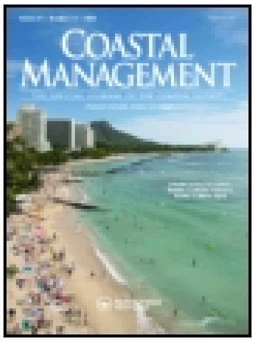

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A Bayesian Methodology for Estimating the Impacts of Improved Coastal Ocean Information on the Marine Recreational Fishing Industry

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The study develops a model of recreational fish catch probabilities, based on angler fishing strategies, that is conditional on uncertain information about the coastal ocean environment. We calculate expected catch based on a hypothetical Baseline Data Set and hypothetical data from an Integrated Ocean Observation System (IOOS) to demonstrate potential benefits from IOOS. The role of Bayesian probabilities in Random Utility Models of recreational fishing is identified. The study discusses the types of information that will be required by recreational anglers in the Gulf of Mexico. Results have implications for the construction of ocean observation systems for recreational fishermen.

Keywords Bayesian models, coastal ocean conditions, recreational fishing

Introduction

The National Ocean Partnership Program (NOPP) supports the establishment of an integrated coastal ocean observation system (IOOS) that will provide improved nowcasts and forecasts of offshore ocean conditions. NOPP recognizes that changing coastal conditions impact many firms and individuals whose activities are dependent on the coastal ocean environment. To this end, the Partnership commissioned a series of studies (see Kite-Powell & Colgan, 2004) designed to identify groups of potential users and to estimate the potential user benefits and costs of an ocean monitoring system. The objective of this article is to design a methodology that can be employed to measure the impacts of improved coastal data generation on one important industry, recreational fishing.

A number of authors have contributed to a robust and growing literature on the benefits derived from recreational fishing. Measurement of the economic impacts of recreational fishing has centered on travel cost models (TCM). TCM consider the impacts of trip costs and of the probability of catch upon the number of angler expeditions and on the value per expedition per angler. TCM also are used to determine the impacts of policies that affect recreational anglers. The random utility model (RUM) has emerged as the preferred technology for describing angler behavior within the TCM framework. (The National Marine Fisheries Service uses the RUM as its standard evaluation tool (Haab, Whitehead, & McConnell, 2000)). RUM utilizes observable environmental constraints and

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angler characteristics to measure angler utility, to explain angler behavior, and to predict and explain outcomes of fishing expeditions as manifestations of utility-maximizing behavior. RUM hypothesize that the individual angler's choices and the outcomes of the choices depend upon both factors observed and those unobserved by the investigator. Unobserved factors introduce a random component to fishing outcomes. Authors have modeled the random component using Poisson and/or negative binomial density functions. Haab and Hicks (1999) summarized the standard behavioral model as an indirect utility function, V_j; $j \in S$

$$V_j(q_j, y - p_j) + \varepsilon_j$$

where

S is the set of choices (or associated states) available to the angler
q_j are environmental parameters of choice j
y is a measure of income
p_j is the cost of the activity j
ε_j is a vector of unobserved attributes of the individual angler

The expected utility of choice j depends upon q_j, y, and pj.[1] If the ε_j follow a type I extreme value distribution, one may use the conditional logit model to "predict" individual choices as functions of the explanatory variables. Represent the expected utility of choice j as vj. If the angler elects the choice providing the highest expected utility, the model generates the predictive equation

$$P(j) = \frac{e^{vj}}{\sum_{k=1}^{S} e^{vk}}$$

The RUM has been employed to estimate benefits (Criddle et al., 2003; Gillig et al., 2000). Thomas and Stratis (2002) evaluated the impacts of pubic policy on angler departure and destination choices using a nested RUM. Whitehead and Haab (2000) examined the impact of the choice set on measures of benefits in the southeast United States. Greene et al. (1997) examined the issue of sample selection bias to evaluate the fishing option to non-participants in Tampa Bay during 1991. Agnello and Han (1993) were able to demonstrate that information about fishing quality is instrumental in angler choice. They showed that the characteristics of alternative fishing sites in Long Island are instrumental in the relationship between site visits and the cost of accessing the site.

Section two of the article defines the information set used by anglers and integrates the information set into angler choice through the construction of a set of Bayesian probabilities. In section three, the location of the Loop Current in the Gulf of Mexico and the quality of water conditional upon current location are contrasted with two alternative hypothetical information sets on the probabilities of occurrence of ocean states. Angler fishing strategy is specified, contingent on the ocean information, and expected fish catch per angler is calculated. Section four discusses existing information on data requirements and current data availability. Section five reports conclusions.

Angler Choice and the Information Set

Uncertainty in RUM models enters in the error terms of the utility function. Aside from this, uncertainty and incomplete information play no part in the current RUM literature related to observed recreational fishing decision(s). However, if the angler's information on state of the environment is uncertain, both the expected values of alternative fishing sites and the behavior of the angler depend on the accuracy and extent of information available to the angler. Thus state-dependent information expands the scope of uncertainty in RUM. This section of the article develops a behavioral model that links fishing outcomes to the quality of information available to the angler. The model incorporates a set of variables that together define the information requirements for implementing the model and for evaluating the impacts of improved environmental information on the fishing outcomes.

The procedure outlined in what follows introduces three types of variables and three added relationships into the RUM. The first variable is the density, D of fish. Fish density may be defined as biomass at a specific location, k and time, t. As an example, the angler may wish to forecast the fish density at 8:00 AM, November 23, 2006, at latitude 26°.20′N and longitude 83°W in the Gulf of Mexico (west of Bonita Springs, Florida). Fish density may be defined as pounds of redfish per cubic mile. D is determined by a distribution function G.

$$G(d_i) = P(D_i < d_i) \qquad i \leq I$$

"I" represents the maximum fish density. $G(d_i)$ produces the various moments of the probability distribution of D.

The first relationship defined is the fish density function. The density function relates $G(d_i)$ to a set of *n* state variables S, each of which reflects ocean quality and each of which is defined by a distribution function $F(s^i)$:

$$F\left(s_i^1\right) = P\left(S_h^1 < s_h^1\right) \quad S^1 \leq H^1$$
$$F\left(s_h^n\right) = P\left(S_h^n < s_h^n\right) \quad S^n \leq H^n$$

Probabilities P relate the information available to the angler to the uncertain state of the ocean at t and k. H^1, H^n represent the maximum values of S^1, S^n. Because the $S^1, \ldots, S^n$ are uncertain, D is also uncertain, and $P(D_i < d_i)$ is conditional on the n environmental state variables:

$$P(D_i) = P(D_i \mid S^1, \cdots, S^n) \qquad D \leq I$$

The third set of variables in the model consists of m predictions of the n state variables. Represent the predictions by $X^1, \ldots, X^m$, $m \leq n$. The second relationship in the model is an information function that that utilizes the environmental state variables to generate the X^i. The output of the information function at t and k is a set of probabilities that are conditional upon the state variables.[2]

$$P(X^1) = P(X^1 \mid S^1)$$
$$P(X^m) = P(X^m \mid S^m)$$

The more accurate the predictions $X^1, \ldots, X^m$, the more the actions of the angler will be based on the true nature of the ocean environment.

The third relationship consists of a set of equations that relate the behavior of the angler to the information set that is available to him or her. The information is relevant because the angler can make a set of choices as to the location and time of the fishing trip and the tactics used to land the catch, and because he or she can base the choices on the relevant information. We reintroduce the indirect utility function from the previous section and allow indirect utility to depend on the information set

$$V_k(q_k, y - p_k \mid X^1.., X^m)$$

The probability of selecting choice j becomes.[3]

$$P(j) = \frac{e^{vj \mid X1..,Xm}}{\Sigma e^{vj \mid X1..,Xm}}$$

This equation shows that the choice function is contingent on the information available to the angler.

The objective of this article is to evaluate the effectiveness of the hypothetical IOOS information set as a recreational fishing tool using the probabilities P(j). Once derived, the relationship between the environmental data and the information set will allow us to compare the effectiveness of alternate information sets. To accomplish this objective, it is necessary to determine, for each ocean observation parameter X^i, the probability that the underlying ocean state is actually S^i. This probability is given by Bayes formula. Bayesian probabilities relate the *a posteriori* probabilities of choosing the environmental states $S_1..,S_n$ given the available information $X_1..,X_n$. For each ocean parameter i,

$$P(S_i \mid X_i) = P(S_i) * P(X_i \mid S_i)$$

This is the posterior probability of S^i given X^i. The observed choice variables P(i) are thus Bayesian probabilities

$$P(i) = \frac{P(S_i) * P(X_i \mid S_i)}{\Sigma P(S_i) * P(X_i \mid S_i)} \qquad i = 1, n$$

Bayesian probabilities can be introduced into the predictive equation via a nested RUM.

Fishing decisions are linked to uncertain ocean quality through probabilities determined by the information set available to the angler. The observed probability distribution function of fishing outcomes varies by site and over time, and V_j becomes dependent on information x.[4] Summarizing, Bayesian probabilities fit directly into the RUM as developed in the literature. The following section contains a hypothetical example of Baysian probabilities applied to an angler who is assumed to operate under alternative information regimes.

In a recreational fishing context, ocean information systems may influence decisions to initiate fishing trips, to select the locations fished, to choose species of fish sought and to select angling tactics. The Bayesian approach to evaluating the impact of ocean observing systems has been applied by Solow et al. (1998). The authors use discrete Bayesian analysis to forecast the welfare impacts of changes in the real-time environmental weather forecasts used by economic agents in decision-making

An Application of Bayesian Probabilities Using Hypothetical Ocean Data for the Gulf of Mexico

This section presents a hypothetical computation of the impacts of improved data on expected fish catch in a deep sea fishing activity in a region such as Florida's west coast, adjacent to the Loop Current and its associated eddies. The exercise provides a concrete example of the Bayesian model in the last section, and identifies the information that will be needed to evaluate and compare ocean-observing systems.

In the hypothetical example developed here, a representative fisherman departs from a launching site and fishes offshore from the Florida coastline. The fisherman uses the information available to him to maximize his expected catch, which can be measured either in pounds of fish or in number of fish caught. The impact of IOOS on the fisherman is the change in probability of choosing the fishing tactics that are better adapted to ocean conditions than the tactics selected on the basis of a Baseline data source. (Current hydrographic models, based on data provided by the National Weather Service, are one source of ocean data that may serve as a baseline.) More accurate information on the states of the Gulf of Mexico alters the decisions of the subject fisherman, lowering the expense and effort of his or her fishing expedition and increasing the expected catch.

The putative angler is presented with two information sets, the first based on Baseline data, the second upon data from an Integrated Ocean Observing System (IOOS). Each data set provides information on two parameters, ocean currents and water quality. These parameters are analogous to the choice set of the site fished and the mode of fishing (including shore, private/rental and charter, and species) employed in Haab, Whitehead and McConnell (2000). The fisherman uses the information on the uncertain location of the current and on the uncertain level of water quality within the current to choose his fishing strategy. We limit the set of choices available to the angler to three choices of distance from the coast and two choices about fishing strategy at the chosen location.

The angler wishes to fish in the warmer and more nutrient-rich offshore current. The probability that he will navigate to the current depends on his or her behavior given knowledge of ocean conditions. Baseline data predict that the uncertain midpoint lies between 30 miles offshore and 100 miles offshore, and that the expected width of the current is 30 miles. The angler knows that, to have a positive probability of catching the current, he or she must sail at least 15 miles from the coast and no more than 115 miles. The relevant probability distribution is rectangular because the baseline data provide no added information about the location of the current. The angler's probability of navigating to a point within the current is 30/100 = 30%.

The benefit of more accurate IOOS information is the increase in the probability that the angler will select the proper location and fish in the current. He or she can utilize the known density function of midpoints of the current to select the fishing location. The angler maximizes his or probability of being in the current by sailing to the expected midpoint of the distribution. We assume that IOOS data predict the expected midpoint of the current at 60 miles from shore, that its width is 30 miles, and that the standard deviation of the distribution is 25 miles. If the fisherman fishes at 60 miles from shore, he or she will miss the current if its midpoint is less than 30 miles from shore or more than 90 miles from shore. The cumulative frequency of the distribution from 0–45 miles is 10.5% and the cumulative frequency of the distribution from 75–115 miles from shore is 10.5%. His probability of being in the offshore current, utilizing the best information, increases to 79%.

The second variable in the angler's choice set—the quality of water inside the current and outside of the current—may be represented also by a probability distribution. Water

Table 1
Probabilities X that the Baseline data will predict the state, S of the location of the Loop Current from a launch-site on the West Coast of Florida

	S1	S2	S3	Totals
State	0.2	0.6	0.2	
Baseline X1	0.7	0.1	0.3	1.1
Baseline X2	0.2	0.8	0.1	1.1
Baseline X3	0.1	0.1	0.6	0.8
Totals	1.0	1.0	1.0	

quality is defined here in terms of the attractiveness of water to fish. That is, water quality is defined as water conditions that that are associated with high concentrations of fish. An advantage to this variable is that it can be easily adapted to various water conditions and geography.

Once at the selected fishing site, anglers relate that they adapt their fishing strategy to the concentration of fish, which depends on water quality. Fishermen describe their allocation of time on the water as divided between fishing and changing locations in search of fish. When fish concentrations are high, it is efficient to allocate more time to fishing and less time to changing locations. When fish concentrations are low, the reverse is true. The second fishing tactic, frequency of changing location, is thus related to perceived water quality.

Tables 1 through 6 present hypothetical frequencies of the mid-point of the Loop Current distance from the coast, and the percent accuracy of hydrographic predictions based on two information sets, one based on Baseline predictions and the second on improved data from an IOOS. The three states are location 30 from the coast (.2), location 60 miles from the coast (.6), and location 90 miles from the coast (.2).

The fisherman utilizes the predictions of Baseline or IOOS to decide how far from the coast to fish. Assuming the current is 30 miles wide, fishing at the midpoint of the current at 60 miles will miss the current altogether 40 percent of the time.

Table 2
Probabilities X that the Integrated Ocean Observation System (IOOS) will predict the state, S of the location of the Loop Current from a launch-site on the West Coast of Florida

	S1	S2	S3	Totals
State	0.2	0.6	0.2	
IOOS X1	0.85	0.05	0.1	1
IOOS X2	0.1	0.9	0.1	1.1
IOOS X3	0.05	0.05	0.8	0.9
Totals	1.0	1.0	1.0	

Table 3
Probabilities that the fisherman will predict the state X given the actual state S using Baseline data

	S1	S2	S3	Totals
p × 1 ǀ S	0.538	0.231	0.231	1
p × 2 ǀ S	0.074	0.889	0.037	1
P × 3 ǀ S	0.1	0.3	0.6	1

Tables 3 and 4 present the conditional probabilities that the fisherman's predictions, X will correlate with the actual state of nature, S given the predictions of the Baseline and the IOOS data.

The hypothetical IOOS data improve conditional forecasts given the underlying ocean states. For example, the probability that the fisherman will predict X1 when the actual state is S1 is 54 percent in Table 3, using Baseline data but 77 percent in Table 4 using IOOS data.[5]

The second parameter, given location in or out of the current, is water quality. Water quality consists mainly of temperature and nutrients, but also current, salinity, water clarity, and absence of pollutants. The probabilities of water quality are conditional on the location of the Loop current. Tables 5 and 6 present Baseline and IOOS forecasts of water quality given that the fisherman is in the Loop Current at 60 miles from shore.

For example, the fisherman will predict state X2, when the actual state is T2 91% of the time in Table 5 with Baseline data and 96% of the time using IOOS data in Table 6. The data in the preceding tables depends on the location of the fisherman and the current. There are 6 tables for each of the data sources, one for each current, water quality combination.

The probability of the fisherman selecting a location-fishing strategy is the joint probability distribution of ocean states and fishing strategies that the angler adopts. The alternatives in the present example are assumed to be independent, so that final probabilities are computed as the products of two states and two choices. There are thirty-six possible combinations:

– Choice –		– State –		– Choice –		– State –	
Location (3)	×	Current midpoint (3)	×	Fishing strategy (2)	×	Water quality (2)	
3	×	3	×	2	×	2	= 36

Table 4
Probabilities that the fisherman will predict the state X Given the actual state S using IOOS data

	S1	S2	S3	Totals
p × 1 ǀ S	0.773	0.136	0.091	1
p × 2 ǀ S	0.034	0.931	0.034	1
P × 3 ǀ S	0.05	0.15	0.8	1

Table 5
Probabilities that the fisherman will predict X when the state is T using Baseline data

	T1	T2	Totals
State	0.25	0.75	
Baseline X1	0.8	0.3	1.1
Baseline X2	0.2	0.7	0.9

Each of the 36 possible outcomes is associated with an expected fish catch. The expected catch per trip is the product of each of the 36 expected catches per state multiplied by the probability that the state will occur. The probability that the state will occur depends on the information set available to the angler and his actions based on the information.[6] There are two sets of probabilities. The first set is conditional on information provided by the Baseline. The second set is conditional on information provided by IOOS. Table 7 reports the 36 state probabilities conditional on Baseline and on IOOS information sets.

Based on the two sets of probabilities, one may calculate the expected catch of fisherman on a representative fishing trip. To implement the model, we require as a final piece of information estimated fish caught for each fish concentration. The data allow us to determine the expected catch for the Baseline and IOOS information sets. We impute an expected catch rate in pounds for each of the 36 combinations of states of nature and angler choices. Table 8 reports the imputed values for each state.

The expected catch in Table 8 for each state may be multiplied by the probability of occurrence in Table 7. The sum over thirty-six weighted probabilities of fish caught is the *ex ante* expected catch. The imputed values of probabilities and expected catch yield expected values and standard deviations of the trip catch when the angler uses Baseline data and IOOS data. Expected catch and standard deviation of catch numbers are:

	Baseline	IOOS
Expected Catch (pounds)	1.70	2.0
Standard Deviation of Catch (pounds)	.245	.40

The use of IOOS data increases the angler's expected catch by 17.6% and increases the standard deviation by 63%.

Table 6
Probabilities that the fisherman will predict X when the state is T using IOOS data

	T1	T2	Totals
State	0.25	0.75	
IOOS X1	0.9	0.15	1.05
IOOS X2	0.1	0.85	0.95

Table 7
Bayesian probabilities: The probability of catch, conditional upon 6 ocean states and 6 angler choices

State	Probability	State	Probability	State	Probability
		State Probabilities Based On Baseline Information			
1	0.0735	13	0.0168	25	0.007
2	0.007	14	0.0032	26	0.002
3	0.0315	15	0.0072	27	0.003
4	0.028	16	0.0128	28	0.008
5	0.0252	17	0.252	29	0.0252
6	0.0048	18	0.024	30	0.0048
7	0.108	19	0.108	31	0.0108
8	0.0192	20	0.096	32	0.0192
9	0.021	21	0.0064	33	0.063
10	0.006	22	0.0036	34	0.006
11	0.009	23	0.0016	35	0.027
12	0.024	24	0.0084	36	0.024
		State Probabilities Based On IOOS Information			
1	0.1083	13	0.0096	25	0.004
2	0.004	14	0.0008	26	0.0005
3	0.0191	15	0.024	27	0.001
4	0.0382	16	0.0072	28	0.0045
5	0.0144	17	0.3443	29	0.0144
6	0.0012	18	0.0135	30	0.0012
7	0.0036	19	0.0608	31	0.0036
8	0.0108	20	0.1215	32	0.0108
9	0.008	21	0.0078	33	0.102
10	0.001	22	0.0026	34	0.004
11	0.003	23	0.0007	35	0.018
12	0.009	24	0.0088	36	0.036

Placing an Economic Value on the Benefits to Anglers of IOOS

IOOS may require the calibration of the fishing strategy model for each species because the value of fish to the angler and the fishing strategy followed depend on fish species.[7] Anglers place different dollar values on different species, and catch different species at different rates. To estimate the value per fisherman of the increase in fish caught by the hypothetical IOOS developed earlier, we utilize the Haab, Whitehead, and McConnell (2000) groupings and estimates of willingness to pay for fish. Existing evidence places the value of an additional fish caught in Florida waters from \$3.00 to \$24.00.[8] Assuming that the 32.2% of the boat-based opportunistic anglers catch and value species at the rate of fishermen who target species, the authors value an additional fish caught at \$9.77. Multiplying this amount by the increase in fish caught using IOOS data, 0.3, the average fisherman derives value of $\$9.77 * .3 = \$2.93$, as measured by willingness to pay, for IOOS data.[9]

Survey results presented in the NOAA report *Current Participation Patterns in Marine Recreation* (Leeworthy and Wiley, 2001) indicate that 4,698,000 individuals participated in

Table 8
Expected catch as a function of current location, angler fishing location, water quality, and angler fishing strategy

Fishing States				
Location of activity	Midpoint of current	Fishing strategy	Quality of Water	Expected Catch
Fish at 30 miles	Midpoint 30 miles	Fish strategy good	Water quality good	2.5
Fish at 30 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	1
Fish at 30 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	1.25
Fish at 30 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	1.75
Fish at 30 miles	Midpoint 30 miles	Fish strategy good	Water quality good	1.25
Fish at 30 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	0.5
Fish at 30 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	0.625
Fish at 30 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	0.875
Fish at 30 miles	Midpoint 30 miles	Fish strategy good	Water quality good	1
Fish at 30 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	0.4
Fish at 30 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	0.5
Fish at 30 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	0.7
	Midpoint 30 miles			0
Fish at 60 miles	Midpoint 30 miles	Fish strategy good	Water quality good	1.25
Fish at 60 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	0.5
Fish at 60 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	0.625
Fish at 60 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	0.875
Fish at 60 miles	Midpoint 30 miles	Fish strategy good	Water quality good	2.5
Fish at 60 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	1
Fish at 60 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	1.25
Fish at 60 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	1.75
Fish at 60 miles	Midpoint 30 miles	Fish strategy good	Water quality good	1.25
Fish at 60 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	0.5
Fish at 60 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	0.625
Fish at 60 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	0.875
				0
Fish at 90 miles	Midpoint 30 miles	Fish strategy good	Water quality good	1
Fish at 90 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	0.4
Fish at 90 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	0.5
Fish at 90 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	0.7
Fish at 90 miles	Midpoint 30 miles	Fish strategy good	Water quality good	1.25
Fish at 90 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	0.5
Fish at 90 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	0.625
Fish at 90 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	0.875
Fish at 90 miles	Midpoint 30 miles	Fish strategy good	Water quality good	2.5
Fish at 90 miles	Midpoint 30 miles	Fish strategy good	Water quality poor	1
Fish at 90 miles	Midpoint 30 miles	Fish strategy poor	Water quality good	1.25
Fish at 90 miles	Midpoint 30 miles	Fish strategy poor	Water quality poor	1.75

Note: Fish catches have been posited to give a clear advantage to making the appropriate decisions about whether to fish deep/good weather, or shallow/bad weather and whether to bottom fish-cold water or surface fish-warm water.

fishing during the 1999–2000 survey period in the state of Florida. The average fisherman spent 12 days fishing annually. Total fishing days were 56,285,000. According to a 2001 survey conducted by the Florida Fish and Wildlife Service, 79% of all fishermen engaged in saltwater fishing. Using this figure and the NMRSS figure of 70% of saltwater fishermen employing watercraft, the estimate of the annual value to boat-based anglers of an increase in the expected catch from the use of IOOS data is $91,198,023.

$$\$2.93 * 56{,}285{,}000 * .79 * .70 = \$91{,}198{,}023$$

Evaluation of Data Availability and Data Requirements

Several types of data are required to populate a Bayesian information-based RUM for recreational fishing with actual data.

1. What ocean characteristics are important in the fish density function?
2. What quantitative relationships hold between the environmental ocean quality and fish density?
3. What types of measurements of ocean quality will be provided by IOOS?
4. How will these measurements be provided to anglers, and how will anglers use the information?
5. What is the relationship between fish density and the actual catch per angler, for each type of angler, and for each species of game fish?
6. How many anglers are involved, and how much value, on average will they place on the increased fish catch?

The skill of the individual angler and the species of fish he or she is trying to catch determine the types of ocean data that may be sought. Individuals also use existing data differently. They may be expected to use data newly provided by IOOS differently as well. However, anglers who are serious about the sport can provide a good deal of anecdotal information about ocean characteristics that contribute to high fish densities. They also can provide much information about how they estimate fish densities, and about strategies they use to locate fish. Sports fishermen in the Gulf of Mexico stress the importance of clear water and abundant nutrients in the major ocean currents in the Gulf, and in numbers of eddies that spin off from the major currents.[10]

Water temperature and quality are important factors in both fish density and fish behavior. Water temperatures vary predictably with the seasons. Gulf water temperature ranges from mid 60s to low 70s degrees in the winter to around 80 degrees in the summer months. However, water temperatures vary considerably between currents and near-coastal waters. Shifting currents alter the temperature of the water at given locations. Water quality is a function temperature and nutrients. Water quality also reflects the salinity, clarity, and an absence of pollutants and unwanted (by the fish) ocean biota. Spawning and migration patterns are the most important factors generating differences in seasonal behavior of various species of fish. These types of information are typical of what one would expect anglers would require of IOOS systems in the Gulf of Mexico.

Some anglers prefer inshore fishing in the shallow waters near the Florida coast. Inshore fishermen select grass flats, mangrove swamp areas, bays, inlets, and the inland waterways, as well as near shore areas along the coastline. Weather is important to the inshore fisherman as well as to the offshore angler. Wind complicates fishing especially in small boats used for inshore fishing. Fishing activity falls prior to the onset of cold fronts during the winter, and responds to warm fronts and rain. Barometric pressure also affects fishing in shallow waters. Tides are important for inshore fishing. Fishing is better on a moving tide whether the tide is incoming or outgoing. The lunar and solunar phase affects the tides.

Much of the currently available ocean observing data comes from the National Weather Service. Images produced by satellite-based weather systems contain a wealth of detail on ocean surface conditions. Fishermen planning to fish in deeper waters offshore can utilize satellite-based information from the NWS to determine their offshore destinations. Anglers attempt to discern locations of major currents and blue water areas. Information from hydrographic models generates useful information about offshore ocean conditions (National Oceanic and Atmospheric Administration, 2003). Hydrographic models use climate theory and NWS historical data. Modelers also may input current and forecast NWS information into the models to generate nowcast and forecast data.

Systematic data on the dispersion of game fish in open waters is difficult to find, and there is little data on the factors that influence fish density (But see Robinson (2004) for a good example of what can be accomplished.) This data deficit must be addressed before analysts can employ the methodology employed in this article, and indeed, other methodologies that utilize concepts such as fish densities and expected catch by time and location.

While the fish side of the equation lacks hard data, systematic information on the angler side of the equation is available. Fishing can be classified as land-based (20%), by chartered vessels (10%), by privately owned or from rented boats (70%). Each of these categories can be further sub-classified, largely in terms of the expense, time, and effort invested in the sport. From the 1999–2000 NOAA survey (Leeworthy & Wiley, 2001), an estimated 4.5 million sports fishermen fish an average of 12 days a year. Gertner et al. (2001) report from the *Marine Recreational Fishery Statistics Survey* (MRFSS) 16 million fishing days by Florida Residents in 1999–2000 and 4 million fishing days by anglers who are visiting from another state. Charter boat expenses run about $250 per day (Whitehead and Haab, 1999). Ownership of an ocean-worthy fishing boat requires expenses of between $3,000 and $60,000 with craft capable of navigating open ocean waters running in the upper range. Daily costs of operating a non-commercial saltwater fishing boat are $195. Fishermen also find value in time they spend fishing. One measure of the value of fishing days is the opportunity cost of foregone activities. Sports fishermen who take time from work to fish lose income in the range of $195 per day (Leeworthy and Wiley, 2001).

Whitehead and McConnell use MFRSS survey data to allocate costs to trips. Average travel costs for anglers in the Southeast Atlantic region were $49. Time costs (allocated only for those who lost income by taking the trip) have been estimated by several investigators at between $100 and $200. The authors report an estimated $282 in time and travel costs per trip. Other costs, including bait and fuel, were $25.

Conclusions

This report has constructed a hypothetical value of improved ocean observing data to recreational fishermen in Florida. The estimate is based on required knowledge of fish concentrations under alternative environmental conditions in offshore waters. Information concerning two crucial elements of the problem is lacking. There is insufficient information about the underlying distribution of water quality, as seen by the fish, in coastal waters. The necessary data can be visualized as one or more maps of the coastal ocean areas with water quality reported as different colors on the map. This information may be forthcoming with further searching. Possibly, some of the required data is available somewhere that we have not looked, or can be assembled or inferred through discussions with knowledgeable individuals. Second, there is a dearth of information about how the concentrations of game fish correlate spatially with measures of water quality. This data is a crucial aspect of measuring the effects of IOOS on fishermen, as this is the use that anglers will put water quality data to.

It is not known at this time how a future IOOS system will measure water quality spatially, and how accurate measurements will be relative to currently available data. Improved forecasts into the near future will be most helpful to anglers, because these will be the most accurate forecasts, and the data will allow fishermen to plan their fishing activities in advance. It seems clear now that these are the data that will be important in delivering the benefits of IOOS to fishermen.

It is apparent that the major currents are important to fishing success in Florida. This is important in designing IOOS to the extent that the nature of and location of currents varies unpredictably during short periods of time. From our information, the location of the current is more variable off the Gulf Coast than off the Atlantic Coast. Also important are secondary currents and eddies associated with the major currents. These vary in nutrient content and temperature sufficiently to make them potentially different in terms of fish content.

Our review of the existing literature on recreational fishing economics finds that researchers have made significant strides in modeling fishing as an uncertain catch per trip and in identifying the role of travel time, other expenses, and angler characteristics in the decision to fish. Researchers have successfully employed nested logit techniques to differentiate fishing behavior by species of fish and by distance to launching sites. An important next step is to model the use of information on where and how to fish and how to value that information; information such as that generated by IOOS.

This article has considered only one aspect of the impacts of IOOS upon the recreational fishing industry—expected catch. Other factors that may benefit anglers are improved safety on the water and better planning of fishing trips. It should also be recognized that the development of IOOS has implications for fishery management as well as for recreational fishermen. IOOS will increase the effective demand for sport fish, which depends upon the catch function. Changes in the extent and form of fishery regulation will be determined by the changes in expected catch by the change in the variance of catch. Employing an effective reporting system of catch volume by time and place, authorities may be able to regulate activity to achieve sustainable catch rates over reproduction cycles.

Notes

1. A simple formulation assumes that y, p_j, and ε_j are independent of x. However, in cases where the fishing decision interacts with the information set, p_j may also be dependent on x.
2. A behavioral relationship can serve as the basis of a conditional distribution. This occurs in the situation where there exists a set of state variables the ocean observation system uses to construct the ocean observations. The same set of state variables generate wholly or partially the observed values $x_1, \ldots, x_n$. State variables may include ambient air temperature, winds, and air pressure, as well as the movement of ocean currents. The ocean observation system may develop models, based on historical weather and current data, to predict the characteristics s_i based on current

weather conditions. The same current weather data contribute to the realization of values of x_i. Thus, a correlation exists between x_i and s_i.

3. The information function x, for one or more of the state variables may depend on more than one of the environmental state variables. The relationship depends on the way in which the information predictions are generated. In this model, the simplified formulation, which assumes that the prediction of each state variable is conditioned on only that state variable, is adhered to.
4. Thus, the model assumes rational behavior by the angler that is consistent with the behavior underlying the theory of consumer choice. The angler will maximize the value of his or her catch based on the perceived choices available, and based on the information about the expected outcomes of those choices under uncertainty. The RUM with Bayesian probabilities is incorporated easily into the familiar mean-variance framework of finance. When the utility function is quadratic in return and risk:

$$V(q, y) = e^{\mu q+\mu y-(\sigma q+\sigma y)^2/2}$$

This formulation presupposes that individuals pursuing sport exhibit risk aversion as in investing. However, this is an empirical question. Anglers may not be risk averse with respect to the expected number of fish caught.

5. The probability that the fisherman will predict X1 when the actual state is S1 is 54 percent ([.7∗.2]/[.7∗.2 +.1∗.6 +.3∗.2]) using Baseline data but 77 percent ([.85∗.2]/[.85∗.2+.05∗.6+.18∗.21]) using IOOS data.
6. From Table 7, the probability #17 in the Baseline, is 0.2517. 0.2517 is the product of the probability that the angler will boat to 60 miles from shore,.54 (from Table 1, 0.54 = .2 ∗.2 +.8∗.6 +.1∗.2) multiplied by the probability that the current will be at 60 miles,.89 (from Table 3, 0.89 = .6∗.8/.54) multiplied by the probability that water at 60 miles will be high-quality, 0.575 (from Table 6, 0.575 = .2 ∗ .25 +.7 ∗.75) multiplied by the probability that the angler will adopt a high-water-quality fishing tactic,.913 (from Table 6, 0.913 = .7∗.75/.575).
7. The 1997 Southeast Socioeconomic Marine Angler Survey found that fishermen targeted the following species:

Species of Fish Targeted by Survey Respondents Percent Responses

Fish species targeted	Percent respondents
Snook	5.65%
Red Drum	6.26%
Spotted Sea trout	8.26%
All Other	26.68%
No Target	53.15%

Responses to the survey indicate that over one-half of the fishermen surveyed targeted no specific species of fish. These results are similar to those of the Marine Recreational Fishery Statistics Survey (MRFSS). MRFSS-AMES data report 52 percent of anglers target specific species, with 21 percent seeking spotted sea trout and 19 percent seeking red drum. Gillig et al. (2000), from results of a 345 fisherman survey, report that 18 percent had identified red snapper as a target species during

1991, whereas 82 percent indicated that no red snapper fishing trips were made during the year.

8. Using a University of Alaska at Fairbanks survey of halibut fishers in the Cook Inlet in Alaska, Criddle et al. (2003) reported average catches per angler day of 1.71 for Alaska residents and 2.43 for nonresidents. Charter-boat fishermen landed 3.51 fish per angler day. Using a random effects probit model they estimate an average compensated value of $98 per fisherman. Gillig et al. (2000) estimated that an increase in the catch rate for red snapper increases consumer surplus by $60–$90. Haab, Whitehead, and McConnell estimated catch rates and willingness to pay for four groups of fish species; big game, small game, bottom, and flatfish (2000). They used several data groupings as well as historic catch rates and catch rates predicted from a Poisson distribution for each group. Estimates for Florida's Gulf Coast and Atlantic Coast, by group are:

Frequency of Fish Categories Targeted By Charter and Private/ Rental Boat Anglers

Big Game	4.8
Small Game	26.1
Bottom	5.1
Flat	2.3
All Others 32.2	

This tally encompasses 70.5 percent of all fishermen in the NMRSS of the southeastern U.S. About 30 percent of anglers fish from shore.

Estimated Willingness to Pay for an Increase in the Historic Catch and Keep Rate in Florida

Species Group	Atlantic Coast	Gulf Coast
Small game	$6.60	$6.81
Big game	$14.63	$15.02
Bottom	$3.01	$3.09
Flat	$22.47	$23.25

The authors predict a catch and keep per trip as about 1 for big game fish, and about 2 for small game, bottom, and flat. (Haab, Whitehead, McConnell, 2000, Table 3.7).

9. Estimates of the value of a fishing day are in the range of $250. And survey results (Leeworthy & Wiley, 2001) indicated that fishermen who take time from work to fish forego income of $195. Compared to these estimates and other estimates of the value of fish caught the figure of $9.77 appears to be conservative.
10. The loop current is the most important current in the Gulf of Mexico. Offshore, at about 50 nautical miles from shore, the Gulf Stream current flows at speeds of 3.5 to 4.5 knots (CIMAS, 2007). Eddies form and move across the Gulf surface in regular patterns (Quarterdeck, 1998 and Matley, 1998). Clockwise eddies, known as anticyclones, have a core of warm water. Anticyclones are low in nutrients and do not attract fish. Counterclockwise eddies, known as cyclones, break from the anticyclones. They draw nutrient-rich cold, deep water from the ocean depths. Fish are attracted to food in the nutrient-rich waters of cyclones.

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