94	123	135
Patch 7	212	183	223
Patch 8	171	119	<b>0</b>
Patch 9	69	94	142
Patch 10	0	3	4
<b>Total Choice Occasions</b>	<b>3738</b>	<b>3738</b>	<b>3738</b>

Table 5

**Aggregate Trip Predictions for 1996**  
**Using Representative Values for Explanatory Variables**

**Actual trips by patch from four main Northern California ports**

Patch	Farallons	1	2	3	4	5	6	7	8	9	10
Trips	32	0	32	267	270	903	348	953	501	166	5
<b>Total</b>	<b>3477</b>										

**Predicted trips by patch from four main Northern California ports**

Patch	Farallons	1	2	3	4	5	6	7	8	9	10
Trips	12	3	127	389	313	939	517	720	290	242	8
<b>Total</b>	<b>3561</b>										

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<sup>1</sup> See, for instance, Botsford, Quinn, Wing, and Brittnacher (1993) or Quinn, Wing, and Botsford (1993).

<sup>2</sup> See Smith (2000) for further discussion and results using the SUR method for estimating patch shares.

<sup>3</sup> In the simpler model in which the  $\epsilon$ 's are independently and identically distributed Type I Extreme Value, utility maximization gives rise to the familiar conditional logit model (McFadden, 1974).

<sup>4</sup> As a consequence of the day-of-week dummies, there is not a separate intercept term, which ensures identification of all other model parameters.

<sup>5</sup> These observations constitute a random sample of thirty divers followed across the entire data set. The data was sampled because the number of observations would otherwise be enormous and would require considerably more computing power and time given the highly nonlinear nature of Nested Logit. Ways of estimating the model using all of the data, a larger sample, and/or multiple samples are currently being investigated.

<sup>6</sup> A different justification, however, can be made for the interactive variable having the opposite sign. Divers on multi-diver boats drive to a different port to reduce travel costs, since we expect that travel by boat is more costly and time-consuming than travel by car.

<sup>7</sup> The choice of the indirect utility for the patch closure only must be small 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.