Available online at www.sciencedirect.com

SCIENCE DIRECT®

Journal of Environmental Economics and Management 52 (2006) 482–500

JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT

www.elsevier.com/locate/jeem

Valuing water quality changes using a bioeconomic model of a coastal recreational fishery☆

D. Matthew Massey[a,*], Stephen C. Newbold[a], Brad Gentner[b]

[a]*US EPA, National Center for Environmental Economics, 1200 Pennsylvania Ave NW, MC 1809T Washington, DC, USA*
[b]*US NOAA, National Marine Fisheries Service, Silver Spring, MD, USA*

Received 25 April 2005
Available online 12 June 2006

Abstract

This paper develops and applies a structural bioeconomic model of a coastal recreational fishery. We combine a dynamic fish population model, a statistical model of angler catch rates, and a recreation demand model to estimate the value of water quality changes for the Atlantic Coast summer flounder fishery. The model predicts that improving water quality conditions in Maryland's coastal bays alone would have relatively small impacts on the fishery as a whole. However, water quality improvements throughout the range of the species could lead to substantial increases in fish abundance and associated benefits to recreational anglers from increased catch rates. We also estimate an alternative version of the catch function, with no direct measure of fish abundance included, and we compare results from this ''reduced form'' approach to results from our structural model.

Keywords: Bioeconomic model; Dissolved oxygen; Recreation demand; Recreational fishing; Summer flounder; Water quality

1. Introduction

Approximately 20 million people went saltwater fishing in the year 2000, making it one of the most popular outdoor recreational activities in the United States [24]. According to the US EPA, 51% of coastal waters are impaired for one or more human uses [48], and studies consistently demonstrate that water quality conditions affect recreation demand. There is a substantial body of research on the relationships between water quality and recreational fishing in particular. However, most previous studies focus on a single element in the chain of effects that connect water quality changes to the welfare of anglers, or they use a reduced form approach based on cross-sectional data on trip frequencies, expected catch, and water quality across fishing sites, thereby avoiding the measurement or modeling of fish abundance altogether. The result is a large number of studies

☆The views expressed in this paper are those of the authors and do not necessarily represent those of the US EPA or NOAA. No Agency endorsement should be inferred.

*Corresponding author. Fax: +202 566 2338.
E-mail addresses: massey.matt@epa.gov (D.M. Massey), newbold.steve@epa.gov (S.C. Newbold), brad.gentner@noaa.gov (B. Gentner).

0095-0696/$ - see front matter © 2006 Published by Elsevier Inc.
doi:10.1016/j.jeem.2006.02.001

that as a group indicate improvements in water quality may lead to substantial benefits for anglers, but individually are difficult to combine to evaluate specific water quality policies in a comprehensive manner.

In this paper, we develop and apply a structural bioeconomic model that integrates the major links in the chain of effects connecting water quality to angler welfare. First, we model the effects of water quality conditions on fish survival and abundance. Second, we model the effect of fish abundance and water quality on angler catch rates. Third, we model the effects of angler catch rates on trip demand. Combined, these form a dynamic bioeconomic model of the effects of water quality changes on recreational fishing.

We have adopted a structural modeling approach for several reasons. First, the available datasets were assembled independently and for purposes other than estimating a model for valuing water quality changes. In our experience this is a common scenario, so it is important to develop methods of integrating disparate datasets and models in an internally consistent way for policy analysis.

Second, the structural modeling approach we use provides the flexibility to evaluate a wider range of water quality policies than most previous models. We take advantage of a detailed water quality dataset to evaluate changes in water quality conditions on time scales as short as quarter hour intervals. Most previous models use average annual or single point in time measures of water quality conditions. The structural model also accounts for fish movements in and out of the study area, so it can be used to investigate the effects of the geographic scope of water quality changes in addition to the magnitude of the changes, unlike standard reduced form approaches. In addition, the structural model treats the recreational fishing sector and the commercial fishing sector separately, which can provide a platform for comparing water quality policies to fishery management policies.

Third, when analyzing a system of multiple interconnected sites, such as a coastal recreational fishery, it is important to distinguish between the short run and long run effects of water quality (and other habitat conditions more generally) on the species' abundance. Given a fixed total population size, the spatial relationship between abundance and water quality will depend on the behavioral responses of fish to the variation in water quality conditions and fish population density across all of the interconnected sites in the range of the species. Individuals will tend to spread out across the available habitat in such a way that balances the positive effects of good habitat conditions and the negative effects of crowding [10,41]. Changes in water quality will have a short run effect on the spatial distribution of individuals in the population through this habitat selection process, and a long run effect on the overall abundance through changes in survival or reproduction. In general the short run relationship between abundance and water quality need not be the same as the long run effect.[1] Thus, a reduced form approach that excludes potentially important dynamics that occur at other times in the species' life cycle can at best only implicitly capture the short run relationship and therefore will likely produce inaccurate forecasts of the long run effects of water quality changes.

In the next section we lay out a stylized bioeconomic model that describes how a recreational fishery evolves over time in response to water quality conditions and angler behavior. The model also provides a convenient organizational structure for discussing previous research on recreational fishing and the structural model developed in this paper. In Section 3, we apply our approach using data on water quality and angler catch rates in Maryland's coastal bays and a stated choice survey of anglers who target summer flounder on the Atlantic Coast. Section 4 summarizes the main results and concludes.

2. A dynamic model of a recreational fishery

Water quality may affect the site choices, trip demands, and ultimately the welfare of anglers through several pathways. First, water quality may affect fish abundance through its impact on the reproductive and survival rates of individual fish. Thus, the abundance of fish in time period t, A_t, will be a function of the abundance, the harvest, H_{t-1}, and water quality conditions, $\mathbf{Q}_{t-1}$, in the previous time period:

$$A_t = f_1(A_{t-1}, H_{t-1}, \mathbf{Q}_{t-1}). \tag{1}$$

[1]The short run (spatial) and long run (dynamic) relationships between fish abundance and water quality could diverge even in a steady-state situation. This could occur for at least two reasons: (1) water quality has different effects on different life stages of the species, and (2) per-capita reproduction or survival rates in pre-harvested life stages are functions of population density (i.e., are "density dependent").

In addition to this long run ‘‘abundance effect,’’ water quality also may influence anglers’ catch rates through short run effects on feeding behavior and fish movements within a time period through the habitat selection process mentioned above. Thus, the average catch per trip for angler i in time period t, C_{it}, will be a function of the angler’s skill and other personal characteristics, $\mathbf{Z}_i$, the current fish abundance, and current water quality conditions:

$$C_{it} = f_2(\mathbf{Z}_i, A_t, \mathbf{Q}_t). \tag{2}$$

Independent of the long run ‘‘abundance effect’’ and this short run ‘‘catchability effect,’’ water quality also may have a direct ‘‘site choice effect’’ on anglers either through potential health risks from exposure to the water or from eating contaminated fish, or through the effect of water quality on the appearance or odor of the water body. Thus, the number of fishing trips angler i takes in time period t, R_{it}, will depend on travel costs (and other site characteristics such as boat ramps, parking, etc), $\mathbf{X}_{it}$, the angler’s personal characteristics, the current (expected) catch, and possibly water quality conditions:

$$R_{it} = f_3(\mathbf{X}_{it}, \mathbf{Z}_i, C_{it}, \mathbf{Q}_t). \tag{3}$$

The total harvest in period t, H_t, consists of the recreational harvest (the average catch per angler multiplied by the number of trips per angler summed over all anglers) plus the commercial harvest, HC_t:

$$H_t = \sum_i C_{it} R_{it} + HC_t. \tag{4}$$

Therefore, the average catch rate and the aggregate trip demand will determine the total recreational harvest level, which in turn will affect the abundance of fish that can spawn to produce fish in future years (H_t will appear in the expression for A_{t+1} as in Eq. (1)), which will affect the catch rate in future years, which will affect trip demand, and so on.

The most common approach for investigating the effects of water quality on recreational fishing is to estimate some version of the trip demand function, Eq. (3), using random utility models of recreation demand (see the reviews by Freeman [9] and Van Houtven et al. [50]). Many of these studies use measures of catch rates as site attributes, but only a few include measures of both catch rates and water quality. Examples include Jakus et al. [18,19], who use the presence of fish consumption advisories and average catch rates as site characteristics, and Kaoru [20], who uses estimates of nitrogen and phosphorus discharge, biochemical oxygen demand, and suspended solids, along with a measure of average catch.

To measure differences in catch rates across sites, most researchers use average historic catch rates at different sites estimated either from the in-hand sample of recreators or from external sources such as the Marine Recreational Fishing Statistics Survey (MRFSS). In cases where no direct measures of water quality are included, catch rates themselves may be thought of as serving as a proxy for water quality conditions; higher catch rates are assumed to be at least partly the result of better water quality. Strand et al. [40], Kaoru [20], Jakus et al. [19], Hicks et al. [17], McConnell and Strand [26], and Morey and Waldman [30] all employ variations of this strategy. However, there are at least two limitations to using average historic catch across all anglers as a proxy for expected catch for individual anglers: it ignores potential variations in catch rates within a season and across years, and it provides no explicit linkage between catch and water quality.[2]

To overcome these limitations, some researchers estimate the catch relationship, Eq. (2), by modeling catch rate as a function of angler and site characteristics.[3] Most of these studies use one or more measures of water quality as explanatory variables, but we are aware of none that use a direct measure of fish abundance. For example, Smith et al. [39] use a household production function approach to model expected catch. Landed fish are treated as a good produced by combining human capital (hours fished, fisherman skill, etc.) and

[2]Another potential limitation, pointed out by Morey and Waldman [30], is that using average catch as a measure of the unknown expected catch for each site can lead to errors-in-variables bias (though Train et al. [43] point out that the solution proposed by M&W itself would be biased if important explanatory variables are omitted). Our recreation demand model described in Section 3.3 uses data from a stated choice survey, so assuming the respondents considered the information presented in the survey accurate and complete our recreation demand model should not be subject to this source of errors-in-variables bias.

[3]A third approach to characterizing expected catch across sites is to use subjective ratings or indices of fishing quality, usually created by fisheries experts [28]. This method is the least common in the literature, presumably due to the difficulties of constructing valid subjective measures.

environmental inputs (water quality). Kaoru et al. [21], Englin et al. [8], and Lipton and Hicks [25] use similar approaches to model expected catch, and then include the estimated expected catch as a site characteristic in random utility models of fishing trip demands, thereby linking the catch and trip demand functions, Eqs. (2) and (3).[4]

Most of the studies cited above use temporally and spatially aggregated measures of water quality conditions, either single point-in-time measures or annual averages over large geographic areas. For example, both Smith et al. [39] and Kaoru et al. [21] include annual county level estimates of biochemical oxygen demand and nitrogen loadings as measures of water quality. Englin et al. [8] rely on measurements of dissolved oxygen (DO) and turbidity taken at a single point in time for each site. These measures ignore the potential correlations between water quality conditions and catch rates at finer scales and severely restrict the policy scenarios that can be addressed with the final model. A few studies have used more temporally detailed measures of water quality conditions. For example, Lipton and Hicks [25] use monthly and biweekly DO and water temperature readings from the monitoring station nearest to the interview location on the closest date prior to the fishing trip.

The only studies of which we are aware that use a direct measure of fish abundance are those by Cameron [4–6] on the effects of water quality on the non-market value of the marine recreational fishery along the Texas Gulf Coast. There is a growing body of research that uses bioeconomic models incorporating both temporal and spatial dynamics [e.g., 35,38], but these studies generally focus on harvesting polices for commercial fisheries. We are aware of no studies that estimate multiple models to operationalize the entire system of Eqs. (1)–(4) to evaluate water quality changes for a recreational fishery.

3. Application: summer flounder in Maryland's coastal bays

In this section, we develop a structural bioeconomic model of recreational summer flounder fishing. The model incorporates data on water quality, flounder abundance, and angler catch rates in Maryland's coastal bays, data from a stated choice survey of anglers who target summer flounder on the Atlantic Coast, and data on commercial harvest levels. We then use the model to evaluate the effect of several illustrative water quality change scenarios on recreational summer flounder fishing, both in the Maryland coastal bays and across the full range of the species.

The complex life cycle of summer flounder makes for a particularly instructive application of a structural modeling approach. Summer flounder on the Atlantic coast of the US spend their first 1 or 2 years as juveniles in coastal bays and estuaries mostly between Cape Hatteras, NC and Long Island, NY [1]. The adults spend the winter months and breed in the open ocean along the continental shelf, where they are subject to a large commercial fishery (average commercial landings between 1982 and 2001 was 8500 metric tons [31]). A large portion of the adult stock spends the summer months along with the juveniles feeding in the coastal bays and estuaries [22,34], where they are subject to an active recreational fishery (average recreational landings between 1982 and 2001 was 5400 metric tons [31]).

Maryland's four coastal bays, shown in Fig. 1, are centrally located in the range of the Atlantic coast summer flounder stock. While the coastal bays are much smaller than nearby Chesapeake Bay,[5] they support a disproportionate fraction of Maryland's summer flounder fishery. According to NMFS, between 1994 and 2002 anglers took roughly 77,000 flounder fishing trips on average in the coastal bays per year, and at least two thirds of the recreational harvest in Maryland during that time was from the coast [7]. The coastal bays also serve as an important nursery for young juvenile summer flounder, who depend on the bays' shelter and food sources for survival in the most vulnerable portion of their lives.

As water quality conditions have worsened in recent decades due to increased residential, commercial, and agricultural development, public concerns about the ecological health of Maryland's coastal bays have grown. Populations of many native fish (including summer flounder), shellfish, and underwater sea grasses have

[4]McConnell et al. [27,28], Jakus et al. [18], and Scrogins et al. [36] also model expected catch rates, but do not include any measures of water quality as explanatory variables.

[5]The Maryland coastal bays have a surface area of 280 km^2 and volume of 322 million m^3, while the Chesapeake Bay has a surface area of 18,000 km^2 and volume of 68 billion m^3 [29].

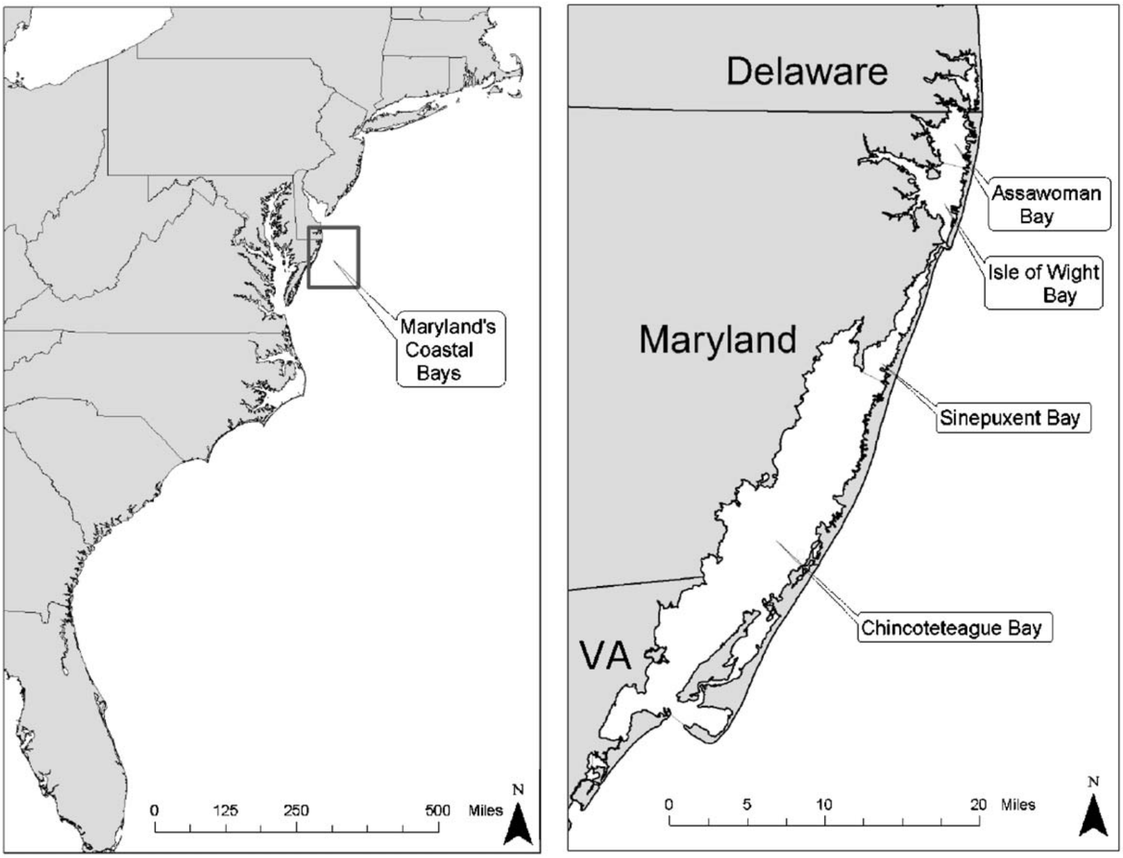

Fig. 1. Maryland's coastal bays.

decreased significantly from their historic levels. These decreases have prompted a number of measures to protect or restore habitat and water quality conditions in the coastal bays ecosystem including a comprehensive conservation and management plan, numerous water quality monitoring programs, and the establishment of Total Maximum Daily Loads [51].

The following sub-sections describe the components of our structural model of the recreational summer flounder fishery in the Maryland coastal bays in detail and present and discuss our estimation results. Sections 3.1–3.3 describe the population model, the catch model, and the recreation demand model, respectively. Section 3.4 combines the models and uses the integrated model to evaluate several illustrative water quality improvement scenarios.

3.1. The population model

The first component of our bioeconomic model is a model of population dynamics that incorporates functional relationships between water quality conditions, summer flounder survival and abundance, and recreational and commercial harvest levels. The model is age-structured to account for different sources of mortality during different flounder life stages, and it is spatially structured to account for annual flounder migrations between coastal waters and the open ocean. In the bays and estuaries during the summer DO affects juvenile flounder and recreational fishing affects adult flounder. In the open ocean during the winter commercial fishing affects adult flounder.

The model is designed to allow simulation of changes in water quality conditions in estuaries and bays in and out of the study area independently. This will be important for evaluating policies that might affect water quality in only part of the species' range, and it provides the flexibility for investigating the effects of the

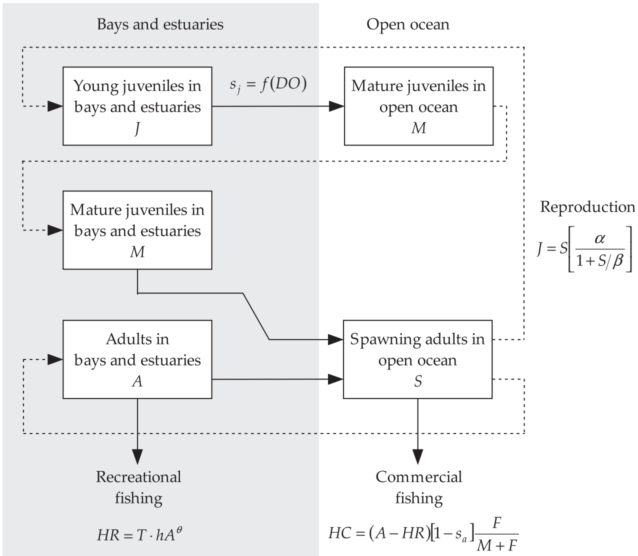

Fig. 2. Schematic representation of the population model.

geographic scope of improved water quality conditions in addition to the magnitude of the changes. The model also is designed to be calibrated using readily available information on recreational harvest levels in and out of the study area and commercial harvest levels for the fishery as a whole. The model is briefly explained in the following paragraphs and summarized in Figs. 2 and 3; the full specification and notes on model calibration are given in Appendix A and in the online supplement.

As shown in Fig. 2, reproduction is modeled as a function of the size of the entire breeding stock in the open ocean. Reproduction and survival through the egg and larval stages are assumed to be density dependent, i.e., the per capita reproductive rate declines with increasing spawning stock abundance. Survival of juveniles is modeled as a function of the time series of DO concentrations during the months of May–August. Young juvenile summer flounder are known to be especially sensitive to DO conditions, particularly in the summer when DO can reach very low levels during the morning hours and when high nutrient loads flushed from agricultural fields after storm events can spur algal growth and subsequent oxygen depletions in the water column [1,49]. The juvenile survival function is based on results from laboratory experiments conducted by the Environmental Protection Agency [46] (see Fig. 4) and is calibrated to match baseline conditions. We use a model that estimates the probability of survival as a function of exposure to a constant DO level for a 15-min interval. To estimate survival over the entire season, a time series of DO levels is simulated by drawing randomly from the empirical DO distribution as measured at two continuous monitoring stations in the study area. The probability of survival over the entire season is then computed as the product of survival probabilities over each interval, assuming survival probabilities from one interval to the next are independent. The survival function will be responsive not only to changes in the annual average DO levels, but also to changes in the variation and the frequency of extremely low DO levels on very short time scales. This provides the ability to model any water quality change scenario that can be described by a frequency distribution of DO levels measured on time scales as short as 15 min, and therefore the flexibility to evaluate a much wider variety of water quality policies than would be possible with models that include only annual average DO levels.[6]

[6]However, our survival function is still overly simplified in one important sense: the cumulative probability of survival over the season will not be sensitive to the temporal ordering of water quality conditions during the season. For example, according to this model a long string of intervals with low DO levels is equivalent to the same total duration of low DO conditions spread out evenly over the season. In reality, survival probabilities are not likely to be independent across time intervals. In future work it will be important to develop improved laboratory or field methods for measuring the frequency- and duration-dependence of survival rates on water quality conditions, and models for translating the results of such experiments to natural settings.

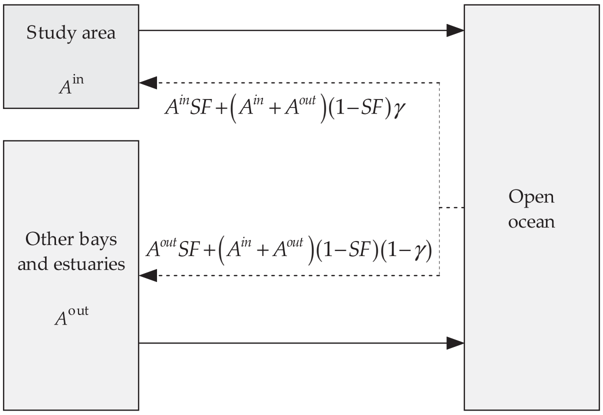

Fig. 3. Sub-population structure used in the population model.

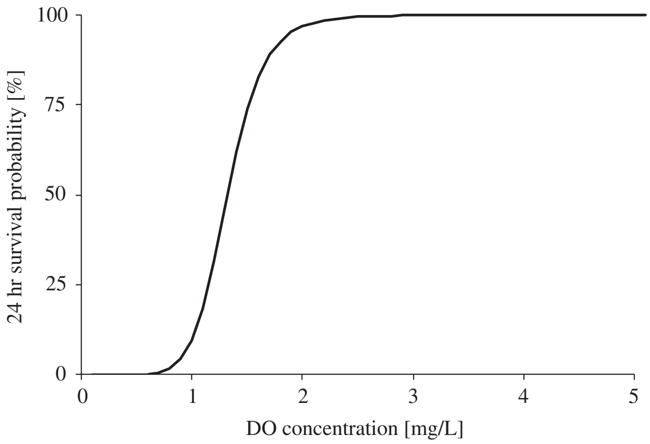

Fig. 4. Juvenile summer flounder DO dose–response function.

Because our study area encompasses only a small part of the range of the Atlantic stock of summer flounder, we must account for the fact that some portion of the population will move in and out of the study area from year to year. We model the stock as consisting of two connected sub-populations defined by the boundary of the study area and the remainder of the range of the stock. As shown in Fig. 3, a fixed proportion SF of adults are assumed to return to the same bay or estuary they inhabited the previous year. (SF represents the species' "site fidelity," i.e., the genetic pre-disposition of individuals to return to the same area in subsequent years.) Also, a fixed proportion γ of the remaining adults and juveniles are assumed to be carried into Maryland's coastal bays with the prevailing tides and currents every year [34].

Parameters for the population model are taken directly from government reports, internet databases, and peer-reviewed literature, or they are estimated by calibrating the model so the equilibrium recreational and commercial harvest levels under baseline conditions match the average historic harvest levels.

3.2. The catch model

To estimate the relationship between fish abundance, water quality, and expected catch, we use three datasets from Maryland's Department of Natural Resources (MD DNR). Water quality data were obtained from the MD DNR Eyes on the Bay program. Monthly water quality measurements taken at 23 monitoring stations located throughout the four coastal bays were used to calculate average levels of DO, water

Table 1
Regression results for the catch function and an alternative "reduced form" version without the abundance index

Variable	With abundance index		Without abundance index		
	Coefficient	*t*-Stat	Coefficient	*t*-Stat	Mean of *X*
Constant	−6.887	−3.159	−6.253	−2.926	
Angler characteristics					
ln (hours fished)	1.509	5.821	1.425	5.687	0.561
ln (anglers)	0.806	5.271	0.849	5.453	0.675
Fished from shore	−0.430	−1.395	−0.509	−1.738	0.036
Fished from charter boat	0.501	2.944	0.475	2.729	0.332
Location fixed effects					
Isle of Wight Bay	−0.121	−0.908	−0.208	−1.664	0.275
Sinepuxent Bay	−0.372	−1.088	−0.932	−3.00	0.403
Chincoteague Bay	−1.250	−2.53	−1.381	−2.682	0.013
Isle of Wight or Sinepuxent	0.206	0.873	−0.079	−0.358	0.220
Water quality conditions					
DO	0.0287	0.431	0.177	3.076	6.250
Water temp	0.109	4.05	0.126	4.55	24.180
Salinity	0.132	1.719	0.077	1.041	30.930
Secci depth	1.067	2.883	1.392	3.829	0.543
Fish abundance					
ln(average trawl catch)	0.328	4.404	—	—	0.286
Number of observations	612		612		
Squared correlation between predicted means and observed catch	0.55		0.55		

temperature, salinity, and secci depth in each bay in 2002 from April through October. Catch data were obtained from the 2002 MD DNR Summer Flounder Volunteer Angler Survey, which asked anglers who fished for summer flounder in Maryland to report the details of each of their fishing trips. The information collected includes the date of each trip, total catch, location fished, fishing method used, party size, hours fished, and several demographic characteristics. Our analysis uses data on 612 trips taken to the four Maryland coastal bays. Fishery-independent data on fish abundance were obtained from the Maryland Coastal Bays Finfish Project, which performs bottom trawl surveys at 20 sites in the coastal bays every month April–October. The average number of summer flounder captured per haul is used as an index of fish abundance for each bay in each month in 2002. Trip and angler characteristics from the Volunteer Angler Survey were matched with water quality measures from the Eyes on the Bay program and the fish abundance index from the Coastal Bays Finfish Project to create the dataset used for estimation.

Because the data on catch per trip come in the form of non-negative integers, we use a negative binomial count regression model to estimate the catch function [3], and we use a standard exponential mean function to specify the average reported catch per trip:

$$E[C_i] = \exp(\mathbf{Z}_i\boldsymbol{\delta} + \mathbf{Q}_i\boldsymbol{\eta} + \theta \ln \tilde{A}_i), \tag{5}$$

where C_i is the reported summer flounder catch, $\mathbf{Z}_i$ is a vector of angler characteristics, $\mathbf{Q}_i$ is a vector of water quality measures, $\tilde{A}_i$ is the index of fish abundance (average trawl catch), and $\boldsymbol{\delta}$, $\boldsymbol{\eta}$, and $\boldsymbol{\theta}$ are parameters to be estimated. Regression results are shown in the first two columns of Table 1. All angler characteristic variables possess their anticipated signs, and coefficients on the log of hours spent fishing, the log of the number of anglers in the party, the "fished from charter boat" dummy variable, and the abundance index are statistically significant at greater than the 99% level. The estimated magnitude of the abundance index coefficient is 0.328, which means that a 1% increase in fish abundance will lead to a 0.328% increase in the average catch rate.[7]

[7]Because the natural log of the abundance index is used in the exponential mean function of our estimating equation, the catch function in Eq. (5) corresponds to the functional form used for the average recreational catch in the population model in the appendix. If the

The coefficient estimates on all water quality variables also are of the expected sign, and the coefficients on water temperature, secci depth, and salinity are statistically significant at the 90% level or greater. Assuming that fish abundance is adequately controlled for by the abundance instrument, these results suggest there also is a "catchability effect" of water temperature, secci depth, and (possibly) salinity. Only the dummy variable for Chincoteague Bay was statistically different from the control bay, Assawoman Bay, which suggests that the measures of water quality and fish abundance explain most of the variation in catch between the bays.[8]

We also estimate an alternative version of the catch function where the abundance instrument is excluded. The results of this regression are shown in the second two columns of Table 1. When the model is estimated with the abundance index excluded, DO becomes highly statistically significant. This indicates a strong positive correlation between fish abundance and DO. Taken together, the results of the two versions of the catch model suggest that the primary effect of DO on catch is through its effect on fish abundance, not through an effect on catchability.

3.3. The recreation demand model

To estimate the relationship between catch and recreation demand we use stated choice data from the 2000 Survey of Northeast Recreational Anglers [16]. The survey was conducted by the National Marine Fisheries Service to evaluate angler preferences for various fishery management alternatives. Each respondent was presented with four stated choice questions in a conjoint format concerning summer flounder fishing in the Mid-Atlantic region. In each question, respondents were asked to choose between two alternative summer flounder fishing trips and a "do something else" option. The attributes that could differ between the options included travel costs, likely total catch, the minimum size limit, the catch limit, the likely number of legal-sized summer flounder caught, and the likely total catch of other fish species.[9]

We model survey respondents' stated choices using a repeated choice mixed logit model [23,33,44]. The utility individual i would receive from selecting alternative k on choice occasion t is specified:

$$U_{ikt} = \mathbf{Z}_{ik}\boldsymbol{\varphi}_i + \varepsilon_{ikt}, \tag{6}$$

where $\mathbf{Z}_{ik}$ is a vector of individual and site characteristics. The model assumes that individuals choose the alternative that provides the maximum utility on each choice occasion. Each individual also is assumed to have a unique vector of coefficients $\boldsymbol{\varphi}_i$ that vary normally across individuals, are uncorrelated with each other, and are constant across choice occasions.[10] The error term ε_{ikt} is assumed to be distributed identically and independently according to an extreme value distribution, which gives rise to the logit probability function. The probability that individual i makes a sequence of choices $\mathbf{y}_i$ over a series of choice occasions $t = 1, 2, \ldots, T$, given their preferences as described by $\boldsymbol{\varphi}_i$, is then the product of logit formulas. However, because the true coefficient values are unknown and assumed to vary across individuals, the logit probability function must be integrated over all possible values of $\boldsymbol{\varphi}_i$. Due to the analytical difficulty

(*footnote continued*)
abundance index, $\tilde{A}_i$, is proportional to the actual adult abundance, A_i, i.e., $\tilde{A}_i = vA_i$, then we can define $h_i = \exp(\mathbf{Z}_i\boldsymbol{\delta} + \mathbf{Q}_i\boldsymbol{\eta})v^{-\theta}$ and rewrite our catch equation as $C_i = h_i A_i^{\theta}$, as in Eqs. (A.10) and (A.11). This allows us to calculate the average catch per angler as a function of adult summer flounder abundance, which provides the link between the catch function and the bioeconomic simulation model. For the link between fish abundance and commercial catch we have assumed that the commercial harvest is directly proportional to the stock size (i.e., $\theta = 1$), which means that the response to increased fish abundance in the commercial fishery will be greater than that in the recreational fishery. This is consistent with standard commercial fisheries models (e.g., [13]), though this convention has been challenged by Harley et al. [15] who found values of θ in the range 0.64–0.75. However, we do not have comparable data on effort and harvests for the commercial fishery so we cannot estimate this relationship directly for our case study.

[8]Other functional forms—with linear or quadratic abundance instrument terms or both—also were estimated for the catch function. None of the alternative specifications clearly performed better that the version reported in Table 1. Furthermore, this functional form facilitated a natural linkage between the catch model and the population models, as discussed in footnote 7.

[9]Note that no water quality characteristics were described in the stated choice survey. Even if they were, this would provide a means of estimating the "site choice effect" of water quality only (Eq. (3)).

[10]The assumption that coefficients are constant across choice occasions is reasonable if tastes are thought to be stable over time.

Table 2
Results of the mixed logit recreation demand model

Variables	Mean coefficient		Standard deviation	
	Estimate	*t*-Stat	Estimate	*t*-Stat
No trip dummy (NTD)	−0.9931	−2.521	2.0333	3.446
Participant characteristics				
NTD∗boat owner	−0.2474	−0.762	0.9702	1.348
NTD∗non-white	−0.7729	−0.642	3.5411	2.001
NTD∗male	−1.6909	−1.346	1.8220	0.858
NTD∗attended college	−0.1780	−0.284	2.0536	1.866
NTD∗work fulltime	−1.1851	−3.368	1.7234	2.733
NTD∗daysfished	−0.0879	−1.856	0.1085	2.679
Trip characteristics				
Travel cost	−0.0175	−13.044	—	—
Total catch	0.0717	12.277	0.0746	6.108
Bag limit	0.1050	16.415	0.0854	5.320
Min size∗legal catch	0.0131	18.135	0.0101	9.039
Other fishing good	0.4208	7.134	0.9699	6.501
Other fishing bad	−0.5767	−10.255	0.7594	6.047
Number of respondents	2392			
Number of observations	9568			
Mean log-likelihood	−0.7806			

of evaluating multiple integrals, results are most easily obtained through simulation. The simulated probability is

$$SP(\mathbf{y}_i|\boldsymbol{\psi}) = \frac{1}{D}\sum_{d=1}^{D}\left[\prod_{t}^{T}\frac{\exp(\mathbf{Z}_{ik_t}\boldsymbol{\phi}_i^d)}{\sum_j \exp(\mathbf{Z}_{ij}\boldsymbol{\phi}_i^d)}\right], \tag{7}$$

where $\boldsymbol{\psi}$ contains the means and variances of the $\boldsymbol{\varphi}_i$ distributions, D is the number of draws, $\boldsymbol{\phi}_i^d$ is draw d from the estimated distribution of $\boldsymbol{\varphi}_i$, and the term in square brackets is the product of logit formulas.[11] The simulated probabilities are used to construct a simulated likelihood function that is then maximized to produce estimates of the parameters of the $\boldsymbol{\varphi}$ distribution.

Results from the repeated choice mixed logit model are shown in Table 2. The travel cost coefficient is negative and statistically significant, as expected, indicating that all else equal anglers prefer to fish at sites closer to home and therefore less costly to visit. The results also indicate that anglers are more likely to visit sites with higher total catch, bag limits, legal take-home catch of summer flounder, and total catch of other fish. Preferences for each trip characteristic (save travel cost, which was not allowed to vary across anglers to aid estimation) were also found to vary significantly across the population. Aside from days fished and working fulltime, which both increased a respondents' probability of taking a trip, respondent characteristic variables explained little of the variation in respondents' participation choices.

The results of the recreation demand model allow us to estimate the value of changes in trip attributes to anglers. Following Small and Rosen [37] and Hanemann [14], changes in expected utility are monetized using the coefficient estimate on the travel cost variable, which is the estimated marginal utility of income.[12] Because the mixed logit model estimates the distributions of the coefficients, calculating the welfare effects of changes to sites in the choice set again requires simulating integration. For example, the expected welfare change for

[11]We use 400 Halton draws for estimation and 250 for welfare calculations [45, pp. 224–234].

[12]Alternative models including participants' income and income squared were also estimated. Income was not statistically significant in either case, so it was dropped from the model. (Also note that the travel cost parameter gives a direct estimate of the marginal utility of income only if income itself does not appear in the model as a separate explanatory variable.)

individual i associated with a change in quality at some or all of the sites would be

$$W_i = \frac{1}{D}\sum_{d=1}^{D}\left[\frac{\ln \sum_{k=1}^{K} \exp(\mathbf{Z}_{ik}\boldsymbol{\phi}_i^d) - \ln \sum_{k=1}^{K} \exp(\mathbf{Z}_{ik}^{*}\boldsymbol{\phi}_i^d)}{\phi_{\mathrm{TC}}}\right], \tag{8}$$

where D is the total number of draws from the estimated distributions, $\boldsymbol{\phi}_i^d$ is draw d from the distribution of $\boldsymbol{\phi}_i$, the numerator of the bracketed term is the difference in the expected maximum utility per choice occasion between the current and changed conditions, ϕ_{TC} is the travel cost coefficient, and $\mathbf{Z}_{ik}^{*}$ is a vector of changed quality measures at some or all of the K sites.

The results indicate that at the average catch rate from the MD DNR Summer Flounder Volunteer Angler Survey, which is approximately two fish per angler per trip, a 1% increase in the catch rate increases the value of each choice occasion by \$0.084. Values for extra percentage point increments are nearly constant over a large range, so the value per choice occasion for a 50% (roughly one fish) increase in the catch rate is \$4.22. This estimate is somewhat larger than the value of an increase of one fish per trip for bottom fish in Maryland reported by Hicks et al. [17], which was \$2.44, but it is near the low end of the range of values for an increase in catch of one fish per trip found in the marine recreation literature summarized by Freeman [9], which was \$2.21–\$85.00 in 1991 (most values were below \$20). Our estimates are per choice occasion values, so all else equal they should be smaller than per trip value estimates because there are more choice occasions than trips taken.

The total welfare change per year in the recreational fishery is computed by multiplying the per angler per choice occasion welfare estimate by the number of potential anglers, N, and the number choice occasions in a season, O. We estimate the product $N \times O$ using the identity $T \equiv N \times O \times p$, where T is the total number of summer flounder fishing trips taken in a year, and p is the average probability of taking a trip on any choice occasion. The average number of summer flounder fishing trips to the four coastal bays between 1994 and 2003 was 76,602 trips per year. We calculate the average probability of taking a trip on any given choice occasion using responses to a supplemental question in the stated choice survey where respondents were asked how many times they took a fishing trip in the previous 2 months. Responses ranged from 0 to 61 days, and the average response was 10.4 days in the previous 2 months, or 17%, which we take as our baseline estimate of p. This gives a value of 450,600 angler choice occasions per year ($N \times O$), which leads to a predicted aggregate welfare change of \$1.9 million per year from increasing the average catch per trip in the study area by 50%.

3.4. Evaluating water quality changes

We can now combine the population model, the catch function, and the recreation demand model to evaluate the long run effects of changes in water quality on summer flounder fishing. A change in DO conditions first causes a change in the survivorship of young juvenile flounder over the summer months, and after 2 years the first new larger cohort of young juveniles is recruited to the adult population (the population model). This increases the availability of catchable fish and therefore the average catch per angler (the catch model),which in turn leads to an increase in demand for trips (the recreation demand model).[13] The increase in catch per angler and demand for trips combine to yield a new, higher total harvest in the recreational and commercial fisheries, which partly offsets the increase in fish abundance from the improved DO conditions (the population model again). After a transition phase the system will reach a new stochastic steady state where the distribution of fish abundances and the harvest levels will remain stable over time.

With the catch and recreation demand parameters estimated and the population model specified, starting values for all state variables are determined by calibrating the population model to current water quality conditions. Benefits are estimated by comparing simulated baseline and water quality change scenarios. For the baseline scenario, a time series of DO levels during the summer is constructed for each year in a 100 year

[13] The effect of changes in expected catch on the probability of taking a trip is calculated using an auxiliary regression. We use results from the mixed logit recreation demand model to estimate the average change in the probability of taking a trip across all individuals in the dataset, $\overline{\Delta p(\mathbf{Z}, \boldsymbol{\phi})}$, for a variety of changes in expected catch rates, ΔC (i.e., for each level of ΔC, $\overline{\Delta p(\mathbf{Z}, \boldsymbol{\phi})}$ was calculated by integrating over the heterogeneity in tastes represented by the estimated random parameter distributions from the Mixed Logit model for each individual and then taking the average over all individuals). We then regress the estimated $\overline{\Delta p(\mathbf{Z}, \boldsymbol{\phi})}$'s on the ΔC's, which provides the link between the recreation demand function and the bioeconomic simulation model.

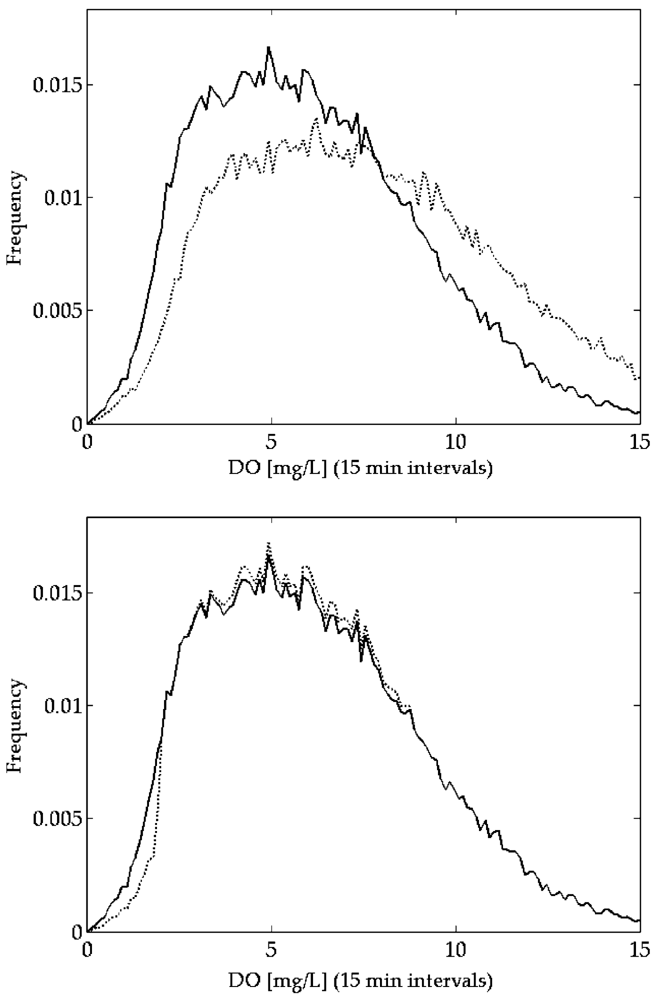

Fig. 5. Two water quality changes scenarios were analyzed: a 25% increase in DO levels at all times (top panel), and a 50% reduction in the frequency of DO below 2 mg/L (bottom panel). In each panel the solid line represents the baseline DO distribution and the dotted line represents the new (changed) DO distribution.

forecast horizon by drawing randomly from the empirical DO distribution. For the water quality change scenarios, time series of DO levels are constructed by modifying the baseline series, as shown in Fig. 5. The top panel illustrates a case where the baseline DO levels are increased by 25% at all times. The bottom panel illustrates a case where 50% of the DO levels below 2 mg/L in the baseline distribution have been replaced by random draws from the remainder of the distribution. The across-the-board increase in DO is typical of the water quality change scenarios examined by previous researchers using reduced form models. The reduction in the frequency of low DO events provides an example of a more complex (and potentially more realistic) scenario that can be directly evaluated by our structural model but not by a reduced form model.

Results from the water quality change scenarios are summarized in Table 3. To account for the natural variability in water quality conditions from year to year, we run the model 100 times using a different simulated DO series each time. The estimated aggregate welfare effects are reported as the constant annual equivalent of the stream of benefits from year 1 onward discounted at 5%.[14] Numbers in parentheses are 95% confidence intervals based on the 100 Monte Carlo trials.

[14]We calculate the annualized aggregate benefits as follows: Benefits $= \bar{V}(1+r)^{-T} + r\sum_{t=1}^{T} V_t(1+r)^{-t}$, where r is the discount rate, V_t is the current value of the benefits in year t, T is the simulation forecast horizon, and $\bar{V}$ is the average benefits for some suitably long span of

Table 3
Summary results for four water quality change scenarios

	Baseline conditions Levels	25% increase in DO levels in the study area [% change]	25% increase in DO levels everywhere [% change]	50% reduction in occurrences of DO < 2 mg/L in the study area [% change]	50% reduction in occurrences of DO < 2 mg/L everywhere [% change]
In the study area					
DO	6.07	25	25	1.0	1.0
s_j	0.452	55.5 (47.5, 64.5)	55.5 (47.5, 64.5)	50.6 (41.3, 59.0)	50.6 (41.3, 59.0)
C	1.93	2.34 (1.97, 2.77)	18.7 (15.7, 22.1)	2.10 (1.74, 2.47)	17.0 (13.9, 20.0)
T	76,600	0.10 (0.08, 0.11)	0.77 (0.65, 0.91)	0.09 (0.07, 0.10)	0.70 (0.57, 0.82)
H	46,033	2.44 (2.05, 2.88)	19.6 (16.5, 23.3)	2.19 (1.81, 2.57)	17.8 (14.5, 20.9)
Benefits [$1,000]		$85.3 ($65.9, $106)	$630 ($483, $789)	$74.4 ($54.8, $94.0)	$556 ($408, $712)
Out of the study area					
DO	6.07	0	25	0	1.0
s_j	0.452	0	55.5 (47.5, 64.5)	0	50.6 (41.3, 59.0)
C	1.93	0.17 (0.14, 0.21)	18.7 (15.7, 22.1)	0.15 (0.12, 0.19)	17.0 (13.9, 19.9)
T	9,920,000	0.01 (0.01, 0.01)	0.77 (0.65, 0.91)	0.00 (0.00, 0.00)	0.70 (0.57, 0.82)
H	5,960,000	0.18 (0.14, 0.22)	19.6 (16.5, 23.3)	0.15 (0.12, 0.19)	17.8 (14.5, 20.9)
Benefits [$1,000]		$715 ($508, $956)	$81,600 ($62,500, $102,000)	$615 ($427, $830)	$72,000 ($52,800, $92,200)
S	29,300,000	0.64	80.2	0.57	71.7
H	7,720,000	(0.51, 0.81)	(64.4, 100)	(0.45, 0.70)	(56.8, 87.0)

Numbers in parentheses are 95% confidence intervals across years based on 100 Monte Carlo trials (accounting for natural variation in water quality conditions only). Benefits are reported as annualized values based on a 5% discount rate in thousands of dollars.

First, we note that the two water quality change scenarios—where DO is increased by 25% across-the-board and where the frequency of DO levels below 2 mg/L is reduced by 50%—have similar impacts. This result may seem surprising at first considering the large apparent differences between the changed DO distributions in Fig. 5, but it follows directly from the highly non-linear DO dose–response function for juvenile summer flounder survival (refer back to Fig. 4). There is a very narrow range of DO levels, between about 1.25 and 1.75 mg/L, through which the 24-h juvenile survival rate increases from near zero to near one. Thus, changes made at the very low end of the DO distribution matter most.

The model predicts that if water quality is improved only in the study area then impacts on the fish population and benefits to anglers will be relatively small. Simulated water quality improvements in the study area alone are predicted to increase catch rates by approximately 2% in and 0.2% out of the study area. However, if water quality is improved in all bays and estuaries throughout the range of the species, then catch rates and harvest levels are predicted to increase by approximately 20%. The differences between

(*footnote continued*)
time towards the end of the forecast series, after the system has reached a new stochastic steady state. New steady-state conditions are reached within approximately 20 years, so we use the last 50 years of our 100 year forecast horizon to calculate $\bar{V}$. The 5% discount rate is between the 2% to 3% recommended by EPA and the 7% recommended by the Office of Management and Budget [47].

the in and out of study area scenarios is due to the mixing of the adult stock in the open ocean during the winter (refer back to Figs. 2 and 3). Only a portion of the juveniles subject to the improved water quality conditions in the study area will return to the study area the next year as adults, and the next year only a fraction of those will return, and so on. Thus, the number of adult fish available to be caught increases by only a fraction of what would occur if either site fidelity were absolute or if the water quality improvements affected the entire population (compare the results in columns 2 and 4 with those in columns 3 and 5 of Table 3).[15]

Note that even in cases where water quality improvements are confined to the study area, the aggregate benefits are much larger out of the study area than in. This is because even though the per angler welfare effects are an order of magnitude smaller out of the study area, the number of anglers to which these external benefits accrue is two orders of magnitude larger than the number in the study area.

As a final illustration we compare results from our structural model to what would be inferred directly from the reduced form version of the catch function (shown in the second two columns of Table 1). First, we can compare the reduced form catch model to the structural model under the assumption that DO is increased by 25% at all times (Fig. 5 top panel). This is a relatively direct comparison because the reduced form catch model includes the average monthly DO level as an explanatory variable and a 25% increase in DO at all times translates directly into a 25% increase in the monthly average. At the observed monthly average DO levels the predicted catch per angler averaged across all individuals in the dataset is 1.93 fish, and if all monthly DO levels are increased by 25% the average predicted catch using the reduced form model is 2.53, an increase of 31%. Compare this to the approximately 2% and 20% increases predicted by our structural model reported in Table 3. In this case, using the reduced form version of the catch function to analyze water quality changes would drastically overestimate the potential benefits to anglers if water quality improvements are confined to the study area. This is because the spillover effects from fish migrations out of the study area are not accounted for in the reduced form model. The reduced form model also would overestimate, though to a lesser degree, the potential benefits if water quality conditions are improved in all bays and estuaries throughout the range of the species. This suggests that in this case the short run spatial relationship between adult fish abundance and water quality (which is all that the reduced form model can possibly capture) is different from the long run effect of water quality improvements on overall fish abundance (which is embodied in our bio-economic simulation model via the effect of DO on juvenile survival).

Second, we can compare the reduced form and structural models under the assumption that the frequency of DO occurrences less than 2 mg/L is reduced by 50% (Fig. 5 bottom panel). This comparison is much less direct than the previous one because the reduced form model cannot accommodate temporal units shorter than a month and therefore will effectively treat any change in the DO distribution that leads to an X% change in the monthly average the same. As shown in Table 3, reducing the frequency of these low DO events by 50% leads to a 1% increase in the average DO level. According to the reduced form model, if the average monthly DO level is increased by 1%, the average catch will increase by 1.1%. This is lower than the change in catch predicted by the structural model for the case where water quality is improved only in the study area ($\approx$2%), and drastically so for the case where water quality is improved throughout the range of the species ($\approx$20%). It is easy to understand why the reduced form model under-estimates the change predicted by the structural model in this case when one considers how the two models incorporate water quality data: monthly averages in the reduced form versus 15 minute increments in the structural. While the reduced form model will treat any change in the DO distribution that leads to an X% change in the monthly average the same, the structural model will treat water quality changes very differently depending on how the DO distribution is modified (particularly at the low end) because of the nature of the juvenile flounder DO dose response function. Thus, the application of the reduced form model is more of a "forced fit" for this water quality change scenario, which highlights another limitation of a reduced form modeling approach.

These results illustrate some of the practical advantages of a structural approach that explicitly accounts for the key biological and economic dynamics over a reduced form approach that would rely mainly on the cross-sectional relationship between catch or trip demands and water quality. A reduced form approach cannot

[15]A sensitivity analysis reveals that the distribution of benefits between the study area and the remainder of the fishery are strongly influenced by SF, the site fidelity parameter. However, the aggregate benefits change only modestly over the full possible range of SF, 0 to 1.

account for the effect of fish migrations on responses to changes in water quality, nor can it be directly applied to scenarios based on water quality changes at temporal scales other than the scale used in estimation. For these reasons, a reduced form model can generate substantially different quantitative predictions than a structural model, even when applied to the same scenarios.

4. Summary and conclusions

In this paper we have developed and applied a bioeconomic model of a coastal recreational fishery for estimating the value of water quality changes. A variety of information sources and datasets were used to specify a biological model of summer flounder population dynamics and to estimate a count regression model of catch rates and a mixed logit recreation demand model. The models were combined in a bioeconomic framework and calibrated to baseline conditions using historic recreational harvest levels from both in and out of Maryland's coastal bays and commercial harvest levels for the entire fishery.

The structural modeling approach developed in this paper can evaluate scenarios based on a wide variety of changes in the distribution of water quality conditions on time scales as short as quarter hour intervals. Standard reduced form approaches using cross-sectional data on trip frequencies or catch rates and water quality conditions across sites typically are able to evaluate changes in average annual conditions only. Furthermore, the structural approach developed here incorporates important effects of water quality on juvenile fish survival, which will influence the long run adult fish abundance and recreational catch. Reduced form models typically cannot capture this effect or other potentially important biological dynamics and therefore will likely lead to inaccurate forecasts of long run changes.

The structural bioeconomic model was used to evaluate two water quality change scenarios based on simulated DO distributions using data from Maryland's coastal bays. The results indicate that substantial increases in summer flounder populations and associated benefits to recreational anglers may be possible if water quality conditions are improved in all bays and estuaries throughout the range of the species. If water quality improvements are confined to a small area, however, only relatively small increases will be possible.

The estimated changes in recreational harvest levels are a consequence of the combined effects of the response of the fish population to changes in DO conditions, the response of catch rates to changes in fish abundance, and the response of trip demand to changes in average catch rates. The estimated harvest changes are appreciable for what seem to be reasonable assumptions about potential improvements in water quality conditions, but such gains may require water quality improvements across large portions of the species' range.

We also showed that very different quantitative results can be obtained if a reduced form approach is used instead of a structural modeling approach. These results highlight the importance of appropriately accounting for the spatial and temporal dynamics of species' responses when valuing changes in environmental conditions.

Acknowledgments

The authors would like to thank Linda Barker, Angel Bolinger, Matthew Hall, Steve Doctor, and Catherine Wazniak of the MD DNR, and Damian Brady and Kevin Stierhof of the University of Delaware, for providing and helping to interpret much of the data and background information used in this paper. We would also like to thank Nancy Bockstael, Bob Leeworthy, David Simpson, and discussants and participants from Camp Resources XI, the NCEE Seminar Series, and 2004 AAEA meeting for comments on earlier drafts of this paper. Any remaining errors are the responsibility of the authors.

Appendix A

This appendix provides the full specification of the population model. Equations and definitions for all state variables are shown below, and definitions and values used for all parameters are given in Table A1. Datasets and Matlab programs used to simulate the bioeconomic model are provided in an online supplement:

$$J_t = S_{t-1}\left[\frac{\alpha}{1 + S_{t-1}/\beta}\right], \tag{A.1}$$

Table A1
Information sources and calibration procedures for key parameters and state variables in the population model

Parameter or state variable	Symbol	Value	Source(s) or calibration procedure
Number of juveniles surviving to the early summer per adult at very low stock size	α	98.1	Estimated by calibrating the model so the dominant eigenvalue of the annual transition matrix with no density dependence or fishing mortality equals λ [11].
Geometric growth rate at low population size	λ	1.728	Estimated from a Ricker stock recruitment model using data from [32] and assuming reproduction begins at age 2 and $M = 0.2$.
Stock size at which egg and larvae survival probability is half the maximum	β	14,820,027	Estimated by calibrating the model so the predicted equilibrium commercial harvest level under baseline conditions equals the average historic harvest.
Proportion of new eggs and larvae deposited in the study area every year	γ	0.0213	Estimated by calibrating the model so the recreational harvest levels inside and outside of the study area match historic average levels.
Site fidelity	SF	0.5	Based on qualitative information in [1,12,22,34].
Winter survival probability of young juveniles (September–April)	s_{jw}	0.205	Adapted from [49]. The value reported for annual survivorship is $e^{-2.38} = 0.093$. We use $e^{-2.38\times 8/12} = 0.205$ for winter survivorship.
Exposure coefficient	x	0.378	Calibrated so $s_{jst} = s^0_{js}$at baseline DO conditions.
Baseline summer survival probability of young juveniles (May–August)	s^0_{js}	0.452	Adapted from [49]. The value reported for annual proportional survivorship is $e^{-2.38} = 0.093$. We use $e^{-2.38\times 4/12} = 0.452$ for summer survivorship.
Maximum quarter hour survival probability	a	0.9976	Set so $s_{jst} = s^{max}_{js}$ when $DO \geqslant 3 \quad \forall t$; i.e., $a = (s^{max}_{j})^{1/123}$.
Maximum summer survival probability of young juveniles	s^{max}_{js}	0.75	Assumed.
Parameters of sigmoid juvenile survival function	b_1	0.4604	[46] and Glen Thursby, US EPA Office of Research and Development (personal communication).
	b_2	−8.23	
Annual survival probability of mature juveniles	s_m	0.819	[49]
		0.27	[12]
Instantaneous natural mortality rate for adults during winter	M	0.2	[42]
Instantaneous commercial fishing mortality rate	F	0.26	[42]
Winter survival probability of adults	s_a	0.632	$s_a = e^{-M-F}$, also see [12]
Average catch per trip under baseline conditions	C^{in}_0	1.93	Average catch per angler per trip reported in MD DNR Summer Flounder Volunteer Angler Survey.
Historic average number of summer flounder recreational fishing trips in the study area	T^{in}_0	76,602	Average number of summer flounder fishing trips in Worcester County, MD between 1994 and 2003 (computed from MRFSS data).
Historic average harvest level out of the study area	HR^{out}_0	5,901,406	Average of total recreational landings between 1994 and 2001 [2] minus $C^{in}_0 \times T^{in}_0$.
Adult abundance outside of the study area under baseline conditions	A^{out}_0		Based on assumption that $HR^{in}/A^{in} = HR^{out}/A^{out}$ under baseline conditions.
Historic average commercial harvest	HC_0	7,720,303	Average total commercial harvest between 1994 and 2001, assuming 0.75 kg/fish [31].

$$J_t^{in} = J_t\gamma, \tag{A.2}$$

$$J_t^{out} = J_t(1-\gamma), \tag{A.3}$$

$$M_t^{in} = J_{t-1}^{in} s_{jt}(SF + (1-SF)\gamma) + J_{t-1}^{out} s_{jt}(1-SF)\gamma, \tag{A.4}$$

$$M_t^{out} = J_t^{in} s_{jt}(1-SF)(1-\gamma) + J_t^{out} s_{jt}(1-(1-SF)\gamma), \tag{A.5}$$

$$s_{jt} = s_{jw}s_{jst} = s_{jw}\prod_{d=121}^{242}\left[\prod_{q=1}^{96}\{xs_{0.25} + (1-x)\}\right], \tag{A.6}$$

$$s_{0.25} = \frac{a}{1 + (DO_{0.25}/b_1)^{b_2}}, \tag{A.7}$$

$$A_t^{in} = [(A_{t-1}^{in} - HR_{t-1}^{in})s_a + M_{t-1}^{in}s_m](SF + (1-SF)\gamma) + [(A_{t-1}^{out} - HR_{t-1}^{out})s_a + M_{t-1}^{out}s_m](1-SF)\gamma, \tag{A.8}$$

$$A_t^{out} = [(A_{t-1}^{in} - HR_{t-1}^{in})s_a + M_{t-1}^{in}s_m](1-SF)(1-\gamma) + [(A_{t-1}^{out} - HR_{t-1}^{out})s_a + M_{t-1}^{out}s_m](1-(1-SF)\gamma), \tag{A.9}$$

$$HR_t^{in} = T_t^{in}C_t^{in} = T_t^{in}h^{in}(A_t^{in})^{\theta}, \tag{A.10}$$

$$HR_t^{out} = T_t^{out}C_t^{out} = T_t^{out}h^{out}\left(A_t^{out}\right)^{\theta}, \tag{A.11}$$

$$HC_t = (A_t^{in} - HR_t^{in} + A_t^{out} - HR_t^{out})(1-s_a)\frac{F}{M+F}, \tag{A.12}$$

$$S_t = A_t^{in} - HR_t^{in} + A_t^{out} - HR_t^{out} - HC_t, \tag{A.13}$$

where J_t is the number of young juvenile summer flounder (less than one year old) laid as eggs in the late months of the previous year (November is the peak of the breeding season) that survive through the egg and larval stages on their journey from the open ocean to the coastal bays and estuaries, S_t is the number of spawning adults in year t, J_t^{in} and J_t^{out} are the number of young juveniles in and out of the study area in year t, M_t^{in} and M_t^{out} are the number of mature juveniles (between 1 and 2 years old) in and out of the study area in year t, s_{jt} is the young juvenile survival probability in year t, s_{jw} is the young juvenile survival probability over the winter months, s_{jst} is the young juvenile survival probability over the summer months in year t, A_t^{in} and A_t^{out} are the number of adults (2 years and up) in and out of the study area in year t, HR_t^{in} and HR_t^{out} are the number of adults harvested in the recreational fishery in and out of the study area in year t, T_t^{in} and T_t^{out} are the number of recreational fishing trips in and out of the study area in year t, C_t^{in} and C_t^{out} are the average catch per angler per trip in and out of the study area in year t, and HC_t is the number of adults harvested in the commercial fishery in year t.

References

[1] K.W. Able, S.C. Kaiser, Synthesis of Summer Flounder Habitat Parameters, NOAA Coastal Ocean Program, Program Decision Analysis Series, No. 1, Silver Spring, MD, 1994.
[2] ASMFC, Addendum VIII to the Summer Flounder, Scup and Black Sea Bass Fishery Management Plan: Allocation Calculations for the Summer Flounder Recreational Fishery, Atlantic States Marine Fisheries Commission, 2003.
[3] A.C. Cameron, P.K. Trivedi, Regression Analysis of Count Data, Cambridge University Press, New York, NY, 1998.
[4] T.A. Cameron, The Effect of Gamefish Abundance on Texas Recreational Fishing Demand: Welfare Estimates, Mimeo, Department of Economics, University of California, Los Angeles, 1989.
[5] T.A. Cameron, Contingent Valuation Assessment of the Economic Damages of Pollution to Marine Recreational Fishing, EPA 230-05-90-078, US Environmental Protection Agency, 1990.
[6] T.A. Cameron, Combining contingent valuation and travel cost data for the valuation of nonmarket goods, Land Econ. 68 (1992) 302–317.

[7] S. Doctor, The status of summer flounder in Maryland during 2000, Maryland Department of Natural Resources, accessed April 15, 2005, http://www.dnr.state.md.us/fisheries/recreational/articles/summerflounder.html.
[8] J. Englin, D. Lambert, D. Shaw, A structural equations approach to modeling consumptive recreation demand, J. Environ. Econ. Manage. 33 (1997) 33–43.
[9] A.M.I. Freeman, The Economics of Valuing Marine Recreation: A Review of the Empirical Evidence, Report to the Office of Policy Planning and Evaluation, US Environmental Protection Agency, Washington, DC, 1993.
[10] S.D. Fretwell, Populations in a Seasonal Environment, Princeton University Press, Princeton, NJ, 1972.
[11] N.J. Gotelli, A Primer of Ecology, Sinauer Associates, Inc., Sunderland, MA, 2001.
[12] B.H. Grimes, M.T. Huish, J.H. Kerby, D. Moran, Species profiles: life histories and environmental requirements of coastal fishes and invertebrates (Mid-Atlantic): summer and winter flounder, US Fish and Wildlife Service Biol. Report 82(11.112); US Army Corps of Engineers TR EL-82-4, 1989.
[13] M. Haddon, Modelling and Quantitative Methods in Fisheries, Chapman & Hall, Boca Raton, FL, 2001.
[14] W.M. Hanemann, Welfare analysis with discrete choice models, in: J.A. Herriges, C.L. Kling (Eds.), Valuing Recreation and the Environment, Edward Elgar Publishing, Inc., Northampton, MA, 1999.
[15] S.J. Harley, R.A. Myers, A. Dunn, Is catch-per-unit-effort proportional to abundance?, Can. J. Fish. Aquat. Sci. 58 (2001) 1760–1772.
[16] R.L. Hicks, Stated Preference Methods for Environmental Management: Recreational Summer Flounder Angling in the Northeastern United States, Department of Coastal and Ocean Policy, Virginia Institute of Ocean Policy, NFFKS-18, Gloucester Point, VA 23062, 2002.
[17] R.L. Hicks, S. Steinback, A. Gautam, E. Thunberg, Volume II: The Economic Value of New England and Mid-Atlantic Sportfishing in 1994, National Oceanic and Atmospheric Administration, Silver Spring, MD, 1999.
[18] P.M. Jakus, D. Dadakas, M.J. Fly, Fish consumption advisories: incorporating angle-specific knowledge, habits, and catch rates in a site choice model, Am. J. Agric. Econ. 80 (1998) 1019–1024.
[19] P.M. Jakus, M. Downing, M.S. Bevelhimer, M.J. Fly, Do sportfish consumption advisories affect reservoir anglers' site choice?, Agric. Resources Econ. Rev. 26 (1997) 196–204.
[20] Y. Kaoru, Measuring marine recreation benefits of water quality improvements by the nested random utility model, Resource Energy Econ. 17 (1995) 119–136.
[21] Y. Kaoru, V.K. Smith, J.L. Liu, Using random utility models to estimate the recreational value of estuarine resources, Am. J. Agric. Econ. 77 (1995) 141–151.
[22] R.T. Kraus, J.A. Musick, A brief interpretation of summer flounder, Paralichthys dentatus, movements and stock structure with new tagging data on juveniles, Mar. Fisheries Rev. 63 (2001) 1–6.
[23] D.F. Layton, Random coefficient models for stated preference surveys, J. Environ. Econ. Manage. 40 (2000) 21–36.
[24] V.R. Leeworthy, P.C. Wiley, Marine recreation, in: Outdoor Recreation for 21st Century America, A Report to the Nation: The National Survey on Recreation and the Environment, Venture Publishing, Inc., State College, PA, 2004.
[25] D. Lipton, R.L. Hicks, The cost of stress: low dissolved oxygen and recreational striped bass (Morone saxatilis) fishing in the Patuxent river, Estuaries 26 (2003) 310–315.
[26] K.E. McConnell, I.E. Strand, Overnight Trip Choice for Marine Anglers, Bockstael, McConnell, Strand, and Associates Inc. for the NMFS (contract #40ANF804203), Hyattsville, MD, 1999.
[27] K.E. McConnell, I.E. Strand, L. Blake-Hedges, Random utility models of recreational fishing: catching fish using a poisson process, Mar. Resource Econ. 10 (1995) 247–261.
[28] K.E. McConnell, I.E. Strand, S. Valdes, Q.R. Weninger, Volume II: The Economic Value of Mid and South Atlantic Sportfishing, University of Maryland for National Marine Fisheries Service and the National Oceanic and Atmospheric Administration, CR-811043-01-0, College Park, MD, 1994.
[29] MDDNR, Maryland's Coastal Bays Ecosystem Health Assessment, Maryland Department of Natural Resources, Annapolis, MD, 2004.
[30] E.R. Morey, D.M. Waldman, Measurement error in recreation demand models: the joint estimation of participation, site choice, and site characteristics, J. Environ. Econ. Manage. 35 (1998) 262–276.
[31] NFSC, Report of the 35th Northeast Regional Stock Assessment Workshop (35th SAW): Public Review Workshop, Northeast Fisheries Science Center, Northeast Fish. Sci. Cent. Ref. Doc. 02-13, Woods Hole, MA, 2002.
[32] NFSC, Report of the 35th Northeast Regional Stock Assessment Workshop (35th SAW): Stock Assessment Review Committee (SARC) consensus summary of assessments, Northeast Fisheries Science Center, Northeast Fish. Sci. Cent. Ref. Doc. 02–14, Woods Hole, MA, 2002.
[33] D. Revelt, K.E. Train, Mixed logit models with repeated choices: households' choice of appliance efficiency levels, Rev. Econ. Stat. 80 (1998) 647–657.
[34] S.G. Rogers, M.J. Van Den Avyle, Species profiles: life histories and environmental requirements of coastal fishes and invertebrates (South Atlantic)—summer flounder, US Fish Wildl. Serv. FWS/OBS-82/11.15; US Army Corps of Engineers, TR EL-82-4, 1983.
[35] J.N. Sanchirico, J.E. Wilen, Bioeconomics of spatial exploitation in a patchy environment, J. Environ. Econ. Manage. 37 (1999) 129–150.
[36] D. Scrogins, K. Boyle, G. Parsons, A.J. Plantinga, Regulations and recreational anglers, Am. J. Agric. Econ. 86 (2004) 963–974.
[37] K.A. Small, H.S. Rosen, Applied welfare economics with discrete choice models, Econometrica 49 (1981) 105–130.
[38] M.D. Smith, J.E. Wilen, Economic impacts of marine reserves: the importance of spatial behavior, J. Environ. Econ. Manage. 46 (2003) 183–206.

[39] V.K. Smith, J.L. Liu, R.B. Palmquist, Marine pollution and sport fishing quality, Econ. Lett. 42 (1993) 111–116.
[40] I.E. Strand, K.E. McConnell, N.E. Bockstael, D.G. Swartz, Marine Recreational Fishing in the Middle and South Atlantic: A Descriptive Study, University of Maryland, Environmental Protection Agency, National Marine Fisheries Service, and National Oceanic and Atmospheric Administration, CR-811043-01-0, College Park, MD, 1991.
[41] W.J. Sutherland, From Individual Behaviour to Population Ecology, Oxford University Press, New York, NY, 1996.
[42] M. Terciero, Stock assessment of summer flounder for 2003, Northeast Fish. Sci. Cent. Ref. Doc. 03-09, Woods Hole, MA, 2003.
[43] K. Train, D. McFadden, R. Johnson, Discussion of Morey and Waldman's, measurement error in recreation demand models, J. Environ. Econ. Manage. 40 (2000) 76–81.
[44] K.E. Train, Recreation demand models with taste differences over people, Land Econ. 74 (1998) 230–239.
[45] K.E. Train, Discrete Choice Methods with Simulation, Cambridge University Press, New York, NY, 2003.
[46] USEPA, Ambient Aquatic Life Water Quality Criteria for Dissolved Oxygen (Saltwater): Cape Cod to Cape Hatteras, Office of Water, EPA-822-R-00-012, Washington, DC, 2000.
[47] USEPA, Guidelines for Preparing Economic Analyses, Office of the Administrator, EPA 240-R-00-003, Washington, DC, 2000.
[48] USEPA, National Water Quality Inventory, Office of Water, EPA-821-R-02-01, Washington, DC, 2000.
[49] USEPA, Case Study Analysis for the Proposed Section 316(b) Phase II Existing Facilities Rule, Office of Water, EPA-821-R-02-002, Washington, DC, 2002.
[50] G. Van Houtven, S.K. Pattanayak, C. Pringle, J.-C. Yang, Review and Meta-Analysis of Water Quality Valuation Studies, US EPA, Office of Water, Washington, DC, 2001.
[51] C. Wasniak, M. Hall, C. Cain, D. Wilson, R. Jesien, J. Thomas, T. Carruthers, W. Dennison, State of the Maryland Coastal Bays, Maryland Department of Natural Resources, Maryland Coastal Bays Program, University of Maryland Center for Environmental Science, Annapolis, MD, 2004.