Bayesian Bioeconomics of Marine Reserves[*]

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Abstract

We use Bayesian econometric methods to estimate dynamic bioeconomic models of marine reserve formation using simulated data and real data from the Gulf of Mexico reef fish fishery. We test the effects of reserves on fish growth and catchability.

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Introduction

There are precious few retrospective analyses of the fishery benefits of marine reserves. This fact has raised concerns amongst fisheries scientists (Hilborn et al. 2004; Sale et al. 2005). The policy reality is that reserves continue to be established in spite of gaps in our scientific knowledge, and they are supported by conceptual models in fisheries science that predict harvest gains (or only modest harvest losses) when large areas are closed to fishing (Polacheck 1990; Bohnsack 1993; Walters 2000; Gerber et al. 2003). However, economic models articulate a limited set of bioeconomic conditions under which reserves would enhance fisheries (Holland and Brazee 1996; Sanchirico and Wilen 2001; Smith 2004), conditions that appear even more limited in models that incorporate the harvest sector's behavior (Smith and Wilen 2003,2004; Dalton and Ralston 2004). In this paper, we take steps toward filling the knowledge gap by adapting new methods from Bayesian econometrics to estimate dynamic bioeconomic models of marine reserve fishery benefits. We use both simulated data and real data from the Gulf of Mexico reef fish fishery, and we explicitly test hypotheses about the effects of marine reserves on fisheries productivity.

To evaluate the effectiveness of existing marine reserves, there are two bio-econometric approaches available: descriptive and structural. The descriptive approach uncovers structural breaks and trend changes in the bioeconomic system by examining the signs of particular parameters. In previous work, we estimate descriptive panel models of marine reserves in the Gulf of Mexico that approach the problem from the perspective of program evaluation (Smith, Zhang, and Coleman 2005a). In other work, using simulated data, we find that the descriptive model can sign policy treatment effects correctly but cannot estimate the magnitudes consistently due to the latency of the state variable, i.e., the fish stock (Smith, Zhang, and Coleman 2005b). In contrast, a structural bio-econometric model accounts for the latent state variable and can estimate unknown biological and economic parameters consistently—as well as the direct structural impact of a policy—with non-experimental data.

The advantages of a structural bio-econometric model come at a cost. In a dynamic bioeconomic system, elements are generally related nonlinearly, imposing a heavy burden on the estimation process. Because the fish stock is not directly observed, backwards recursion is necessary to generate an estimation equation in terms of observable quantities and parameters, a process that amplifies the nonlinearity in the bioeconomic model. Such complexity may account for the relatively small number of empirical bioeconomic papers in the fisheries literature that are dynamic and for the modeling simplifications that are typically made, e.g., a Schaefer production function (Wilen 1976; Bjorndal and Conrad 1987; Homans and Wilen 1997).

Bayesian techniques provide a promising new direction for estimating nonlinear dynamic structural bioeconomic models for several reasons. First, the Markov Chain Monte Carlo (MCMC) simulation simulates but does not maximize the likelihood function (Hong 2004), an advantage over traditional methods when the objective function is not well behaved. Second, Bayesian methods have a natural way of incorporating prior information on the parameters (Gelman et al. 1995). This is particularly important for incorporating fishery-independent biological information (Hilborn and Mangel 1997), and can be useful for general bounds on the parameter space such as non-negativity constraints. Third, there may be computational gains from generalizing a Bayesian model to account for economic or biological heterogeneity through random parameters in comparison to introducing simulation-based estimation to an already highly nonlinear maximum likelihood problem.[1]

We estimate two Bayesian bioeconomic models with logistic growth. The first model uses simulated data for which we know all of the true biological and economic parameters as well as the true policy impact of establishing a marine reserve. The data assume that there is a single representative fishing vessel. We find that the Bayesian model using MCMC converges near the true parameter values in the simulated data exercise. In the second model, we estimate biological and economic parameters with real data from the Gulf of Mexico reef fish fishery for which we have more than ten years of logbook records. Two marine reserves were established in-sample, so we can examine the structural impact on the bioeconomic system. We find that the MCMC approach estimates plausible parameter values. More specifically, we find in one case that the marine reserve did not reduce fishing area enough to have a net negative effect on catchability. There is some indication that the reserve stimulated fishery production, but the result is not statistically significant. These results are preliminary, and we are continuing to explore the robustness of these findings. In the next section, we describe the Gulf of Mexico reef fish fishery and the biology of the gag. We then develop a discrete-time bioeconomic model of marine reserve formation that embeds a reserve within a larger and observable harvest area. The

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[1] This point is somewhat speculative, but there are results that suggest MCMC estimation estimates faster for some classes of discrete choice models with heterogeneity. See Train (2003).

following section summarizes our preliminary empirical results with both simulated data and real data. We then conclude with a discussion of next steps for this research.

The Gulf of Mexico Reef Fish Fishery and Gag

The Gulf of Mexico reef fish complex is extremely diverse (with 62 species commercially harvested reef species), and involves a wide variety of gears, thus presenting managers with substantial challenges. The most common gears are hook and line (including handlines, electric bandit reels, buoy gear, and conventional rod and reel) bottom long line, and traps (although traps are being phased out completely in the next couple of years). Existing management includes limited entry (there are currently approximately 1200 federal commercial Gulf of Mexico reef fish permit holders), size limits, trip limits, season closures, quota management, and more recently marine reserves. Only a fraction of permitted vessels regularly engage in commercial reef fish fishing. For example, 25% of vessels account for 75% of fishing trips over the 1993-2002 period.

Economically-important species such as gag (*Mycteroperca microlepis*), scamp (*M. phenax*), and red grouper (*Epinephenlus morio*) could gain some long run biological benefits from marine reserves. These species are long-lived, slow-growing protogynous hermaphrodites (Coleman et al. 2000). Protogynous hermaphrodites mature first as females and then transform to males later in life. Because fishing tends to select for larger individuals, it tends to select for males. This selection reduces male-to-female sex ratios (Coleman, Koenig, and Collins 1996;

McGovern et al. 1998), and some traditional fisheries management tools, particularly size limits, may exacerbate this effect. For Gulf of Mexico gag, the percentage of males from the 1970s to the 1990s has declined from 17% to 2% (Coleman et al. 2000). The same decline does not appear in red groupers, which do not aggregate to spawn (Coleman, Koenig, and Collins 1996). Thus, we focus on gag in this paper. An empirical examination of reserves for the gag fishery is particularly timely, since recent life history modeling of gag population dynamics suggests that, among available management alternatives, closing spawning sites to fishing ranks highest for sex ratio recovery and close to the top for overall growth rate of the population (Heppel et al. 2005).

The two marine reserves in the Gulf of Mexico that we study—Madison-Swanson Marine Reserve and Steamboat Lumps Marine Reserve— went into effect in June 2000 to address concerns about this skewed sex ratio. They were announced to the fishing community one year before being established. They were authorized as experimental reserves with a sunset of four years, and were recently reauthorized for an additional six years, based exclusively on biological data within and outside of each reserve and anecdotal information about the fishery outside each reserve. To date, there have been no systematic evaluations of these reserves as management tools other than our previous empirical work (Smith, Zhang, and Coleman 2005a), and understanding their performance will be critical for future reauthorizations.

The reserves are located in two of the thirteen distinct National Marine Fisheries Service (NMFS) fisheries statistical zones in the Gulf of Mexico (Figure 1). These two zones represent the heart of the gag fishery in the Gulf of Mexico. Madison Swanson is located in zone 8, comprising 115 square nautical miles (NM^2) of this 9,570 NM^2 zone, whereas Steamboat

Lumps is located in zone 6, comprising 104 NM^2 of this 8,100 NM^2 zone. Each reserve captures 1.2 and 1.3% respectively of the total area in the NMFS statistical zone within which they occur. There is, thus, substantial fishable area left open within each of the statistical zones as well as elsewhere on the West Florida Shelf. However, percentage area is misleading in a fisheries context, because not all ocean bottom is alike. The reserves in question are located in deep water along the continental shelf edge and contain distinct patch reef formations where reef fish aggregate in general and many grouper species aggregate to spawn (Koenig et al. 2000).

There is not a one-to-one relationship between NMFS fishing zones and what we might reasonably deem a patch from a bioeconomic perspective. The spatial resolution of the logbook data is extremely coarse, which is typical, and the NMFS fishing zones are spatial aggregates of the underlying biological and economic processes. The empirical challenge is to use this coarse information to infer how policy changes affect fishery outcomes.

Complete fishing logbook data exist for all reef species in the Gulf of Mexico from 1993 through 2004. Thus, there are substantial data before and after the policy change to assess reserve performance. We cut the data after October 2004 because some logbook records for 2004 may not have been submitted or processed in the most recent database that we received in February 2005. This leaves us with 142 months of data.

A Discrete-Time Model of Marine Reserve Formation

In this section, we develop a stylized spatially-explicit bioeconomic model to understand how a reserve might appear in a fishery that extends over a large contiguous region. While some might argue that this exercise attempts to re-invent the wheel, the existing literature does not match the spatial scale of available data for doing *ex post* assessment of marine reserves. We begin with a discrete-time (t) lumped-parameter model of the fish stock (X) and harvest (H) in each fishing zone (j).:

$$X_{j,t+1} = X_{j,t} + r_j \gamma_1^{Z_{jt}} X_{j,t} \left(1 - \frac{X_{j,t}}{K_j}\right) - H_{j,t}\,. \qquad (1)$$

The parameters r and K are the conventional intrinsic growth and carrying-capacity parameters. Z is an indicator variable that denotes when a reserve is in effect such that:

$$Z_{j,t} = \begin{cases} 1 & \text{if there is a reserve in } j \text{ at } t \\ 0 & \text{if no reserve or pre-reserve} \end{cases}. \qquad (2)$$

Thus, γ_1 scales intrinsic growth when a reserve is established somewhere within the zone. As we can see from Figure 1, the Madison-Swanson and Steamboat lumps reserves are located within larger fishing areas. The idea is that equation (1) forms a lumped-parameter description of how biological returns would operate on the surrounding area of a reserve. That is, if a reserve generates spillovers, it would appear to stimulate growth in the zone that contains the reserve. However, the reserve also closes off part of the fishing area, which might affect the production function for fishermen. As such, harvest is given by the following function of stock and effort (E):

$$H_{j,t} = q \left(E_{j,t}\right)^{\alpha} \gamma_2^{Z_{j,t}} X_{j,t}\,. \qquad (3)$$

In this form, q is a catchability coefficient, α is a Cobb-Douglas production parameter (the corresponding parameter on X is assumed to be one), and γ_2 scales the production function to account for reduced fishing area when a reserve is in place.[2]

In essence, this model allows the reserve to influence biomass in the larger zone within which the reserve is embedded, but scaling the harvest function only permits harvesting in the open portion of the zone. This setup is consistent with many logbook data sets for which reserves do not correspond to an entire fishing zone.

As a first step, we take fishing effort as given and focus on estimating the biological and production parameters. Smith, Zhang, and Coleman (2005b) take the extra step of closing this model with a Vernon Smith (1968) effort adjustment equation and derive some basic theoretical predictions based on a single-area fishery. Our simplification allows us to derive and estimate a single-equation model where the goal is to use data on catch and effort alone to infer the latent stock dynamics. Through recursive substitution of (3) into (1), we are able to predict the catch (*H*) in period *t+1* without knowing the stock (*X*):

$$H_{t+1} = \left(1 + r\gamma_1^{Z_t} - qE_t^{\alpha}\gamma_2^{Z_t}\right)\gamma_2^{Z_{t+1}-Z_t} H_t \left(\frac{E_{t+1}}{E_t}\right)^{\alpha} - \frac{r}{qK}\gamma_1^{Z_t}\gamma_2^{Z_{t+1}-2Z_t} H_t^2 \left(\frac{E_{t+1}}{E_t^2}\right)^{\alpha} \qquad (4)$$

This model is equivalent to the original setup, and we will use this one as our data generating process in both the simulated data analysis and the real data analysis. At this stage, two comments are worth mentioning. First, even without the complication of a reserve effect, estimating intrinsic growth and carrying capacity jointly in a surplus production model is problematic because the data often do not span the population range (Hilborn and Mangel 1997).

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[2] It is also possible that the reserve could appear to increase catchability if reserve establishment provides spatial information to the fleet that was not common knowledge previously. This information gain would likely apply to only a subset of fishing vessels. Our model is only able to test the net effect of reduced fishing area and increased information.

Second, introducing marine reserves puts sharp edges in this model. While this is what our theoretical model predicts, it may create difficulties as a practical matter for estimation.

We add an error term (ε_t) to the above model with the assumption that it is iid normally distributed with zero mean and known variance (σ^2). Variance is assumed to be known in the simulated data Monte Carlo experiment just for simplicity and assumed to have a diffuse distribution in the real data analysis. The model to be estimated is thus:

$$\begin{aligned} H_{t+1} &= \gamma_2^{Z_{t+1}-Z_t} H_t \left(\frac{E_{t+1}}{E_t}\right)^{\alpha} + r\gamma_1^{Z_t}\gamma_2^{Z_{t+1}-Z_t} H_t \left(\frac{E_{t+1}}{E_t}\right)^{\alpha} - q\gamma_2^{Z_{t+1}} H_t E_{t+1}{}^{\alpha} \\ &\quad - \frac{r}{qK}\gamma_1^{Z_t}\gamma_2^{Z_{t+1}-2Z_t} H_t{}^2 \left(\frac{E_{t+1}}{E_t{}^2}\right)^{\alpha} + \varepsilon_{t+1} \end{aligned} \quad . \tag{5}$$

To simplify notation, we define the following:

$$A_{t+1} = \gamma_2^{Z_{t+1}-Z_t} H_t \left(\frac{E_{t+1}}{E_t}\right)^{\alpha}, \tag{6}$$

$$B_{t+1} = \gamma_1^{Z_t}\gamma_2^{Z_{t+1}-Z_t} H_t \left(\frac{E_{t+1}}{E_t}\right)^{\alpha}, \tag{7}$$

$$C_{t+1} = -\gamma_2^{Z_{t+1}} H_t E_{t+1}{}^{\alpha}\text{, and} \tag{8}$$

$$D_{t+1} = -\gamma_1^{Z_t}\gamma_2^{Z_{t+1}-2Z_t} H_t{}^2 \left(\frac{E_{t+1}}{E_t{}^2}\right)^{\alpha} \tag{9}$$

To reduce some of the nonlinearity in estimation, we re-parameterize the model as follows:

$$k = \frac{r}{qK} \tag{10}$$

Then the model can be rewritten as,

$$H_t = A_t + rB_t + qC_t + kD_t + \varepsilon_t \, . \tag{11}$$

One favorable feature of the above model is that it is linear in the parameters *r*, *q* and *k*.

Preliminary Empirical Results

In the simulated data analysis, we use 500 periods for one fishing zone. A reserve is formed after 300 periods, so it is in place for the remaining 200 periods. For prior information we make very conservative assumptions. Defining *I* as the indicator function, we first assume $I(q>0)$ and $I(k>0)$. These are the least restrictive assumptions. Given that groupers are slow-growing, we restrict the possibilities for intrinsic growth $I(0<r<1)$. Prior biological knowledge could be used in a similar fashion for other species. We assume diminishing returns to fishing effort $I(0<\alpha<1)$. Finally, We assume that the impact of the reserve on growth is positive (growth is scaled upward) but less than 100% $I(1<\gamma_1<2)$, and the reduction in fishing area is no more than 50% $I(0.5<\gamma_2<1)$. In the real data analysis, we also assume the prior distribution of σ^2 is diffuse, that is, $p\left(\sigma^2\right)\propto 1/\sigma$.

Given our parametric assumption on the error term, the joint posterior distribution for the parameters is:

$$\begin{aligned}
&p\left(r,q,k,\alpha,\gamma_1,\gamma_2,\sigma^2\left|H,E\right.\right)\propto \\
&\exp\left\{-\frac{\sum_{t=1}^{T}\left(H_t-\left(A_t+rB_t+qC_t+kD_t\right)\right)^2}{2\sigma^2}\right\}\times\frac{1}{\sigma} \qquad (12)\\
&\times I\left(0<r<1\right)I\left(q>0\right)I\left(k>0\right)I\left(0<\alpha<1\right)I\left(1<\gamma_1<2\right)I\left(0.5<\gamma_2<1\right)
\end{aligned}$$

The exact posterior distributions of *r*, *q* and *k* are given by:

$$r \,|\, \cdot \sim TN\left(\frac{\sum_{t=1}^{T} B_t \left(H_t - \left(A_t + qC_t + kD_t \right) \right)}{\sum_{t=1}^{T} B_t^2}, \frac{\sigma^2}{\sum_{t=1}^{T} B_t^2} \right) I\left(0 < r < 1\right), \tag{13}$$

$$q \,|\, \cdot \sim TN\left(\frac{\sum_{t=1}^{T} C_t \left(H_t - \left(A_t + rB_t + kD_t \right) \right)}{\sum_{t=1}^{T} C_t^2}, \frac{\sigma^2}{\sum_{t=1}^{T} C_t^2} \right) I\left(q > 0\right), \tag{14}$$

$$k \,|\, \cdot \sim TN\left(\frac{\sum_{t=1}^{T} D_t \left(H_t - \left(A_t + rB_t + qC_t \right) \right)}{\sum_{t=1}^{T} D_t^2}, \frac{\sigma^2}{\sum_{t=1}^{T} D_t^2} \right) I\left(k > 0\right), \text{ and} \tag{15}$$

$$\sigma^2 \,|\, \cdot \sim IG\left(T, \sum_{t=1}^{T} \left(H_t - \left(A_t + rB_t + qC_t + kD_t \right) \right)^2 \right), \tag{16}$$

where *TN* is a truncated normal distribution and *IG* is an inverted gamma distribution. In MCMC estimation, these three parameters are estimated through Gibbs sampling. Because it is difficult to find the exact posterior distribution of α, γ_1 and γ_2, these parameters are estimated through Metropolis-Hastings sampling. Appendix A contains a brief overview of the estimation procedure, and further details on Gibbs sampling and Metropolis-Hastings can be found in a textbook on Bayesian statistics such as Gelman et al. (1995).

The results of the simulated data exercise with 2,000,000 MCMC simulations (discarding the first 1,000,000 as burn in) are summarized in Table 1. Since the data are simulated, we know the true value of each parameter. True values are reported in the second column. The estimates are in the third column along with standard errors in the fourth column. Qualitatively, none of the estimates are far from their true values, and none of them are statistically different. This suggests that the MCMC methods work well on this difficult estimation problem, at least when the data set is ideal. Figure 2 shows the empirical distributions for each parameter.

Turning to the real data, we restrict the analysis to gag fishing. As discussed above, gag is the species that the two marine reserves are most likely to enhance through recovery of the sex ratio. There are 142 months of data, and we define effort as total crew days at sea. Though not a perfect measure, this allows us to aggregate across gear types for the gag fishery. Compared to the simulated data exercise, we make even more conservative assumptions about priors. In particular, we now assume diffuse priors for all parameters, and, with the exception of q—which we force to be strictly positive—we do not force the other parameters to be within specified ranges. At a later time, we could incorporate more prior information from stock assessments.

As a first step, we estimate the MCMC model on NMFS Zone 6 data. This is the zone in which the Steamboat Lumps marine reserve is located. Table 2 reports estimates and standard errors, while Figure 3 shows the empirical distributions for each parameter. All of the parameters are statistically significant, i.e. statistically different from zero. The magnitudes of γ_1 and γ_2 are of greatest interest. Under the null hypothesis that the marine reserve has no effect on growth of gag, $\gamma_1=1$. Though the mean of the distribution of $\gamma_1>1$, this result is not statistically significant ($t = 0.70$). Thus, we fail to reject the hypothesis that the reserve has no effect on gag growth. Similarly, under the null hypothesis that the reserve does not have a net effect on catchability, $\gamma_2=1$. Here again we fail to reject this hypothesis ($t = 0.21$). Table 2 also reports implied carrying capacity and maximum sustainable yields (MSY) without and with the marine reserve. Here we take the point estimates as given, and thus the MSY with the reserve is 35% higher.

Discussion

Many authors have used modeling to predict that marine reserves enhance growth of fish species, but demonstrating actual growth empirically in a functioning marine reserve is the real currency of a reserve effect. Only a handful of papers have conducted retrospective analyses of the empirical effects of marine reserves on fisheries (McClanahan and Kaunda-Arara 1995; Murawski et al. 2000; Roberts et al. 2001; Russ and Alcala 1996, 2004; Smith, Zhang, and Coleman 2005). To our knowledge, no previous paper has done so with a structural model. Our structural approach uses a simple surplus production model and adds two features to account for the effects of marine reserves. Although our model cannot measure the mechanisms through which reserves could contribute to fish growth, it serves as an important step towards assessing the net effect of a policy change in a bioeconomic system. In contrast, non-structural approaches may be subject to bias due to the presence of nonlinearities, dynamics, and latent state variables.

We have several directions for future research. First, we plan to estimate the MCMC model on multiple zones simultaneously. Here we plan to allow carrying capacities to vary over space but restrict intrinsic growth to be the same over space. The effects of a reserve will be allowed to vary by treatment zone. This model essentially will allow data from non-treated zones to help refine our estimates of intrinsic growth. Second, we plan to estimate the model at the level of individual fishing vessels and allow for heterogeneity in fishing skill. This exercise will more closely parallel the work that we have done using program evaluation. Third, we plan to add depensation to the net growth function. This change will add at least one parameter to the estimation and will allow the net growth function to be asymmetric. Finally, we plan to build a behavioral model such as dynamic open access into the structural bioeconomic model.

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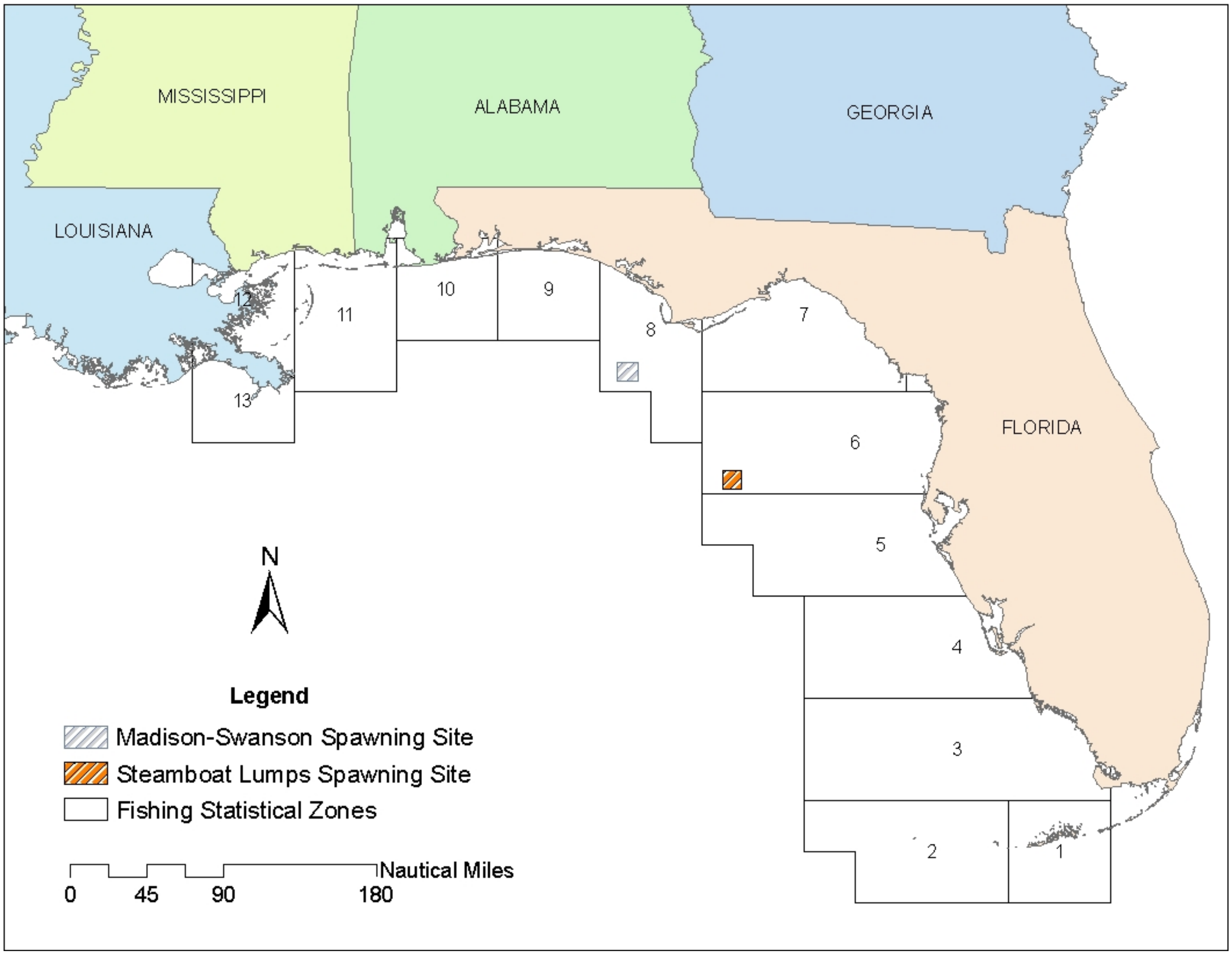

Figure 1 Gulf of Mexico Reef No-take Marine Reserves Established in June 2000

Marine reserves are contained within National Marine Fisheries Service statistical zones.

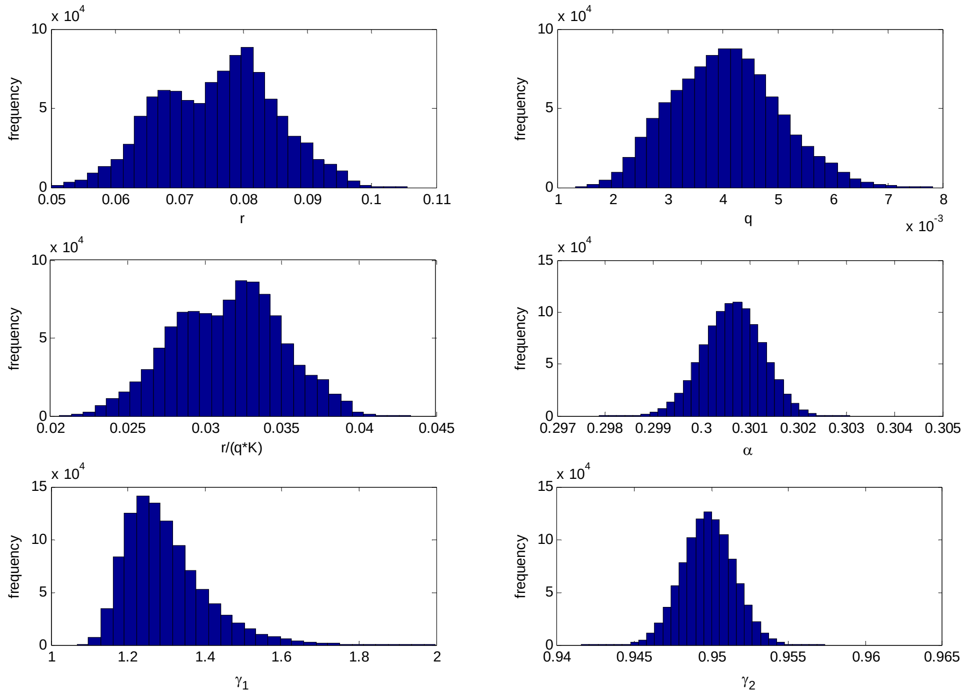

Figure 2: Empirical Distributions of MCMC Simulations on Simulated Data

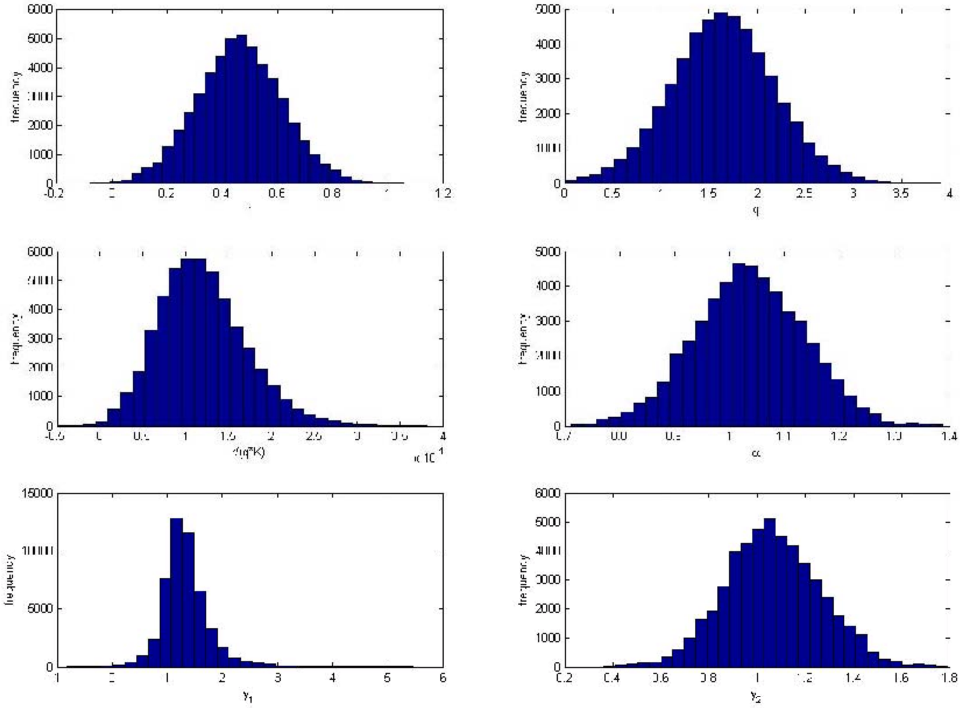

Figure 3: Empirical Distributions of MCMC Simulations on Gulf of Mexico Gag Fishery Data – NMFS Zone 6 Only

Table 1: Results of MCMC Estimation on Simulated Data

	True Value	Estimated Value	Standard Error
r	0.08	0.0760	0.0091
q	0.005	0.0041	0.0010
k	0.032	0.0315	0.0035
α	0.3	0.3006	0.0006
γ_1	1.2	1.2993	0.1078
γ_2	0.95	0.9498	0.0017

Note: results are based on 2,000,000 simulations in the Markov Chain and discarding the first 1,000,000.

Table 2: MCMC Results for the Gag Fishery in NMFS Zone 6

Parameter	Estimate	St. Error
r	0.46083	0.15457
q	1.65410	0.54001
k	0.00012	0.00005
α	1.03811	0.10200
γ_1	1.35215	0.50517
γ_2	1.04560	0.19261
σ^2	8579	1059

Implied Carrying Capacity in Zone 6 (pounds)
234,774

Implied MSY for Zone 6 (no reserve)
27,048

Implied MSY for Zone 6 (with reserve)
36,573

Appendix A – Details on MCMC Estimation

The MCMC estimation algorithm uses the following steps:

1. start at an initial parameter vector $\theta^0 = \left(r^0, q^0, k^0, \alpha^0, \gamma_1^0, \gamma_2^0\right)$;
2. generate θ^{i+1} from $p\left(\theta_j \middle| \theta_{-j}^i, x\right)$ sequentially, which includes two parts in this study:
   - 2.1 Gibbs sampling (for *r*, *q* and *k* with exact posterior distributions):

     $$r^{i+1} \sim p\left(r \middle| q^i, k^i, \alpha^i, \gamma_1^i, \gamma_2^i, H, E, \sigma^2\right),$$

     $$q^{i+1} \sim p\left(q \middle| r^{i+1}, k^i, \alpha^i, \gamma_1^i, \gamma_2^i, H, E, \sigma^2\right),$$

     $$k^{i+1} \sim p\left(k \middle| r^{i+1}, q^{i+1}, \alpha^i, \gamma_1^i, \gamma_2^i, H, E, \sigma^2\right).$$

   - 2.2 Metropolis-Hasting sampling (for α, γ_1 and γ_2):
     - 2.2.1 With r^{i+1}, q^{i+1} and k^{i+1} generated in the last step, draw θ_{new} (α, γ_1 and γ_2) from a proposal density $q\left(\theta_{new} \middle| \theta_{old}\right)$ sequentially. We adopt the random walk sampler with a normal kernel:

       $$q\left(\theta_{new} \middle| \theta_{old}\right) \propto \exp\left(-\frac{\left(\theta_{new} - \theta_{old}\right)^2}{\sigma_{proposal}^2}\right),$$

     - 2.2.2 set $\theta^{i+1} = \theta_{new}$ with a probability of *u*, and $\theta^{i+1} = \theta_{old}$ with a probability of *1-u*, where

       $$u\left(\theta_{new} \middle| \theta_{old}\right) = \min\left[1, \frac{p\left(\theta_{new}\right) q\left(\theta_{old} \middle| \theta_{new}\right)}{p\left(\theta_{old}\right) q\left(\theta_{new} \middle| \theta_{old}\right)}\right],$$

3. Increase *i* and repeat step 2.