THREE ESSAYS IN THE ECONOMICS OF MARINE RESOURCE MANAGEMENT

By

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I must, however, take credit for all errors and omissions in this document.

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THREE ESSAYS IN THE ECONOMICS OF MARINE RESOURCE MANAGEMENT

By

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During the past 200 years the world's oceans have experienced drastic changes as a result of increasing pressure from a growing population whose appetites for seafood, recreation, energy sources and other marine resources seem to have no bounds. The oceans, once thought of as an indestructible and inexhaustible resource, are now under great pressure from overfishing, pollution, and modification of marine and coastal environments. Society is learning to cope with the resulting disruption of ecological processes while trying to maintain the flows of marine resources on which it depends.

This dissertation focuses on the role that approaches based on economic inquiry can play in the management of marine resources. We focus on two particular problems facing the earth's oceans and coastal areas. The first of these problems is water pollution and its effect on recreational use of marine resources. The second problem is the study and management of marine resources from a holistic perspective on an ecosystem-wide scale. Both of these problems have become central in today's marine resource management, as a burgeoning population increases its standards of living and demands an ever increasing amount of seafood, energy, and recreational opportunities.

This dissertation is an attempt to better understand the effects of this increased demand and propose ways in which society's management of marine resources can be improved.

The first essay deals with the effects of pollution of the marine environment from the worst oil spill in U.S. history—the *Deepwater Horizon*—on recreational use of marine resources, specifically recreational fishing. The main result from this essay is the estimation of monetary compensation measures which could be used in damage assessment and litigation. The second essay reviews the use of portfolio theory for natural resource management and illustrates the approach by developing portfolio selection models that could be used to set allowable catch policies in marine ecosystems. The third essay summarizes the development of a simple ecosystem model in *Ecopath with Ecosim*, one of the leading platforms for development of these models, and its use for conducting analyses of an economic nature.

CHAPTER 1
GENERAL INTRODUCTION

The human population has changed dramatically in the past 200 years. Compared to previous population growth rates, we have recently experienced an outright explosion. It took more than 100,000 years since the first *Homo sapiens* walked the plains of Africa for the world's population to reach the 1 billion mark around AD 1810. Just over a century later, by 1930, the world's population had doubled. By the turn of the millennium, more than 6 billion humans populated every region in Earth, perhaps with the exception of Antarctica (Brown et al. 1999). We could argue that this population explosion was made possible by an equally dramatic expansion in mankind's capacity to alter its environment. Advances in several fields of science, for instance, now allow us to live comfortably and in large numbers in places like Florida and the Brazilian Amazon, where tropical diseases and other inconveniences kept our forefathers at bay for generations. These advances have allowed us to dramatically decrease our mortality rates, thus making it possible for our numbers to swell to the levels we see today.

One of the first ecosystems to experience mankind's quest to transform the Earth may have been the sea, or more specifically, the waters off coastal South Africa. Before the first modern humans migrated out of Africa about 120,000 years ago, a small group of *Homo sapiens* learned to harvest fish and shellfish near a place called Pinnacle Point close to the Indian Ocean. This development turned the coastline into an attractive place for settlement and movement, and allowed these early humans to be better suited to survive changes in environmental conditions. Interestingly, use of pigment and development of advanced stone tools also took place in the same location and time period. The harvest of shellfish, a relatively sedentary food source, may have allowed

for social organization of higher complexity and lower mobility, which in turn enhanced the development of symbolic behavior or use of pigment for religious or artistic motives. This ability to harvest marine resources also played an important role in determining the migration routes that humans would follow to colonize the rest of the world (Marean et al. 2007). Thus it appears that the resources of the sea played a crucial role in the development of modern man, and that the relationship between humans and the oceans is as old as mankind itself.

The origins of fishing as a subsistence activity may be as old as mankind, with fishing playing an important role in the development of our species. Recreational fishing, or fishing for fun, is not a new trend either. The earliest evidence of fishing for fun is from Egyptian murals painted more than 4,000 years ago depicting members of the aristocracy fishing in man-made ponds (Pitcher and Hollingworth 2002). Furthermore, the fish and seafood trade, or fishing for profit, is also a relatively old activity. In ancient Rome, for instance, trade routes were established to transport catfish from the lower Nile as far as modern day Turkey (Arndt et al. 2003). Also, the global trade in cod (*Gadus morhua*) began in medieval times and played an important role in the colonization of the Americas (Kurlansky 1998). Some ancient cultures that were especially dependent on marine resources even developed informal systems for managing fisheries, as was the case in some islands in tropical Oceania (Johannes 1982).

Harvest of marine resources for different motives has taken place in different parts of the globe for thousands of years, and until recently it seemed that mankind could have no lasting impact on the world's oceans. As the biologist Thomas Huxley

noted in 1883, “all the great sea fisheries are inexhaustible: that is to say that nothing we do seriously affects the number of fish” (quoted in Gordon 1954, p.126). The natural fluctuations in harvests, which puzzled fishermen for centuries, were blamed on pollution, migratory patterns, changes in climate and ocean currents, as well as more obscure reasons such as “the ringing of church-bells and the wickedness of people” (Smith 1994, p. 9). Indeed, Gordon’s (1954) notion that “fishery resources are the richest and most indestructible available to man” was prevalent in fishery management circles until a relatively short time ago.

However, changes in human demography and technological developments have impacted the ways in which we interact with marine resources and the effect humanity has on marine ecosystems. The human population of the world has grown more in the last century than it had ever before, and more than 60% of all people on Earth live in coastal areas (Brown et al. 1999). Furthermore, developments such as high powered engines, sonar and global positioning system technology, refrigeration and low cost transportation have increased the efficiency of fishing activities and the demand for seafood. Some of these developments have also expanded the set of resources that we expect to obtain from the oceans. For instance, a large portion of our energy sources come from offshore oil drilling or are transported by sea, both of which result in benthic ecosystem impacts and higher pollution risks for marine ecosystems.

The effect of increased global demand for seafood has become evident in the status of fish stocks around the world. FAO (2010) estimates that the proportion of under-exploited or moderately exploited stocks declined from 40% in the mid-1970s to 15% in 2008. Thirty-two percent of global stocks are deemed to be over-exploited,

depleted, or recovering from depletion. The global marine-capture fishery production peaked in the mid-1990s and has remained stable since. However, the worldwide annual per capita consumption of fish, estimated to be around 17 kilograms, continues to grow despite the burgeoning population. This growth in consumption is due to the recent dramatic growth of aquaculture. The composition of the global fish catch has also been shifting away from long-lived piscivorous ground fish, such as cod, haddock, and hake, toward invertebrates and planktivorous pelagic fish, a process known as “fishing down marine food webs” (Pauly et al. 1998).

The effects of capture fisheries may go beyond the impacts on the target stock or fish population. In fact, there is a growing body of evidence to support the existence of ecosystem effects of fishing (for a summary, see National Research Council 2006, Chapter 2). Brodziak and Link’s (2002) overview of the recent history of the Georges Bank off the coast of New England provides a telling example of the ecosystem effects of fishing. For centuries European and American vessels have fished the Georges Bank and have targeted several species of groundfish. However, the number of groundfish vessels increased dramatically in the late 1970s, which resulted in overfishing of the groundfish stocks. The eventual collapse of the groundfish stocks, which were the dominant biomass group in the ecosystem, opened the way for pelagic species such as herring to become the dominant biomass group. This effect of fishing on the ecosystem—or ecosystem overfishing—is in part responsible for the non-recovery of groundfish even after fishing effort has been drastically curtailed.

The three essays in this dissertation are an effort to better understand the changing relationship between mankind and the oceans. The first essay addresses

water pollution and its effect on recreational use of marine resources. Specifically, we study the impacts of the *Deepwater Horizon* spill, which took place in 2010, on the choices of recreational fishers in the Southeastern U.S. and use our analysis to estimate monetary compensation measures that could be used for damage assessment and litigation. The second essay reviews the use of portfolio theory for natural resource management and illustrates the application of portfolio selection models that could be used to set allowable catch policies in marine ecosystems. The third essay summarizes the development of a simple ecosystem model in Ecopath with Ecosim, one of the leading platforms for development of such models, and its use for conducting analyses of an economic nature.

CHAPTER 2
A REVEALED PREFERENCE APPROACH TO VALUING NON-MARKET RECREATIONAL LOSSES FROM OIL SPILLS

Introduction

Oil spills and other anthropogenic environmental disasters have economic consequences that transcend business losses and property damages. Such non-market losses include those accrued by recreational users. Measurement of the non-market economic consequences of man-made disasters is often complicated by the ex-post nature of such analysis, as most researchers do not have the necessary foresight to collect data before, during, and after the event (Grigalunas et al. 1986). Researchers are thus forced to rely on counterfactuals and hypothetical scenarios to re-create what behavior would have been in an alternate state of the world where the event does not occur. However, continuous data collection efforts such as that of the Marine Recreational Information Program (MRIP) in the US provide opportunities for study of the non-market impacts of oil spills and other coastal and marine disasters in an ex-ante/ex-post fashion.

Considerable research has been conducted on the valuation of the non-market impacts from oil spills in the past 35 years. The earliest research relied mainly on market data or valuation estimates from similar areas or ecosystems to determine damages. For instance, Grigalunas et al. (1986) used a suite of direct and surrogate market methods to value losses to commercial and recreational interests from the 1978 Amoco Cadiz oil spill off the coast of Brittany, France. Similarly, Mazzotta et al. (1994) estimated losses from the 1986 Amazon Venture oil spill in the Savannah River, Georgia, using benefits transfer and focusing their discussion on restoration of the affected resources. The 1989 Exxon Valdez oil spill in Prince William Sound, Alaska, is

perhaps the most widely studied oil spill in terms of non-market valuation. Two seminal articles remain as proof of the methodological advances that resulted from these efforts. Hausman et al. (1995) used a random utility or choice modeling approach to estimate recreational losses from the Exxon Valdez, while Carson et al. (2003) use a contingent valuation survey to measure losses of non-use value to the residents of the Continental US. To set reference points for the damages from oil spills, Carson et al. (2004) and Van Biervliet et al. (2005) use contingent valuation to obtain estimates of damages from potential (hypothetical) spills in the central coast of California and the coast of Belgium, respectively. Most recently, Loureiro et al. (2009) and Loureiro and Loomis (2012) also used the contingent valuation method to value the effects of the Prestige oil spill in Spain on residents of different Spanish provinces, as well as residents of the United Kingdom and Austria.

The Deepwater Horizon (DWH) oil spill presents an opportunity to use MRIP to analyze the effects of a man-made environmental disaster before, during, and after the event. On April 20, 2010, the largest marine oil spill in US history began off the coast of Louisiana in the Gulf of Mexico. By the time the leaks in the DWH offshore drilling rig were fully contained on July 15, 2010, surface oil had reached several areas along the Gulf Coast. A large expanse of the Gulf of Mexico Exclusive Economic Zone (EEZ) had been closed to fishing, accounting for 37% of the US EEZ at the height of the spill (Figure 2-1). State waters throughout the Gulf were also impacted, resulting in closures ranging from 95% of state waters in Mississippi, 55% in Louisiana, 40% in Alabama, and 2% in Florida (Upton 2011). Federal and State authorities responded to the oil spill by deploying large-scale cleanup and mitigation efforts throughout the affected areas.

For example, the state of Florida launched a massive campaign to ensure potential beach-goers and recreational anglers that coastal areas of the state were still “open for business” and included “free-fishing days” during which the state fishing license requirement was temporarily lifted.

Aside from the effects on marine ecosystems and the commercial fisheries that depend on them, the DWH spill can also be expected to have impacted recreational use of coastal and marine resources in many areas of the Gulf. Under the Oil Pollution Act of 1990 (OPA), Federal, State, and Tribal authorities have standing to claim and recover losses on behalf of the public from responsible parties. Recoverable damages include both the costs of primary restoration and losses in value from the time of the incident until recovery, where losses include direct use and passive use values (Jones 1997). Recreational use of natural resources falls under the direct use value category, implying that beach-goers and anglers may be entitled to compensation for interim losses in value in the form of compensatory restoration (Mazzotta et al. 1994; Jones and Pease 1997; Flores and Thacher 2002; Parsons and Kang 2010). More importantly, recreational demand may offer a litmus test of whether primary restoration under Natural Resource Damage Assessment (NRDA) plans have been effective by determining whether affected locations are as desirable after restoration as they were before the oil spill.

In this study, we develop an approach to value quality changes in natural resources with recreational use values that occur throughout large regions and where quality changes occur asymmetrically through time and space. Our empirical application uses MRIP intercept data from the Southeast US to examine the effects of the DWH oil

spill on recreational anglers and estimate the relevant compensation measures that would make anglers “whole” pursuant to the OPA specifications. Specifically, our empirical model is designed to test the null hypothesis that the DWH oil spill had no impact on marine angler behavior in the Southeast US. We contribute to the literature by using two innovative aspects in our analysis, some of which are necessary due to the large scale of impacts of the DWH oil spill. First, given the large spatial extent of the DWH oil spill, we use a coarser definition of geographical zones than is usually used in non-market valuation, but one that permits substitution between areas that were or could have been affected by the spilled oil and those that were not. Second, we develop a quasi-real time binary measure of oil spill impacts using fishery closure maps published during the DWH oil spill, which gives us a closer glance at behavioral changes that occurred as a result of the oil spill than those used in previous studies dealing with spills. Our approach is appropriate in situations where the quality change under study affects large regions, where the quality change is experienced differently at different points in time, or as was the case with the DWH oil spill, where the quality change affects large areas asymmetrically through time.

A RUM to Measure Oil Spill Impacts

A random utility model (RUM) of site choice is well suited to analyze situations where recreational users have alternative locations to visit (Bockstael et al. 1991). The RUM models human behavior based on observed choices assumed to be driven by the characteristics of each alternative. The RUM was introduced by McFadden (1974, 1978), who developed the conditional and nested logit specifications. Bockstael et al. (1987) used the nested logit to model recreational choices by swimmers in the Boston area and value the associated water quality attributes. Morey et al. (1991) also used a

nested RUM to control for the decision of whether or not to participate in recreational fishing in the Oregon coast and value the elimination of fishing opportunities at particular locations. Similarly, Greene et al. (1997) used a nested RUM of fishing in the Tampa Bay region to value the loss of access to fishing grounds. Kaoru's (1995) nested site choice model values changes in combinations of quality for anglers in coastal North Carolina. Similarly, Thomas et al. (2010) created a model of site choice using ramp access points as nests and on-water locations as the elemental sites, and use their model to value the benefits of maintaining and improving boat ramps in the Fort Myers, Florida area.

The commonly used RUM procedure developed by McFadden, the conditional logit, is limited by the assumption of independence of irrelevant alternatives (IIA). The IIA assumption is violated when unobserved characteristics are correlated between alternatives. While the nested logit allows the researcher to establish a priori which alternatives are expected to be correlated with each other through the specification of nests, some problems may not be amenable to such specification or the specification may not be intuitive. The mixed or random parameters logit (Train 1998, 2003) and the latent class logit (Boxall and Adamowicz 2002) do not rely on the restrictive IIA assumption, with the added benefit that heterogeneity in the sample can be explicitly accounted for either by the estimation of distributions of the parameters in the former, or separation of the sample into latent classes in the latter. Haab et al. (2012) show the difference in results due to different specifications of the RUM in a study that estimates the marginal benefits of an additional fish caught in marine recreational trips to the Southeast US.

The RUM is a model of choice among a set of available alternatives. In the case of recreational fishing, the RUM models the choice an individual angler makes between available fishing sites because of the attributes of the site, such as the costs of travel, the historic and expected catches of fish, and the popularity or accessibility of the fishing site (Bockstael et al. 1991). In our case, we also consider the presence of oil near the coastline as an indication of site quality.

Following Train (2003), an angler (*n*) decides to go fishing and must choose from among a set *J* of available alternatives (*j* = 1, 2, …, *J*). Angler n selects alternative *j* if that is the alternative that maximizes their utility:

$$U_{nj} > U_{nh} \forall h \neq j. \tag{2-1}$$

However, the angler's utility is unobservable. Instead, we observe some attributes of the fishing locations as faced by the angler (q_{nj}), including travel costs (TC_{nj}) or the costs of accessing the location. Based on these observables, we specify an indirect function that relates these attributes to the angler's choice, $V_{nj}(TC_{nj},q_{nj})$. Since there are likely to remain unobserved factors in the angler's utility function, we can express utility as a deterministic component (V_{nj}) and a stochastic component (ε_{nj}) that captures the factors that affect the angler's well-being but are not observed, such that:

$$U_{nj} = V_{nj}\left(TC_{nj}, q_{nj}\right) + \varepsilon_{nj}, \tag{2-2}$$

where the joint density of the random component $\varepsilon_n = [\varepsilon_{n1},\ldots, \varepsilon_{nJ}]$ is denoted $f(\varepsilon)$.

The probability that angler *n* chooses alternative *j* is thus given by

$$\begin{aligned} P_{nj} &= \Pr(V_{nj} + \varepsilon_{nj} > V_{nh} + \varepsilon_{nh} \forall j \neq h) \\ &= \Pr(\varepsilon_{nh} - \varepsilon_{nj} > V_{nj} - V_{nh} \forall j \neq h). \end{aligned} \tag{2-3}$$

Using the density of the stochastic terms $f(\varepsilon)$, this cumulative probability can be expressed as

$$P_{nj} = \int_{e} I\left(\varepsilon_{nh} - \varepsilon_{nj} > V_{nj} - V_{nh} \forall j \neq h\right) f(\varepsilon_n) d\varepsilon_n, \tag{2-4}$$

where $I(\cdot)$ is the indicator function that equals one when the expression in parenthesis is true and zero otherwise. Assuming that the stochastic terms are independent and identically distributed extreme value yields McFadden's (1974) conditional logit, where the probability takes the form

$$P_{nj} = \frac{e^{V_{nj}}}{\sum e^{V_{nh}}}. \tag{2-5}$$

The conditional logit can be estimated using maximum likelihood methods.

We specify the indirect utility function (V_{nj}) to be linear in the attributes of the alternatives to ease derivation of the measures used to assess the impacts of the DWH oil spill. The utility that angler n obtains from choosing alternative j can then be expressed as

$$U_{nj} = \beta' q_{nj} + \varepsilon_{nj}, \tag{2-6}$$

where q_{nj} is a vector of attributes and β is a vector of model parameters. Preferences for the different attributes of available alternatives are reflected in the estimated parameters (β). Heterogeneity in preferences can be introduced by allowing a cumulative density function $f(\beta)$ for the estimated parameters. In this case, the choice probability becomes

$$P_{nj} = \int \left(\frac{e^{\beta' q_{nj}}}{\sum e^{\beta' q_{nh}}}\right) f(\beta) d\beta, \tag{2-7}$$

which is referred to as the mixed or random parameters logit model, which can be estimated using simulated maximum likelihood methods.

To examine the welfare impact of a change in a quality attribute across all sites, we decompose the indirect utility function explicitly into travel costs (TC_{nj}) and other attributes so that angler *n*'s utility from choosing alternative *j* is given by

$$U_{nj} = \alpha TC_{nj} + \beta' q_{nj} + \varepsilon_{nj}, \tag{2-8}$$

where α is interpreted as the marginal utility of income.

Now, suppose we want to evaluate the welfare impact of a proposed change in quality from the initial level (q_{nj}) to an alternative level (q_{nj}*), where

$$q_{nj}^{*} = q_{nj} + \Delta q. \tag{2-9}$$

The welfare measure for such a quality change is given by the difference in the sum of the indirect utilities across sites under both states of the world, weighted by the marginal utility of income as follows

$$W = \frac{1}{\alpha}\left[Ln \sum_{j=1}^{J} exp\left[V_{nj}^{*}\left(TC_{nj}, q_{nj}^{*}\right)\right] - Ln \sum_{j=1}^{J} exp\left[V_{nj}\left(TC_{nj}, q_{nj}\right)\right]\right], \tag{2-10}$$

which, as shown by Haab and McConnell (2002), reduces to

$$W = \frac{1}{\alpha}\beta' \Delta q. \tag{2-11}$$

This is the per trip welfare measure or willingness-to-pay to prevent a decrease in quality, or conversely, to purchase an increment in a quality attribute. Accordingly, the sign of *W* depends on whether anglers perceive the quality change as an improvement or damage to the fishing experience. In our case, *q* is an indicator of the impacts of the DWH spill.

Data Sources, Variables and Model Specification

The Marine Recreational Information Program (MRIP), formerly known as the Marine Recreational Fishery Statistics Survey (MRFSS), conducts intercept surveys of saltwater recreational anglers throughout the year (Hicks et al. 2000). These surveys

focus on the level and composition of catch to provide statistics on catch and fishing effort by species. The data are reported by two-month periods referred to as waves. For this study, we assembled the unweighted intercept datasets for years 2006 through 2010, the latter being the year in which the DWH oil spill occurred. Variables of interest in the dataset are shown in Figure 2-2.

Two main issues have been identified regarding the estimation of site choice models with the MRIP data (Whitehead and Haab 2000). The first is the computing power required to estimate models with many alternatives. The second is the limited scope of demographic information collected during intercept surveys. Researchers can aggregate or eliminate sites to reduce the number of choices modeled and several studies have investigated the merits of each approach. Parsons and Needleman (1992) developed a site choice model of fishing in Wisconsin lakes to analyze the effect of aggregating recreational sites on estimates of the value of different site characteristics, and caution against the use of aggregation schemes due to the introduction of bias on welfare estimates. Parsons and Kealy (1992), using the same study region, modeled choices of recreational users engaging in different activities and use the model to analyze the effect of using randomly drawn subsets of alternatives—rather than the complete set—to estimate the RUM parameters. These two studies suggest that using random draws from the alternative set may be more effective than aggregating sites as a way to ease computational requirements. These conclusions are echoed by Feather's (1994) analysis of sampling and aggregation using a site choice model of sport fishers in Minnesota. Lupi and Feather (1998) offered a pragmatic solution in which unimportant sites are aggregated, while those that are heavily visited or will be affected

by policy changes are kept in their elemental form. Whitehead and Haab (2000) used a different approach by examining the use of distance and historical catch to eliminate sites that are either too far or too unproductive to warrant inclusion as a viable choice; they found that results are not significantly affected by the elimination of non-viable choices determined using these criteria for marine recreational anglers in the Southeastern US. We use suggestions from these most recent studies to help define the size and scope of regions in this study.

MRIP intercepts in the Southeast US are conducted in several locations from Louisiana to North Carolina. Several authors who have worked with MRIP have used county level aggregation to define their sites (e.g., Morey et al. 1991; McConnell et al. 1995; Whitehead and Haab 2000; Haab et al. 2001; Hindsley et al. 2011; Haab et al. 2012). We aggregate further given the objective to measure the impact of the DWH oil spill, which occurred in a large area of the Gulf of Mexico, and define a set of 10 regions. The states of Louisiana, Mississippi, Alabama, Georgia, South Carolina, and North Carolina are defined as individual regions. Florida is divided into four regions: Northwest, Southwest, Florida Keys, and Florida Atlantic (Figure 2-3).

We then develop a binary measure of oil spill impacts using Federal fishery closure maps (Figure 2-1). During the DWH spill, the National Oceanic and Atmospheric Administration (NOAA) instituted a series of fishery closures in Federal waters throughout the affected areas of the Gulf of Mexico. The closures changed through time as the area affected grew until mid-July and shrank thereafter once the well was capped. We create the binary index of spill impacts using a rule of thumb that defines a region in the study to be affected by the spill at a given period of time if federal waters

are closed up to the state line. For each region we then have six different waves or time periods with their own indicator of oil spill impacts. Therefore, we include the effects of the DWH oil spill in a spatially and temporally explicit manner. While the availability of GIS-based data might suggest a finer spatial resolution, reducing the size of the region to capture such detail would necessarily reduce the overall geographic scope of the model or increase the number of discrete alternatives above what is manageable. Given that we are primarily interested in incorporating broad substitution patterns on a scale suitable for trustees (i.e., states and tribal nations), we opt for an approach that allows us to look at the oil spill at a regional scale throughout time on a somewhat coarse manner. The final alternative set for each angler includes the 10 alternative sites in six possible seasons for a total of 60 available alternatives in a given year.

The second issue with respect to using MRIP data for site choice models is the need to have estimates of travel costs for all alternative trips in addition to the observed trip. Since the zip code of their permanent home residence is the only information we have on each angler, we created a matrix of distances between all alternative sites and all counties of residence of intercept respondents. Travel related expenses incurred by angler *n* traveling to site *j* were calculated as twice the product of the driving distance and the standard IRS mileage rate in 2009.

In order to engage in a recreational activity such as fishing, participants must not only spend some of their disposable income to pay for travel related expenses, but in many cases must give up work or other wage-earning opportunities. This opportunity cost of time must also be factored into travel cost recreational demand models for a more accurate measure of the value of the recreational experience (Palmquist et al.

2010). In our case, the angler's opportunity cost of time is assumed to equal the median income in his or her county of residence from the most recent U.S. Census. With these assumptions, the total travel costs (*TC*) are the sum of travel and time related expenses:

$$TC_{nj} = 2(0.55)D_{nj} + \gamma\left(\frac{Medincome_n}{2080}\right)\left(\frac{2D_{nj}}{40}\right), \tag{2-12}$$

where D_{nj} is the one-way distance between the angler's county of residence and the fishing site, $\gamma = 0.33$ indicates the share of the value of travel time used to account for the cost of leisure time (this is a commonly used share and was first proposed under Executive Order 11747), and med_income_n is the median annual income in the respondent's county of residence during the year the fishing trip took place. Median income is divided by 2,080, the number of full-time hours potentially worked in a year. The distance term is divided by 40, reflecting the assumption that road travel takes place at an average speed of 40 miles per hour (Haab et al. 2001). Total travel costs are expected to be inversely related to site choice for all modes.

Our analysis rests strongly on the two attributes developed above, the oil spill measure (*spill*) and travel costs (*TC*), as well as four other types of attributes found in the MRIP dataset (Table 1). The first type of attributes, denoted P_n, are those related to the angler and include the number of days the angler has fished in the last year (*ffdays12*), the median income in the angler's county of residence (*med_income*), and whether the angler is a shore based fisher (*mode1*), a for hire based fisher (*mode2*) or a private/rental boat based fisher (*mode3*). The second type of attributes, which we denote L_j, have to do with the area or location in which fishing takes place and include the historical catch per unit effort for all species combined (*hckr*), the number of anglers

in the sample who visited the site (*popularity*), the number of interview locations or access points in a particular area (*sites*), and an indicator for whether the site is located in the Gulf of Mexico (*gulf*). The third type of attributes, denoted E_j, is related to the season in which the fishing trip takes place and includes indicators for the three warmest seasons (*spring*, *summer*, and *fall*). The fourth type of attributes, which we denote T_{nj}, are related to the specific trip and include the length of the fishing trip in hours (*hrsf*), an indicator of whether the angler was targeting a particular fish species at the time (*targ*), and whether fishing took place in the ocean, close to shore (*area1*), in the ocean, offshore (*area2*), or in an inland or inshore location (*area3*).

One commonality among site choice models of recreational fishing is the use of catch as a quality attribute, primarily because catch rates are policy relevant. While trip-level data includes catch and fishing location, it does not include expected catch at alternative sites the individual considered but did not visit. McConnell et al. (1995) proposed a two stage process in which a catch equation is estimated in the first stage and used to create a quality attribute for the alternatives used in the site choice model, the second stage. This process gives a proxy of the angler's ex-ante expectation of catch and thus expected quality of the fishing experience at the chosen site. Such an approach allows variation in site attributes among alternatives at the trip level. Haab et al. (2012) follow this approach to value additional catches of different marine species of management interest in the Southeastern United States using a series of site choice models that allow for heterogeneity in anglers' preferences. One of their important findings is that heterogeneous angler preferences are a staple of the MRIP data, in particular fishers' response to travel costs.

We consider these findings by first specifying a negative binomial model of the catch and keep rate experienced by each angler in all observed trips (C_{nj}). The predicted catch serves as an individual-specific indicator of site quality, which allows greater heterogeneity in estimation of the site choice models (McConnell et al. 1995). We use three types of regressors that can be expected to influence the number of fish that an angler might be able to catch in a given trip, namely those that are related to the angler (P_n), location (L_j), and fishing trip (T_{nj}):

$$Ln(C_{nj}) = \delta_0 + \delta_1 P_n + \delta_2 L_j + \delta_3 T_{nj} + \eta_{nj}, \tag{2-13}$$

where δ_0 is the intercept term, δ_1, δ_2, and δ_3 are vectors of estimated parameters and η_{nj} is an error term. We refer to this model as the catch model.

We then consider three types of site choice models, one for each fishing mode. This segregation allows us to estimate distinct compensation measures for shore based, for hire, and private or rental boat fishers, as well as to examine whether preferences differ across modes. Separating out the modes also has the added benefit of reducing the dimensionality of the models and allows for a better representation of site choice, which is *a priori* expected to vary by mode.

We construct our indirect utility function by excluding characteristics of the individual anglers but maintain independent variables that can be expected to influence the probability of choosing a particular combination of fishing site and season. For instance, we include travel costs to the site (*TC*), expected catch ($Ln(\hat{C}_{nj})$), the indicator of whether the DWH oil spill was affecting a given area during a given wave (*spill*), as well as location-specific attributes (L_j) and seasonal indicators (E_j)

$$U_{nj} = \alpha TC_{nj} + \beta_1 Ln(\widehat{C_{nj}}) + \beta_2 spill_j + \beta_3 L_j + \beta_4 E_j + \varepsilon_{nj}, \tag{2-14}$$

where α is the marginal utility of income, β_1 and β_2 are parameter estimates associated with the respective variables, β_3 and β_4 are vectors of parameter estimates and ε_{nj} is an error term. The models are estimated for 2010, the year in which the oil spill occurred. Similarly, we use two different estimation techniques for comparison of results across specifications of the RUM, the conditional and the mixed logit. Thus, we have a total of four distinct models for each fishing mode considered.

Results

Site Quality Measure

The independent variables in the catch model perform well as predictors of the catch and keep rate an angler experiences in a particular trip (Table 2-2). All the estimated coefficients are statistically significant at the 0.01 level, except for the coefficient on popularity, which is not significantly different from zero. The site-specific attribute historic catch per unit effort (*hckr*) has the expected effects on the numbers of fish caught and kept. High historic catches are likely related to high stock levels and suitable fish habitat, and it is no surprise that anglers fishing in locations with high historic catches enjoy high catch rates.

Other than fishing experience, it is difficult to assess ex-ante what the effects of angler-related attributes are on catch. It is clear that fishing experience (*ffdays12*) can be expected to have a positive impact on catch, as more experienced anglers possess some knowledge regarding bait, tackle, technique and fish behavior that less experienced anglers lack, and we observe this effect in our catch model. In addition, our model indicates that median income has a small negative effect on catch. We also find that anglers who fish from shore experience lower catches than those who fish from

private and rental boats, while those who use the for-hire sector generally catch more fish than either shore or private boat anglers.

Besides the kind of area in which fishing takes place, the expected effects that trip-specific attributes have on catch are clear. All things held equal, longer fishing trips (*hrsf*) can be expected to yield higher catches. Similarly, targeting a particular species, which involves a series of decisions regarding bait, location, tackle, and fishing technique, among others, can be expected to result in higher catches. Both of these effects are observed in our model. In addition, we find that anglers in the Southeast generally enjoy higher levels of catch when fishing in the open ocean than they do when fishing inshore, and that anglers fishing offshore experience higher catches than those fishing in the open ocean close to shore.

Choice Models

Estimation of discrete choice models allows us to obtain information regarding people's preferences toward the good or service that is being chosen. In the case of recreational fishing, the coefficients in a site choice model indicate whether the presence or absence of a given attribute increases or decreases the likelihood that an angler will choose an alternative or season-site combination. In our case, these parameters can also be interpreted as the marginal utility of the attribute they are associated with. For instance, an attribute with a positive coefficient can be interpreted as a desirable attribute that anglers will seek in their choice behavior. Conversely, attributes with negative coefficients are undesirable, and anglers try to avoid alternatives with these attributes. In addition, with the mixed logit we can learn not only whether anglers seek or avoid certain attributes, but also whether there is heterogeneity in preferences. By estimating the standard deviations of parameters, we can learn

whether most anglers prefer or avoid a certain attribute to the same degree—when the standard deviation is not statistically significant—or whether that preference or avoidance behavior is stronger in some individuals and weaker in others. In other words, a statistically significant standard deviation of a coefficient for a particular attribute indicates that anglers' preferences toward that attribute are heterogeneous across the population of recreational fishers.

Shore fishing mode

The site attributes in the shore fishing models perform well and the model gives a good representation of angler behavior (Table 2-3). All the means of the parameters are statistically significant and of the expected sign. Increases in travel costs decrease the likelihood that anglers choose a site, which results in a downward sloping demand curve for recreational fishing. Anglers are also more likely to choose the more popular fishing locations than less popular ones. Similarly, anglers prefer locations in which their expected catch is high. In terms of seasons, shore-based anglers exhibit a strong preference for fishing during the fall and summer but still prefer the spring over the winter. Areas in the Gulf of Mexico are preferred over areas in the Atlantic Coast for shore-based fishing.

The mixed logit results for the shore-based fishing mode show that shore-based anglers exhibit heterogeneous preferences on travel costs and the number of access points (*sites*) in the fishing location. That is, while anglers perceive travel costs as a negative attribute and prefer locations that are closer over those that are far away, some anglers are more averse than others to travel far to engage in recreational fishing. Angler preferences on the number of access points in a fishing location are a bit more complex. The conditional logit results would suggest that anglers prefer locations with

fewer access points. The mixed logit, however, tells a more complicated, and perhaps realistic, story. The mean of the parameter is positive and statistically significant, albeit small. However, the large and statistically significant estimates of standard deviation of the sites parameter imply that while some anglers do indeed avoid locations with high numbers of access points other anglers actually prefer locations with many access points. In this case, the attribute is seen as a positive by a group of anglers and a negative by another group.

Anglers fishing from shore also avoided alternatives affected by the DWH oil spill, thereby expressing a preference for fishing trips in locations that were not affected by the oil spill, or at times in which the spill was not affecting the chosen location. However, the standard deviation of the spill parameter shows that not only are preferences for trips affected by the DWH oil spill heterogeneous, but that some shore-based anglers' choices were not at all affected by the oil spill.

For-hire fishing mode

The for-hire fishing model also provides an adequate depiction of angler behavior with the expected signs on most parameter coefficients (Table 2-4). As expected, anglers are averse to high travel costs and prefer locations close by than those far away. Individuals who take guided fishing trips in the Southeast US also prefer locations that are popular fishing destinations and see the Gulf Coast as a superior alternative when compared to the Atlantic Coast. Rather than fishing during the fall, as shore-based anglers prefer to do, individuals using the for-hire sector prefer to take their fishing trips during the summertime, and springtime is preferred over the fall. Wintertime is the least preferred season of the year for guided fishing trips. The for-hire models show something that might be considered an anomaly. Rather than preferring locations

that can be expected to yield high catches, anglers taking guided trips choose locations in which their expected catches are low. This abnormality may be due to lack of information by anglers regarding other locations where guided trips are available or limited availability of for-hire operators in areas with high expected catches. It is also likely that anglers learn about high and low catch locations in an iterative manner after repeated trips. However, it is less likely that anglers fishing in guided trips make enough repeated visits to discover the higher catch locations, especially since this would involve taking trips with different fishing guides.

Anglers in the for-hire sector also exhibit heterogeneous preferences for travel costs and the number of access points available. As in the shore-based models, some anglers taking guided fishing trips are more averse to pay high travel costs than others. Similarly, some anglers prefer locations with many access points, while other anglers prefer locations with few access points. Individuals taking guided fishing trips in the Southeast also perceived the oil spill as a negative attribute and avoided areas affected by the DWH oil spill during the time periods in which oil was present. For-hire angler preferences toward the oil spill, however, are homogeneous, implying that all anglers using this fishing mode are just as averse to fishing in areas affected by oil spills.

Private and rental boat fishing mode

The discrete choice model of private and rental boat fishing also depicts angler behavior appropriately, and the attributes used perform well explaining recreational fishers' choices (Table 2-5). Anglers fishing from private or rental boats are more averse to travel long distances than shore-based and for-hire anglers, most likely due to higher travel costs as a result of these individuals pulling their boats in trailers. Private boat anglers also prefer popular locations as well as locations in which they can expect to

catch higher numbers of fish. Summer and fall are the preferred fishing seasons, but spring is also seen as a better season for fishing than winter. As with the other fishing modes, areas in the Gulf of Mexico are preferred over those in the Atlantic Coast.

Anglers fishing from private and rental boats have heterogeneous preferences for more site attributes than any other fishing mode. Similarly to anglers fishing from shore and using the for-hire sector, private boat anglers' preferences for travel costs and number of access points are heterogeneous. The degree of aversion to travel long distances varies across anglers, and some anglers using this fishing mode prefer locations with many access points while others prefer locations with fewer access points. In addition, preferences for expected catch are also heterogeneous, implying that while for some anglers the expected level of catch plays a pivotal role in the decision of where and when to fish, it plays a lesser role for other anglers.

Similarly to anglers fishing from shore, individuals in the private and rental boat fishing mode exhibit a heterogeneous aversion for areas affected by the DWH oil spill. This heterogeneity appears to be greater for private anglers than shore-based ones, which is likely a reflection of greater heterogeneity in preferences overall in the private boat fishing mode compared to other modes.

WTP to avoid spilled oil

The estimates of WTP for prevention of the DWH oil spill differ between estimation procedures (Table 2-6). In the conditional logit models, for instance, we find that the mean monetary compensation due to anglers is $125 for anglers in guided trips, $65 for anglers fishing from shore, and $10 for anglers using private and rental boats (Figure 2-4). On the other hand, the estimates of WTP we obtain from the mixed logit model are more conservative at $34 in the for-hire sector, $28 in the shore-based

sector, and $1.60 in the private and rental boats sector (Figure 2-5). The relative magnitude of WTP across modes, however, is quite similar across estimation procedures, with the compensation for anglers in guided trips being the largest of the three modes and that for anglers using private boats being the smallest. We obtain confidence intervals for WTP using the Krinsky-Robb (1986) procedure with 10,000 draws.

To compute estimates of total damages to marine anglers in the Southeastern United States as a result of the DWH spill (Table 8), we multiply our per trip measures of WTP for prevention of the spill by the total number of marine fishing trips estimated by MRIP in the States considered in our study (Table 7). The total damages as estimated using the conditional logit model have a 95% confidence interval spanning between $1.3 and $1.6 billion, with a mean of $1.4 billion. Our most conservative estimate of total damages obtained using the mixed logit model has a 95% confidence interval that spans between $459 million and $625 million and is centered at $542 million. Given that the mixed logit addresses the IIA problem associated with the conditional logit, this conservative estimate of total damages of $542 million is the most credible estimate.

Discussion

The most important finding of this study is the rejection of the null hypothesis that the DWH oil spill had no impact on marine recreational fishing in the Southeastern United States. In fact, the 2010 DWH oil spill in the Gulf of Mexico had a negative and statistically significant impact on marine anglers across all fishing modes, and using choice modeling we have found that the monetary compensation due to them is in the order of half a billion dollars. However, while this estimate represents losses in non-

market values, it does not reflect the totality of economic losses as a result of the DWH oil spill. Our estimates reflect losses in direct use value of the Gulf's fishing grounds to marine recreational anglers only. Losses to commercial fishing, the tourism industry and other interests who depend on recreational expenditures are not accounted for in our study; neither are losses to other recreational users of the Gulf of Mexico, such as beach-goers, scuba divers, and recreational boaters. Finally, and perhaps more importantly, our study does not measure losses in ecosystem service flows or passive use values as a result of the oil spill.

Another aspect that merits clarification is the relative magnitude of our estimates of WTP for prevention of the DWH oil spill. Common sense could suggest that anglers whose fishing expenses are highest can be expected to have the highest WTP for prevention of the DWH oil spill. However, our compensation measures are not related to fishing related expenses but to behavioral responses to two attributes of fishing trips. In particular, the compensation measure developed here (Equation 2-11) is inversely related to anglers' response to travel costs (consisting of the standard mileage and opportunity cost measures using Census data) and directly related to their response to oil spill impacts. For instance, the response of private boat anglers to travel costs is the largest of the three modes, showing that anglers who haul their own boats are less willing to travel long distances than other anglers who are just traveling with their fishing gear (shore-based) or those who have no need to carry fishing gear or boats (for-hire). Since the compensation measure is inversely related to the response to travel costs, this makes the compensation measure for private boat anglers smaller than that for other modes, other things held equal. Similarly, private boat anglers' response to the oil

spill is the weakest of the three modes. A possible explanation is that anglers driving their own vessel have more flexibility to find fishing spots that are oil free, even when the region they are fishing in is experiencing the impacts of the oil spill. This weaker response translates into smaller compensation measures for private boat anglers and explains why the monetary compensation for shore-based anglers is consistently larger than that for private boat anglers.

The use of the mixed logit allows us to find the attributes of fishing trips for which anglers have heterogeneous preferences. Our findings in this respect are similar to those from Haab et al. (2012), who also find preferences for travel costs to be heterogeneous among anglers in the Southeastern US. In addition, we also find heterogeneity in preferences for site popularity, expected catch, and the number of elemental sites among these same anglers, depending on the fishing mode. Our models may differ from those in Haab et al. in terms of the number of heterogeneous attributes due to our higher level of aggregation and the consideration of different groups of anglers. The aggregation in Haab et al. is county-level, a finer scale than our regional aggregation. This may be the reason for the discrepancy in heterogeneity of preferences for the number of elemental sites, as our regions have many more elemental sites than their counties, as well as site popularity, since our sites are essentially different. Similarly, their focal groups are anglers who target particular groups of fish species, while ours are anglers who use particular fishing modes. The sample sizes used in each model are much larger in our study, but their study uses a much larger number of models. The catch attribute also plays more important role in the Haab et al. study than in ours, as it is the attribute that is valued. In that sense, the

catch attribute serves the same purpose in Haab et al. as the oil spill attribute serves in this study.

Another critical attribute for which anglers appear to have heterogeneous preferences is the DWH oil spill itself. That different people would respond differently to an oil spill is not an entirely surprising result or one without a precedent in the literature. Researchers investigating the effects of the Prestige oil spill found that Spanish tourists actually increased their visits to the affected coastline during and after the spill (Garza Gil et al. 2006). Loureiro et al. (2006) call this the “solidarity effect” as individuals choose to visit the affected coastline as a result of public interest surrounding the oil spill and to experience first-hand the magnitude of the disaster. In the case of the DWH oil spill, it is possible that many marine anglers actually took trips to affected areas as a result of “free fishing days” in which license restrictions were lifted, or just to see the effects of the oil spill personally.

Table 2-1. Model Variables

Type	Name	Description
	spill	Dummy for oil spill effects on intercept zone
	TC	Round trip travel cost to site ($)
P_n	ffdays12	Number of days fished in last year
P_n	med_income	Median annual income in respondent's county of residence ($)
P_n	mode1	Dummy for 1st mode (shore fishing)
P_n	mode2	Dummy for 2nd mode (for hire fishing)
P_n	mode3	Dummy for 3rd mode (private or rental boat)
L_j	hckr	Historic mean number of fish caught and kept by wave and mode[a]
L_j	popularity	Number of intercepts in region
L_j	sites	Number of access points in region
L_j	gulf	Dummy for Gulf of Mexico
E_j	summer	Dummy for May-August
E_j	spring	Dummy for March-April
E_j	fall	Dummy for September-October
T_{nj}	C_{nj}	Observed catch (all species) per hour fished
T_{nj}	$\hat{C}_{nj}$	Predicted catch (all species) per hour fished
T_{nj}	hrsf	Hours spent fishing during intercepted trip
T_{nj}	targ	Dummy for targeting any species
T_{nj}	area1	Dummy for fishing in the ocean, close to shore
T_{nj}	area2	Dummy for fishing in the deep ocean, offshore
T_{nj}	area3	Dummy for fishing inland or inshore

[a] Fish kept are those that have been landed and the angler is taking for consumption, not fish caught during the trip and used as bait.

Table 2-2. Negative binomial predicted catch model of fish caught and kept

Variable	Coefficient	Standard Error	Z
ffdays12	0.0023*	0.0003	8.28
med_income	-0.0000081*	0.0000	-6.70
mode1	-0.1575*	0.0344	-4.58
mode2	0.1590*	0.0546	2.91
hckr	3.2739*	0.1192	27.47
popularity	-0.0000007	0.000000	-0.35
hrsf	0.2069*	0.0074	28.14
targ	0.4374*	0.0270	16.19
area1	0.1372*	0.0320	4.29
area2	0.5068*	0.0468	10.82
constant	-2.1457*	0.0798	-26.89
Model Statistics:			
Log-likelihood	-59604.009		
LR chi2(10)	4440.2		
Pseudo R^2	0.0359		

* Significant at the 0.01 level.

Table 2-3. Models of shore fishing site choice

	Conditional Logit				Mixed Logit			
	Baseline (2009)		Event (2010)		Baseline (2009)		Event (2010)	
Variable	Coef.	Z	Coef	Z	Coef.	Z	Coef	Z
Travel Cost	-0.0096	-102.69	-0.0096	-105.63	-0.0243	-47.53	-0.0260	-48.09
Popularity	0.0269	62.64	0.0229	54.86	0.0423	43.40	0.0357	39.40
Exp. Catch	0.6339	3.00	1.2719	5.80	0.7996	3.45	1.3466	5.73
Spill			-0.6306	-17.74			-0.7227	-13.26
Summer	0.6088	31.23	1.0185	50.88	0.6081	30.67	1.0168	50.11
Spring	0.3474	14.24	0.4664	18.93	0.3483	14.27	0.4649	15.44
Fall	0.6830	30.73	1.0391	48.58	0.6760	27.14	1.0494	48.18
Gulf	1.1743	38.20	1.2025	40.68	1.9179	31.00	1.8459	30.77
Sites	-0.0704	-19.05	-0.0116	-3.10	-0.0469	-7.79	0.0391	6.46
SD (Travel Cost)					0.0132	38.89	0.0140	40.12
SD (Popularity)								
SD (Exp. Catch)								
SD (Spill)							1.1820	8.97
SD (Sites)					0.1886	18.82	0.1832	17.88
Model Statistics:								
Log-likelihood		52583.05		68906.44		4154.9		4749.74
Pseudo R2		0.3478		0.3891				
Alternatives		60		60		60		60
Cases		18,463		21,628		18,463		21,628

Table 2-4. Models of for-hire fishing site choice

	Conditional Logit				Mixed Logit			
	Baseline (2009)		Event (2010)		Baseline (2009)		Event (2010)	
Variable	Coef.	Z	Coef	Z	Coef.	Z	Coef	Z
Travel Cost	-0.0036	-78.15	-0.0034	-78.89	-0.0077	-45.85	-0.0073	-47.16
Popularity	0.0064	21.14	0.0042	13.99	0.0105	23.48	0.0094	21.21
Exp. Catch	-0.3125	-19.41	-0.4901	-27.18	-0.2159	-12.80	-0.3701	-19.85
Spill			-0.4289	-12.43			-0.2528	-6.90
Summer	1.0014	39.66	1.1944	45.70	0.9955	39.12	1.1257	42.87
Spring	0.6943	22.56	0.8882	30.68	0.6682	17.40	0.8409	26.48
Fall	0.6169	19.40	0.7456	24.71	0.5851	15.19	0.6867	16.57
Gulf	0.7816	30.38	0.8255	33.02	0.9536	27.14	0.9162	27.48
Sites	0.0030	0.99	0.0398	12.63	-0.0157	-4.10	0.0107	2.61
SD (Travel Cost)					0.0082	40.48	0.0079	39.60
SD (Popularity)								
SD (Exp. Catch)								
SD (Spill)								
SD (Sites)					0.0926	9.65	0.1323	17.32
Model Statistics:								
Log-likelihood		12182.08		15545.85		2506.58		2521.87
Pseudo R2		0.1257		0.1423				
Alternatives		60		60		60		60
Cases		11,835		13,338		11,835		13,338

Table 2-5. Models of private and rental boat fishing choice

	Conditional Logit				Mixed Logit			
	Baseline (2009)		Event (2010)		Baseline (2009)		Event (2010)	
Variable	Coef.	Z	Coef	Z	Coef.	Z	Coef	Z
Travel Cost	-0.0137	-137.86	-0.0140	-139.24	-0.0382	-55.46	-0.0384	-61.53
Popularity	0.0282	74.67	0.0271	70.65	0.0479	52.76	0.0416	55.72
Exp. Catch	0.6210	9.59	0.7935	12.75	0.2145	2.30	0.3281	3.70
Spill			-0.1392	-5.67			-0.0636	-2.01
Summer	0.5501	41.32	0.8295	54.56	0.5518	41.14	0.8411	54.46
Spring	0.2401	14.09	0.4209	23.36	0.2354	13.47	0.4458	24.07
Fall	0.3358	20.40	0.7687	46.74	0.3351	17.38	0.8044	46.73
Gulf	1.6001	63.57	1.5871	62.54	2.7791	44.64	2.4053	48.12
Sites	-0.0382	-13.05	-0.0288	-9.13	-0.0171	-3.29	0.0081	1.49
SD (Travel Cost)					0.0191	47.74	0.0193	50.63
SD (Popularity)					0.0156	17.33		
SD (Exp. Catch)					1.2498	5.29	1.5079	7.22
SD (Spill)							1.3786	16.45
SD (Sites)					0.0433	2.65	0.0538	3.13
Model Statistics:								
Log-likelihood		116517.35		126430.99		10149		11309.3
Pseudo R2		0.3917		0.4134				
Alternatives		60		60		60		60
Cases		36,327		37,346		36,327		37,346

Table 2-6. Per trip willingness-to-pay for prevention of the Deepwater Horizon oil spill

	Conditional Logit			Mixed Logit		
		95% CI			95% CI	
	Mean	Lower	Upper	Mean	Lower	Upper
Shore	$65.57	$57.99	$73.05	$27.76	$23.53	$32.14
For Hire	$125.63	$104.54	$146.15	$34.53	$24.22	$44.96
Private	$9.95	$6.40	$13.47	$1.64	$0.01	$3.31

Table 2-7. MRIP participation estimates by state and mode (2010)

State	Shore	For-Hire	Private
Alabama	812,275	33,505	840,377
Florida	10,038,324	579,314	13,866,273
Georgia	335,219	7,359	530,224
Louisiana	728,670	78,886	3,054,931
Mississippi	596,544	6,842	629,207
North Carolina	3,313,215	165,304	2,199,055
South Carolina	1,142,892	76,834	1,078,462
Total	16,967,139	948,044	22,198,529

Table 2-8. Total loss estimates (in Millions USD)

	Conditional Logit			Mixed Logit		
	Mean	95% CI		Mean	95% CI	
		Lower	Upper		Lower	Upper
Shore	$1,112.50	$983.90	$1,239.50	$471.00	$399.20	$545.30
For Hire	$119.10	$99.10	$138.60	$32.70	$22.90	$42.60
Private	$220.90	$142.10	$299.00	$36.40	$0.20	$73.40
Total	$1,451.36	$1,296.99	$1,601.65	$542.25	$459.93	$625.39

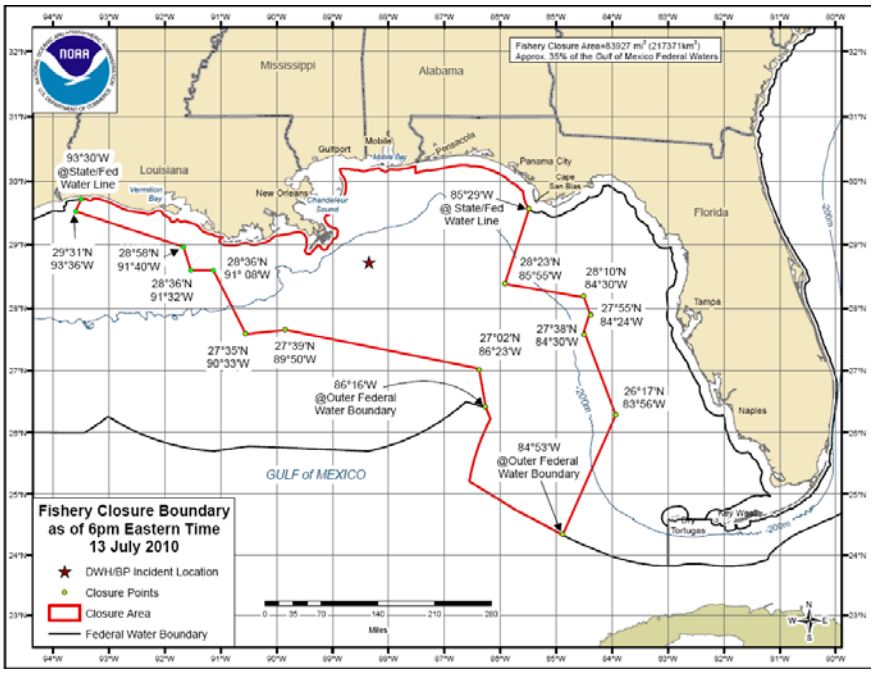

Figure 2-1. Federal fishery closure in the Gulf of Mexico in response to the Deepwater Horizon oil spill, July 13, 2010

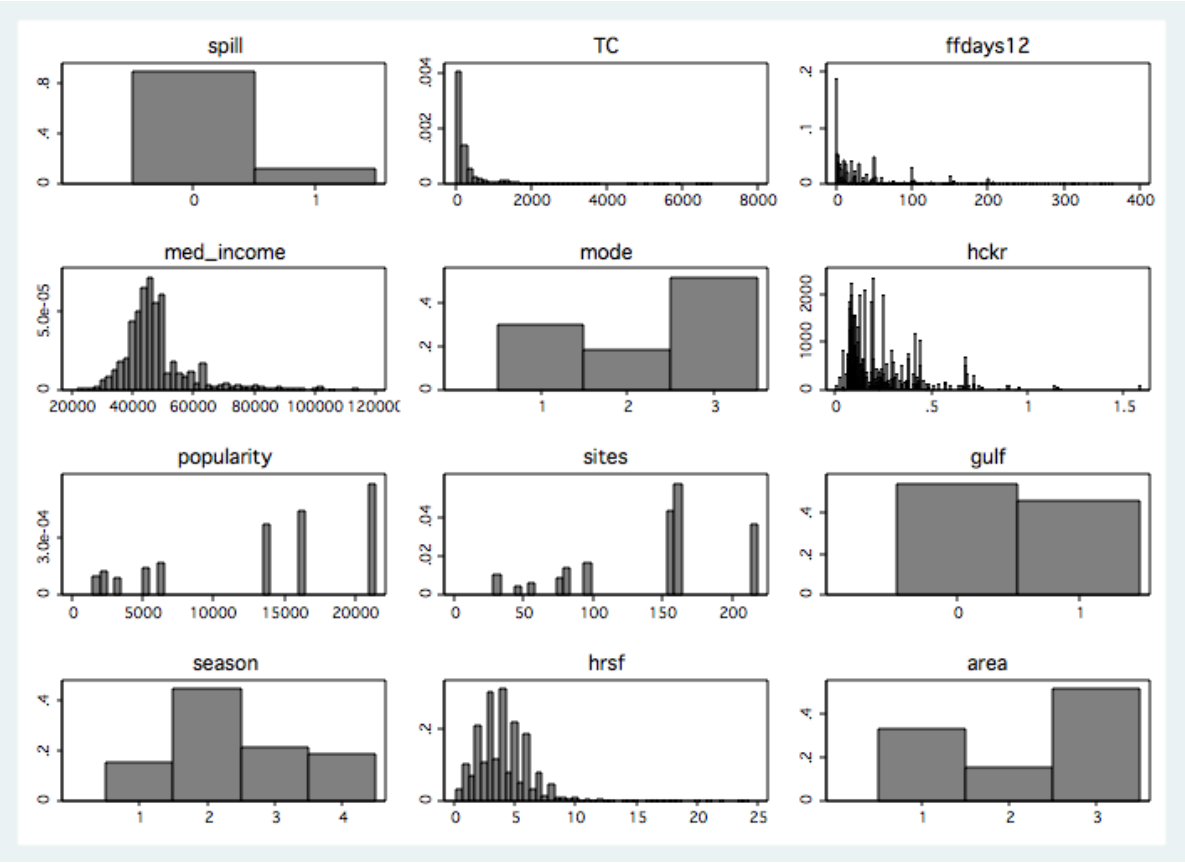

Figure 2-2.Density histograms of important variables

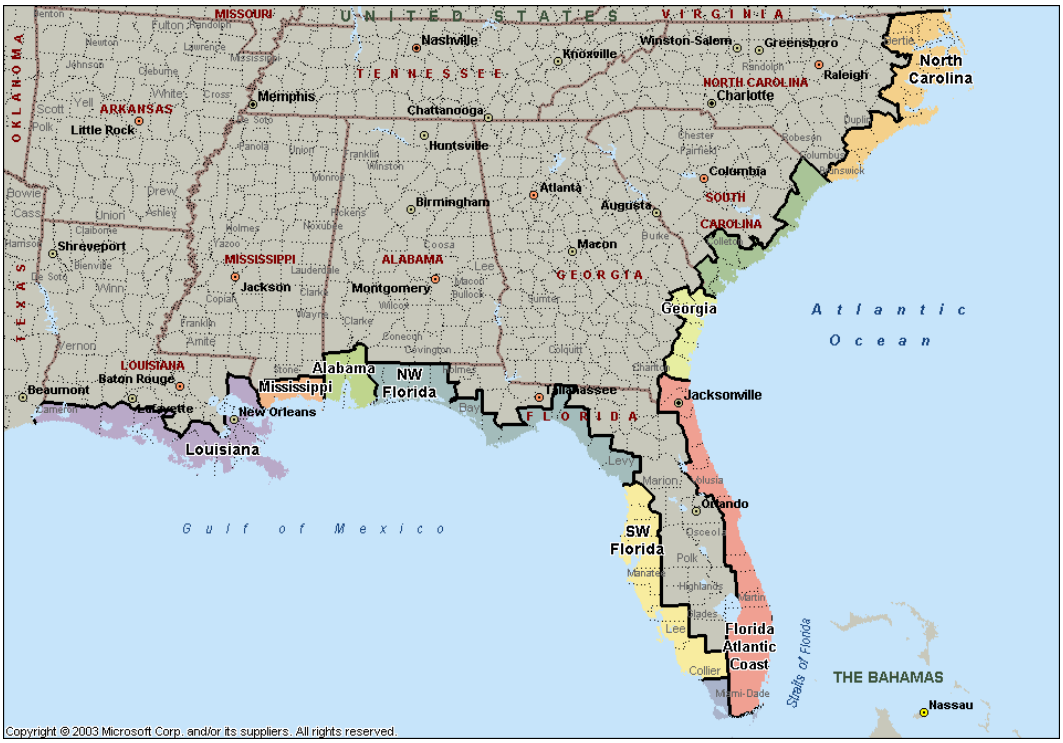

Figure 2-3. Ten coastal regions in the Southeastern U.S.

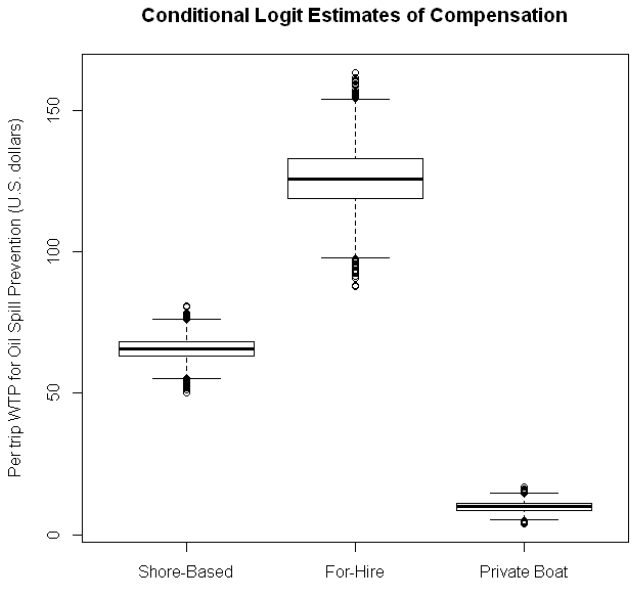

Figure 2-4. Conditional logit estimates of per-trip willingness-to-pay for prevention of the DWH spill

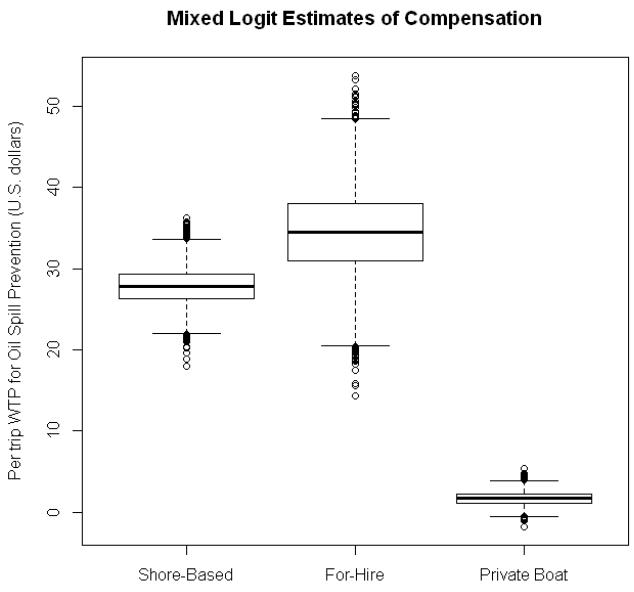

Figure 2-5. Mixed logit estimates of per-trip willingness-to-pay for prevention of the DWH spill

CHAPTER 3
USING PORTFOLIOS TO MANAGE NATURAL RESOURCES

Introduction

Use of natural resources often requires the balancing of alternatives and groups of alternatives and their associated payoffs. Private users face choices with different costs and benefits, as well as differing levels of risk depending on each alternative's propensity to natural and market variability. For instance, farmers must choose among crops to be planted and fishers must choose which species to target while considering variation in weather, prices, input costs and other factors. But in a society where public trustees manage use of natural resources, it is these trustees who have the responsibility for such decisions. Therefore, natural resource trustees must make the same choices that individual farmers, fishers, and foresters make on a daily basis, except at a much larger scale that may sometimes include entire landscapes or seascapes. Portfolio selection is a tool that can help natural resource managers by systematically weighing returns and risks of different alternatives.

The portfolio approach has its roots in the economics of finance. Financial investors must choose from among a pool of assets with varying rates of return. Harry Markowitz (1952) recognized that investors could ameliorate their investment risk by holding a variety of assets whose returns fluctuate in opposite directions. In addition, he proposed the portfolio selection model to systematically choose the combinations of assets that would yield the maximum returns at the lowest possible risk. In recent years, the portfolio selection method has been proposed and illustrated as a tool for managing natural resources so as to yield the highest possible returns at minimum risk.

The concepts and language from portfolio selection have been permeating the study of natural resources for some time. In the context of fisheries management, for instance, Lauck et al. (1998) liken the use of marine reserves to the practice of portfolio diversification as a measure to reduce risk. Similarly, Hanna (1998) argues that the creation of property rights institutions in fisheries that are more amenable to management using ecosystem or species portfolios is necessary to deal with the multiple objectives inherent in fisheries management. Edwards et al. (2004) propose the use of portfolio selection to manage capture fisheries with multiple objectives at the ecosystem level and discuss the institutional changes required to make portfolio management of fisheries feasible. Their proposal rests on the similarities between individual species in an ecosystem and financial assets.

In the context of biodiversity conservation, Figge (2004) draws an analogy between market assets and conservation units—genes, species or ecosystems—and argues that the diversification inherent in portfolio management can be an effective tool for conservation. Ecologists have also recognized a portfolio effect at work in natural systems (Tilman et al. 2006; Schindler et al. 2010), by which ecological communities with high diversity tend to produce more stable streams of ecosystem services. Similar to investors, ecosystems appear to benefit from holding a diverse set of species, as the effects of natural variability are partially dampened by diversification.

Empirical applications of the portfolio approach for natural resource management in the literature have mostly dealt with issues in fisheries, although some innovative applications in the fields of spatial planning, range management and climate change adaptation have also been proposed. The fisheries-related applications include

decision-support tools for individual fishers, seafood processors and brokers, aquaculture firms, and fisheries managers dealing with single and multiple-species problems. Baldursson and Magnusson (1997) were the first to implement the approach and the problem they studied was that of fisheries managers regulating the catch of Icelandic cod. Their decision-support tool was designed to aid in the optimal targeting of different age-classes of cod and their model is explicitly tied to an age-structured population model, where fish of different ages and sizes have different harvest costs and prices. Larkin et al. (2003) take a similar approach and use portfolio selection to examine the problem of diversification of whiting and pollock products in the Pacific U.S. from the perspective of seafood brokers, seafood processors, and fisheries managers, with a fisheries manager portfolio that is tied to a population model for Pacific whiting. Similarly, Perruso et al. (2005) examine the optimal targeting portfolios of U.S. based fishers operating in the pelagic long line fleet in the South Atlantic, Caribbean, and Gulf of Mexico, and use their model to study the impact of area closures on fishers' optimal targeting strategies. The problem of multi-species or ecosystem-based fisheries management was studied by Sanchirico et al. (2008), who developed optimal portfolios of catch for several commercially caught seafood species in the Chesapeake Bay using sustainability constraints. In the same vein, Radulescu et al. (2010) use portfolio selection to develop optimal catch strategies for an aquaculture facility in Romania cultivating several species of fish. Two commonalities in these studies are the definition of assets as commercially harvested marine organisms and the measure of returns in monetary units, usually profits or revenues.

Outside of fisheries, the first empirical application of portfolio theory to natural resources was Koellner and Schmitz's (2006) study on grassland biodiversity and risk-adjusted returns from experimental plots reported in the ecological literature. While their approach did not go as far as selecting optimal portfolios, an innovative aspect of their study is the measurement of returns in non-monetary units, namely biomass yields. In another inventive study, Crowe and Parker (2008) find optimal seed portfolios for regeneration of white spruce forests in Canada under a variety of climate change scenarios. In the realm of spatial planning, Hills et al. (2009) measure the risks and returns of biomes in different seascapes using qualitative indices to plot the corresponding portfolio frontiers and use their approach to find inter-related threats to biomes and measures of biome resiliency within the seascape, although portfolio selection is not used. Most recently, Halpern et al. (2011) develop optimal portfolios of spatially defined commercial and recreational activities in the Channel Islands, California, and use the spatial variability of the portfolio as a measure of social equity in the distribution of returns. The main innovations of the non-fisheries empirical portfolios are the inclusion on non-monetary measures of return as well as spatial and scenario-based assets.

To help guide the development and implementation of portfolios for natural resource management we briefly review the portfolio selection method and develop a series of essential questions for using this approach. Available data and intent of the decision-maker in large part dictate how these essential questions are to be answered. This in turn determines the type of portfolio model that results and the kind of management questions that can be analyzed. We also discuss the time series

properties of returns and sustainability constraints, two aspects of natural resource portfolios that are of special importance in fisheries related applications. Finally, two illustrations of the approach dealing with the choice of Total Allowable Catches (TACs) of different species in marine ecosystems are provided. Specifically, we develop portfolios of catch for the Colombian Pacific Coast and the Gulf Coast of Florida using different measures of return. We use our results to assess the efficiency of the observed portfolio of ecosystem-wide landings in both locations and discuss the advantages and shortcomings of the portfolio selection approach to natural resource management.

Portfolios for Natural Resource Management

Portfolio selection can be applied in situations where there are several options available, each with their own observable stream of potential payoffs. For our purposes, we refer to each of these options as an asset, and the payoff from each asset is referred to as the asset's return. In such situations, the decision-maker must choose which assets to hold or invest in. The deciding agent, whom we refer to as the portfolio manager, is presumed to be seeking high returns at low levels of risk. Portfolio managers trading in financial markets can choose from among a myriad of assets such as bonds, stocks, derivatives, futures, options and swaps (Cvitanic and Zapatero 2004). For each of these assets, the investor has expectations regarding returns and the variation in those returns. Observations of past returns, coupled with other information at the investor's disposal, are often useful in the formation of these expectations.

The starting point for portfolio selection is then a vector of expected returns from the n available assets at time t, denoted $\mu(t)$, and a matrix of covariance in returns at time t, denoted $\Sigma(t)$. In practice, portfolio developers will rely on time series data of returns in past time periods to obtain the vector of expected returns and the covariance

matrix. If the asset's series is perceived to be stationary, a measure of central tendency can be used to obtain the expected returns. If the series is non-stationary or if recent time periods are expected to have a stronger influence on the value and covariance of expected returns, portfolio developers can use methods such as the value-at-risk, vector autoregression, or conditional heteroskedasticity (Sanchirico et al. 2008) to improve the performance of their selection models.

The portfolio manager then chooses a vector of weights for all assets, denoted *c*(*t*), which dictates how much of the asset is purchased or held. In financial portfolios, the weights dictate what portion of the total investment is allocated to purchasing each asset. The expected returns of the portfolio are given by

$$E\left(R_p\right) = c(t)'\mu(t), \tag{3-1}$$

which is essentially a weighted average of the returns of all assets included. Similarly, the variance of the portfolio, which is seen as a measure of the inherent risk, is given by

$$V_p = c(t)'\Sigma(t)c(t). \tag{3-2}$$

The efficient, or minimum risk set of portfolios can be found by choosing the c(t) vectors that solve the programming problem

$$\begin{aligned} &\text{Minimize} && c(t)'\Sigma(t)c(t) \\ &\text{Subject to} && c(t)'\mu(t) \geq M(t), \end{aligned} \tag{3-3}$$

where *M*(*t*) is a minimum returns target that is iteratively changed so as to recover the set of *c*(*t*) vectors that solve the problem for a wide range of expected returns. Additional constraints can be placed on the programming problem to obtain solutions that reflect the objectives and limitations of the portfolio manager. For instance, financial portfolio managers may include constraints on the amount of funds to be invested, as

well as non-negativity constraints on the weights to ensure that no short sales are allowed.

There are some important elements in which the application of portfolio selection to natural resources diverges significantly from its use in finance. Natural resource managers may be acting on behalf of society rather than as private individuals, and their motives may not always be profit-related. Natural resources are also very different from financial assets, not only in terms of their diversity, but also in terms of how their returns are measured and distributed over time. We can also expect the difference in the manager's objectives as well as physical limitations on managers and resources to dictate programming constraints of a very different nature. We can therefore identify four essential questions that deal with 1) the nature and objectives of the portfolio manager, 2) the definition of an asset to be included in the portfolio, 3) the way in which returns are measured and expected to be distributed, and 4) the definition of constraints in the programming problem whose solution yields the optimal portfolios. These four questions, whose answers turn out to be inter-related, are discussed in turn.

Four Questions for Portfolio Development

Who is the Portfolio Manager?

Financial portfolio managers are generally investors acting on their own behalf or that of some other individual with the objective of gaining as much monetary returns as possible under a tolerable amount of risk. Firms or individual natural resource users such as farmers, fishing vessels, seafood brokers and processors, for instance, will act under similar motivations. In natural resource related decision-making, however, portfolio managers can also be acting on behalf of a community or society as a whole. Fisheries and range managers, land and seascape planners, and agencies in charge of

planning and preparation for long-term environmental changes, are some examples of potential natural resource portfolio managers.

The main difference between these social planners and the individuals and firms who also manage natural resources lies in the objectives they pursue and the geographic and temporal scales at which their decisions must be taken and hence the range of effects they may have. Notably, for the social planner or resource trustee the maximization of revenues is only one among a competing set of interests. Other relevant objectives may include biomass yields, social equity, employment levels, adaptation capacity, and ecosystem resilience, among many others.

Likewise, the temporal and spatial scale in which natural resource trustees and social planners operate is much wider than that of the individual resource user and the financial portfolio manager. Decisions regarding natural resource use and management can have impacts that span throughout entire ecosystems and regions. In some cases, such as large-scale deforestation and use of fossil fuels, the impacts of such decisions can be felt throughout the globe. The consequences of these decisions can also affect multiple generations, and in those cases these effects must be taken into account by the decision-maker. Natural resource managers, therefore, face optimization of objective functions that can be much more complex than that of the financial portfolio manager not only in terms of objectives but also in considerations of space and time.

What Constitutes an Asset?

Once the temporal and spatial scale of the problem under consideration is defined and the management objectives are set out, the next step is to define what the assets of concern will be. Financial assets are generally not physical entities but rather contractual agreements that bind parties to some payoff—be it positive or negative—

under uncertain states of the world. These contractual agreements are tied to seemingly unpredictable events such as commodity prices, corporate profitability, performance of other assets, or in some cases the payoff is guaranteed simply by the future solvency of one of the parties involved. Return-yielding natural resources are similar perhaps with the exception that natural variability, rather than human events, is the major source of uncertainty in payoffs.

Natural resources can be considered assets in the broad sense if their management can in any way yield returns to individuals or society. This includes consumptive uses such as planting crops and harvesting wild animals as well as non-consumptive uses such as recreation and services related to ecosystem functions. These assets and their respective returns can be defined in a temporal sense if returns are realized at different times throughout the year. For example, if the same asset can yield different returns at different times of the year due to seasonal fluctuations in prices, then two or more assets can be defined for low and high value periods. Similarly, if what could be considered the same asset yields different returns according to spatial location, then several assets can be defined, one for each relevant location. Also, the asset's returns may not be relevant under the present state of the world but rather under a variety of future scenarios. For instance, an asset can be seen as yielding a return not today but at a future time for which a set of likely scenarios has been developed. This is the case of portfolios that seek optimal adaptation alternatives for environmental change scenarios, where returns are not based on past performance but rather on the asset's expected performance under a variety of scenarios where inferences on the relationships between asset performance and environmental conditions can be made.

How can we Measure Returns?

Once the management objectives and the assets under consideration are defined, measures of return for each asset must be identified. Financial assets such as stocks generally yield returns in the form of dividends and valorization. To measure the return of such assets, a financial portfolio manager needs only to consider the costs of acquiring the asset and the potential benefits or earnings that the asset might bring. Financial assets therefore yield returns that are predominantly monetary in nature, which is fitting given that financial portfolio managers are mostly concerned with maximizing earnings. In the case of corporate stocks future performance of the asset is generally unknown. However, portfolio managers can look at previous performance to aid them in forming expectations of future dividends and valorization of the asset. For instance, financial investors can develop an annual rate of return measure using the costs of acquiring the stock at the beginning of the year, the value of the stock at the end of the year, and any dividends paid throughout the year, and use the distribution of such a rate of return through time to form an expectation of next year's rate of return. If the average rate of return is considered stable or stationary, the financial investor needs only to consider the mean return of assets and their covariance to develop optimal portfolios of stocks.

In cases where returns from natural resource management are monetary or can be readily monetized, such as yields from marketable crops, harvests of wild finfish and shellfish or timber, the natural resource portfolio manager can rely on these monetized yields to created measures of returns from each asset. If management costs for each asset are also available, then measures of net benefits similar to those used for financial stocks can be developed. In some cases, however, benefits from natural

resource management cannot be easily quantified in terms of money. This typically occurs when markets for the good or service in question do not exist, which may happen for a variety of reasons generally stemming from the public good characteristics of some natural resources. In these cases, it may be better for the portfolio manager to measure returns from each asset directly in terms of the service provided rather than attempt to monetize the service flows in question. For instance, portfolio managers that seek to maximize yields can measure returns in terms of biomass, while those whose objective is to maximize recreational use can measure returns in terms of visitor-days.

If observable measures of returns are not available, the portfolio manager can use a series of subjective rules or judgments to place a non-monetary value on the returns of each asset. For instance, Hills et al. (2009) use a participatory approach to develop categorical measures of returns and risks of different biomes in a seascape. The key aspect of any decision rule to assign values to returns of different assets is that such rules follow the strong monotonicity assumption of consumer preference theory by giving larger values to assets that are perceived to be more valuable and larger risk scores to assets that are deemed more risky. While portfolio selection may not be as useful in these cases as in those where observable measures of return are used, the development of these measures and their comparison across different assets may in itself be of use to managers and decision-makers.

In cases where observable measures of return exist, the portfolio manager must pay particular attention to the distribution of returns over time. Specifically, the existence of increasing or decreasing trends or seasonality in returns must be examined so as to form more informed expectations of future returns. Natural resource management may

be plagued with situations where ecological or human-induced change may be affecting the distribution of returns through time. For example, many fish stocks have been experiencing decreasing trends in landings due to resource over-exploitation or dynamic changes in the structure of ecosystems (Mullon et al. 2005; Pinsky, et al. 2011). In these cases, using simple averages to create expectations of landings in future years may be misleading. In cases such as this where the distribution of returns is non-stationary, use of statistical methods that allow for correction of measures of expected value and covariance is warranted.

What Constraints do Decision-Makers Face?

Once management objectives have been set and assets and their respective returns have been defined, the portfolio manager must consider any constraints that should be used in the optimization. Constraints are placed to ensure that solutions remain in the feasible realm and they may include limitations on the amount of resources under the manager's disposal, such as labor, time and capital inputs, as well as factors that may limit the sustainability of the system or those that are related to the policy environment under which the portfolio manager operates. Financial portfolios are generally constrained by the amount of capital to be invested, and in some instances non-negativity constraints are used to ensure that no short sales are included in the optimal solutions.

In situations where the amount of existing resources or the growth and recruitment of living assets limit the possible levels of harvest, it is appropriate to place constraints to ensure that solutions remain within these limits. Harvest or management costs can also be explicitly included as a portfolio constraint rather than implicitly in the development of measures of return. Alternative policy scenarios, such as area closures

or different levels of maximum sustainable yields, can also be set as constraints. Finally, the optimization algorithm finds the efficient frontier by including a minimum return (maximum allowable risk) constraint when the procedure is set to find the minimum risk (maximum returns) portfolio.

Answers to these four questions are largely responsible for the objectives and scope of the portfolio selection model that can be constructed. Similarly, the answer to one question plays a large role in how the following questions can be answered. For instance, the choice of portfolio manager in great part determines the scope of the analysis and hence the scale at which assets must be defined. Similarly, both the choice of portfolio manager and definition of assets dictate the way in which returns are to be measured. On the same vein, all these factors affect any special constraints that should be included in the selection model. To illustrate the possible answers to the four essential questions, Table 3-1 shows the different applications of portfolio selection to natural resources and the way these questions were answered, and Figure 3-1 shows a downward directed flowchart of possible answers to these questions.

Time Series Properties of Returns in Natural Resource Portfolios

One aspect of natural resource portfolio development that has received very little attention is the time series properties of returns. As seen in Table 3-1, of all the NRM portfolio studies, only Sanchirico et al. (2008) address this issue. In essence, the problem arises when returns in the past differ significantly from current returns and returns that can be expected in the future. Alternatively, the relationship between assets—which is captured using the covariance—may have changed through time. In natural resource management the main reason for such structural changes in returns or relationships between assets is environmental or ecological change. In fisheries, for

instance, the decline in worldwide capture fisheries is a factor that must be accounted for by portfolio managers.

In this section we focus on returns that change through time. To illustrate this problem, we show the historical trends in revenues from Gag grouper (*Mycteroperca microlepis*) in Florida's Gulf Coast from 1986 to 2009 (Figure 3-2). Even though the time series is too short to make a judgment on the long term returns from gag, it is clear that revenues increased after 1995, peaked in 2001, and have experienced a decline since then. The decline of gag is usually attributed to overly high fishing pressure from commercial and recreational fishers coupled with a red tide event in 2005 that resulted in a large-scale fish kill. Currently gag are considered overfished in the Gulf of Mexico and a recovery plan has begun to be implemented (Salamone 2012). This combination of anthropogenic and natural pressures has ensured that returns or revenues from gag will remain at low levels at least in the short term.

If fisheries managers wanted to include the stock of gag grouper as an asset in a natural resource portfolio, the naïve advisor would probably suggest that the mean of the observed returns be used as the expected returns for the stock of gag. This value is represented by the dotted line in Figure 3-2. The mean is well below the historic peak in returns, a level that is unlikely to be observed in the near future. However, if levels of fishing revenue near the mean were to be observed in the following year it would amount to a five-year high. An informed advisor with information regarding the current status of gag would probably point out the difficulties that the stock is currently undergoing and advocate for a lower expectation of fishing revenue for gag grouper in the following years.

The fisheries manager in data constrained ecosystems, however, may have very little or no information regarding the current state of fish stocks. In such systems, the fisheries manager must make decisions regarding allowable catch and other restrictions without the benefit of ample knowledge on the biology and behavior of the fish in question or the status and health of the overall stock. If the fisheries manager only had data on historic revenues at her disposal, she could use it to create a more informed expectation about the performance of the stock in the near future using an integrated autoregressive moving average or ARIMA model. Such models take into account seasonality, reaction lags and trends in the time series to formulate predictions of returns in the following periods (Cryer and Chan 2008). ARIMA models differ from each other by the number of parameters used, and the choice of parameters itself depends on the characteristics of the time series.

In our analysis, we use the *forecast* package developed by Hyndman and Khandakar (2008) to formulate expectations regarding future fishing revenues, landings and prices. Given that not all fish stocks are expected to have the same reaction lags or be experiencing similar trends, a unique ARIMA model is required for each time series. Annual time series, such as the ones used in this analysis, can be modeled using a non-seasonal ARIMA (p,d,q) process, which can be represented by

$$\phi(B)(1 - B^d)Y_t = c + \theta(B)\varepsilon_t, \tag{3-4}$$

where $\{Y_t\}$ represents the observed time series, $\{\varepsilon_t\}$ is a white noise process with mean zero and variance σ^2, B is the backshift operator, d is the order of differencing, and $\phi(\cdot)$ and $\theta(\cdot)$ are polynomials of order p and q, respectively. The analyst must choose the parameters p, d and q that best explain the variation in the time series. This process

generally requires careful examination of the time series, including differencing the series *d* times to obtain a stationary series, and examining the autocorrelogram and partial autocorrelogram of the stationary series to determine the number of significant lags, which determine the choice of parameters *q* and *p*, respectively (Cryer and Chan 2008).

To find the ARIMA model that best describes each time series we use the *auto.arima* function available in R's forecast package (Hyndman and Khandakar 2008). This package uses a stepwise algorithm to find the best values of the ARIMA parameters. The value of *d* is selected based on successive Kwiatkowski–Phillips–Schmidt–Shin (KPSS) root tests, while *p* and *q* are found by iteratively using Akaike's Information Criteria (AIC) to find the most parsimonious model. The *auto.arima* forecast for gag revenues, shown as the dotted line in Figure 3-2, is lower than the average level of revenues and is likely to be a better indicator of expected revenues.

Sustainability Constraints Using Historical Catch

Natural resource portfolios, like their financial counterparts, are not inherently bounded by the laws of thermodynamics and may yield solutions that are not feasible in the real world. For instance, the 'optimal' solution may involve harvest rates that exceed the current stock of the natural resource. To prevent such solutions, the portfolio selection problem can include a set of constraints that ensure that thresholds of feasibility are not exceeded. In fisheries applications, for example, there is only a given amount of fish that can be harvested even if fishers possess perfect technology that allows them to harvest up to the last fish. However, harvesting up to the last unit of fish, or even up to an extinction threshold, will ensure that the stock of fish will cease to exist and all future returns disappear. Fisheries managers and fish harvesters therefore

benefit from the existence of some level of maximum harvests that limits the amount of fish taken in any given period and hence ensure the survival of the stock for future time periods.

Modern fisheries science has developed a variety of stock assessment methods that allow estimation of the size of the fish stock as well as maximum sustainable yield levels of harvest. In many cases, fisheries scientists can determine minimum size limits for harvest that ensure the health of the population and support higher yields. Size limits are especially important in the management of fish and shellfish species with complex life histories, as limiting the size of individuals harvested may ensure that there are enough breeding individuals in the population to maintain healthy stock levels.

The fisheries portfolio manager can take into account the knowledge of fisheries scientists by setting constraints to the portfolio selection problem. For instance, in a portfolio problem that seeks to find the optimal combinations of harvest from different fish stocks, maximum sustainable yield targets developed by fisheries assessment scientists can be incorporated to the selection problem by constraining harvest rates in the solution set to be below these targets. If this kind of information on the size of the stock and sustainable harvest targets has not been developed, the fisheries manager might instead take a precautionary approach and limit harvests to be below some previously observed level that is deemed appropriate. In the analyses that follow we use sustainability constraints similar to those developed by Sanchirico et al. (2008), which ensure that prescribed landings of a given stock do not exceed their historical maximum. The fisheries manager can easily set the threshold level relative to this

historical maximum by changing the value of one of the parameters of the optimization problem (γ).

Namely, in each time series we observe a historical maximum level of harvest, measured in tons, which we denote h_{max}. A vector of maximum harvest levels for all assets, H_{max}, is then created. If the selection model is optimizing biomass yields directly, as in the Colombian Pacific Coast example that follows, then the constraint we impose is simply

$$c(t)'\mu(t) \leq \gamma H_{max}, \tag{3-5}$$

where expected returns $\mu(t)$ are given in tons and γ dictates the fraction of the historical maximum landings that will be allowed for harvest ($\gamma = 1$ in the examples that follow). Alternatively, if the selection model is set to optimize monetary returns as in the Florida Gulf Coast example, the creation of the H_{max} vector is followed by the creation of a vector of expected prices, P_e, using ARIMA forecasts of observed prices. We can then create a vector of maximum revenues, $\pi_{max} = H_{max}P_e$, which is used in the constraint

$$c(t)'\mu(t) \leq \gamma \pi_{max}, \tag{3-6}$$

where expected returns, $\mu(t)$, are given in dollars. It is important to note, however, that rather than using observed historical maximum levels of harvest, the portfolio manager could easily replace H_{max} with a vector of threshold levels of landings mandated by policy or recommended by fisheries scientists. Alternatively, the fisheries managers could set $\gamma < 1$, to ensure that only levels below the historical maximum landings are allowed.

Portfolios of Total Allowable Catches Using Biomass

The Colombian Pacific Coast

We first turn our attention to the Colombian Pacific Coast (CPC), a tropical region where multiple species are harvested predominantly by industrial and artisanal fishers (Figure 3-3). The Colombian Pacific coastline spans nearly 1,300 km from the border with Panama in the north to the border with Ecuador in the south and includes two remote islands (Gorgona and Malpelo) and four states or departments: Choco, Valle del Cauca, Cauca, and Nariño (Corporacion Colombia Internacional 2006). There is one major port city, Buenaventura, but otherwise the region is remote and road access is virtually non-existent. This is also one of the poorest regions in the country and government services are quite limited. The remoteness of the region and the lack of government services translate into major challenges for the fishing sector that include high prices of fuel and fishing gear, lack of access to credit, and lack of access to markets for the sale of seafood products (Conde Castro 1991).

As can be expected for a remote area with little government services, fisheries data is quite limited. Involvement of the national government is limited to providing fuel subsidies to the industrial fishing fleet and collecting data on landings. There is also a random sampling of landings to measure and identify the different marine species that are caught throughout the area, but some fishing towns are never sampled. The purpose of these sampling efforts is to determine whether juvenile fish are being harvested and if so recommendations are made regarding regulations that could prevent such taking of juvenile fish (Corporacion Colombia Internacional 2006). The CPC data used in this study is a time series of landings by 28 species groups spanning from 1995 to 2008 obtained from the Colombian Institute of Agriculture and Fisheries

(Instituto Colombiano Agropecuario - ICA), housed within the Colombian Ministry of Agriculture and Rural Development. Data on prices or revenues could not be found in public records, and it is likely that such data is not collected.

Given that the data available for the fisheries in this region include only landings in metric tons by species group, we use that as our measure of returns. The problem is solved from the viewpoint of the regional fisheries manager and the objective is to obtain the largest amount of fish biomass, regardless of species. Each species group is defined as an individual asset. In this case, this presents some problems, as some species groups include a variety of marine species (Table 3-2). For instance, tunas (*atunes*), snappers (*pargos*) and groupers (*meros*) are all grouped as a single entity, preventing management at a finer scale. A sustainability or maximum catch constraint is set to ensure that our solutions do not dictate landings greater than the historic observed maximum.

CPC Results

The optimization in equation (3-3) yields the efficient frontier that represents the set of portfolios of catch that result in the highest level of biomass harvested with the lowest possible expected variability. In other words, the efficient frontier shows the minimum level of risk or variability in harvests attainable at different levels of total harvest. All points to the right of the frontier are in the feasible region but are inefficient, as returns can be increased without increasing risks. All points to the left of the frontier are unattainable. The frontier for the CPC is shown in Figure 3-4, where circles represent individual species groups and the cross represents the current portfolio of catch.

There are a few features of this plot that deserve special attention. First, note that at the low-risk, low returns end of the plot (left hand side) we see that fisheries managers can eliminate risk by closing the fishery, a solution in which risk and return are virtually zero. Increasing harvests from that point requires managers to cope with higher levels of risk. Second, the expected returns and risk from individual assets are included in the plot as circles, and all lie to the right of the frontier in the low-return areas of the feasible region. Third, the current portfolio of catches, which is included in the plot as a small cross, also lies to the right of the frontier. This implies that the current combination of harvest rates for all species groups in the CPC is inefficient, and that reorganization could lead to higher returns (more landings) with no increases in allowable risk being necessary.

We calculate the extent of harvest inefficiency by comparing the actual portfolio to efficient portfolios that lie directly to the left (E-1) or above (E-2) the actual portfolio (Table 3-3). Results indicate that the ecosystem wide fishery could benefit by reducing the fishery's risk or variability of landings by 46% without significant effect on expected landings if some reallocation of species-targeted effort occurred. Similarly, expected fishery returns—or total biomass extracted—could be increased by 26% without significant increase in the level of risk allowed.

Along with the efficient frontier, which simply summarizes the returns and variance of the minimum variance set of portfolio returns, we also obtain the matrix of efficient harvest policies corresponding to each point in the frontier. That is, for each point in the efficient frontier, there is a unique set of prescribed policies that dictate the harvest level that must be sought from each species group. Since in this case returns

are given directly by biomass or landings, this matrix identifies the efficient set of prescribed catch policies. For visualization we use a transition plot that shows the prescribed levels of catch for each species group at different levels of allowable risk (Figure 3-5).

Portfolios of Total Allowable Catches Using Revenues

The Florida Gulf Coast

We now consider the case of the Florida Gulf Coast (FGC), which spans north and west to the border with Alabama near Pensacola, and south and east to the southwest tip of Everglades National Park near Lake Ingraham. There are several major fishing ports in this region including Apalachicola, Port St. Joe, Steinhatchee, and Fort Myers, among many others. We exclude the Florida Keys from this analysis. Besides some remote areas of Everglades National Park, the entire coastline is well connected to the rest of the country by a modern system of roads and highways and several major airports are located very close to the coastline. Major cities in this region include Pensacola, Panama City, Tampa, Saint Petersburg, Sarasota, Fort Myers and Naples. Fisheries in state waters are managed by the Florida Fish and Wildlife Conservation Commission, while those in federal waters are managed by the Gulf of Mexico Fishery Management Council. In addition, several offices of the National Marine Fisheries Service (NMFS) are located in Florida, including the Southeast Regional Office in Saint Petersburg and the Southeast Fisheries Center in Miami, both of which are heavily engaged in research and management of these fisheries and regularly conduct stock assessments.

In many ways, the FGC with its modern infrastructure, scientific support for management, and state-of-the-art fisheries data collection programs, is the antithesis to

the remote Colombian Pacific Coast. Information on the health of recreationally and commercially important fish stocks is routinely collected and fishing regulations and programs such as catch and size limits, transferrable quotas, and fishing seasons are developed and implemented in a transparent fashion through the Gulf of Mexico Fishery Management Council. In terms of portfolio development, information on returns in terms of biomass and fishing revenues is readily available on NMFS' website. In particular, time series beginning in 1986 are available for 69 species groups landed by commercial vessels in the FGC (Table 3-4). Previous to 1986 several species were identified only to the family taxonomic level, and data on returns for many important species cannot be recovered. We therefore use time series data on fishing revenues and landings between 1986 and 2009 and exclude all previous years. We extract information on average annual prices by dividing fishing revenues by the corresponding level of landings, and obtain vectors of average annual prices in dollars per metric ton. Both prices and revenues in the time series are normalized to 2009 dollars using the Producer Price Index.

Once again we set up the portfolio selection problem from the fisheries manager's perspective and use individual species or species groups—as available in the dataset—as our assets. In this case, however, we measure returns in terms of fishing revenues rather than landings, as we had done for the CPC. Thus, the objective is to maximize ecosystem wide fishing revenues while minimizing ecosystem wide risk by choosing the optimal set of prescribed catch levels for all species groups. Finally, we set a sustainability constraint to prevent landings of all species to exceed their observed historic maximum.

FGC Results

Solving the selection problem yields the efficient frontier in Figure 3-6, where circles represent the expected fishing revenues and risk from individual species and the cross represents the current portfolio of landings. In this case, the efficient frontier represents the set of portfolios of catch that result in the highest level of fishing revenues with the lowest variability in revenues. Conversely, the efficient frontier shows the minimum level of risk or variability in fishing revenues attainable at different levels of total harvest.

Similar to the CPC, the current portfolio of catches in the FGC is inefficient as it lies to the right of the efficiency frontier. Through a reorganization of targeting effort (Table 3-5), fisheries managers could achieve a 16% increase in fishing revenues without the need to increase the allowable level of risk. Fisheries managers could also attain the same level of revenues as under the current portfolio of catches with a 44% reduction in the level of allowable risk through reallocation of targeting effort.

Along with the efficient frontier, solving the portfolio selection problem yields the matrix of expected revenues from the minimum risk set of catch policies. This information can be visualized in the transition plot shown in Figure 3-7, which shows the efficient level of expected fishing revenues from each species group in the selection model at each level of allowable risk. The minimum variance set of expected revenues can be used to obtain the set of prescribed catch policies, which determine the harvest level that should be sought from each species at different levels of allowable risk. To do so, we divide the prescribed fishing revenues in the minimum variance set by the expected price of each species group. As previously mentioned, expected prices are

estimated using an ARIMA model. This information, visualized in the transition plot in Figure 3-8, shows the prescribed level of landings for different levels of allowable risk.

Discussion

Portfolio selection, in its most basic form, is a flexible tool that can be used for natural resource decision-making. The approach can be used in a variety of natural resource decision-making contexts, and the essential questions presented here should serve as a guide to future natural resource portfolio developers. While the selection approach rests heavily on historic measures of returns from different natural resources, information related to carrying capacity, sustainability, and biophysical limits obtained by scientists studying the resources can be systematically integrated into selection models through the use of optimization constraints. Similarly, policy or regulatory constraints can also be taken into account.

Some of the approaches to Ecosystem-Based Management currently under development rest on the creation of highly complex models of ecosystem dynamics that include nutrient cycles, ocean currents and food web interactions in a temporally and spatially explicit manner (Plagyani 2007). Compared to many of those models, portfolio selection may seem an overly simple approach and hence one with limited practical value. However, some of the results from portfolio selection are quite unique and obtaining similar information from more complex models of ecosystem dynamics may be quite difficult.

For instance, the portfolio selection approach as illustrated here allows the natural resource manager to quantify—in terms of the ecosystem returns being used—the costs of inefficient decision-making. Specifically, the distance between the current portfolio of decisions, which is shown as the cross in Figures 3-4 and 3-6 for the CPC

and FGC respectively, and the efficient frontier can be easily calculated. In the case of the CPC and the FGC, the inefficiencies found range between 16% and 26% in terms of revenue and around 45% in terms of risk. If there were significant costs to reorganization of catch, for instance, such measures could be used on the benefits side of a benefit-cost analysis.

Selection models like the ones developed here could be used to aid in fisheries policy making as a tool complementary to stock assessments and reference point rules. For instance, managers could substitute the sustainability constraints we use with science-based rules such as maximum allowable harvests developed with stock assessment methods or reference points. These policies would replace the sustainability constraint thereby making all prescribed policies more precautionary than mandated by maximum allowable harvest policies. The implication is that resource users may actually gain from obtaining harvests that are lower than those mandated by science-based policies, at least when judged from a risk-return framework.

There is also important information conveyed in the matrix of prescribed landings corresponding to the minimum risk set of portfolios, which we visualize as transition plots. A case in point is the prescription for tuna landings in the Colombian Pacific Coast. For some time it has been argued that this region is in a uniquely favorable position to become a significant source of different species of tuna. While the tuna fishery has been quite important in the region for some time, the increased incidence of El Niño Southern Oscillation (ENSO) events, which heavily affect salinity and water temperatures in this region, have changed the migratory patterns of several species of tunas in a way that makes it more likely for them to be present in this region (Conde

Castro 1991). While these oceanographic dynamics are not explicitly included in the portfolio selection model, the approach does prescribe an increase in tuna landings, and tuna is a major player in all the minimum risk portfolios.

Another interesting facet of the selection approach to natural resources is the relationship between diversity and returns. Figge (2004), Koellner and Schmitz (2006), and Schindler et al. (2010) among others have argued that there is a relationship between diverse portfolios and stability of returns. We also see this effect in our portfolios for fisheries management, as the high return portfolios are highly diversified. In fact, it seems that high returns from fisheries are only possible through a diverse composition of landings. However, the low-return, low-risk portfolios are usually dominated by few species, and other species only enter the minimum risk set of portfolios as sustainability constraints for the dominant species become binding. This is indicated in the transition plots by areas that stop increasing in size and become flat.

This feature of our models is quite different from what is commonly seen in financial portfolios. The low-risk, low-return efficient financial portfolios, for instance, are generally characterized by a varied combination of assets. In particular, a large number of assets with negative covariances are present in this section of the frontier, as the negative covariances attenuate risk and allow for very low-risk portfolios. The high-return, high risk portfolios, on the other hand, are dominated by a few high-risk, high-return assets, and portfolios in this section of the frontier are not very diverse at all. The large discrepancy between the diversity of low-return and high-return portfolios in financial and natural resource applications may be due to the normalization of financial returns, which are generally calculated on a per dollar invested basis. Such

normalization is not required in natural resource portfolios, and in fact may be difficult to achieve, as the meaning of “investment” in a natural resource portfolio is quite different from that in a financial portfolio. This is an important issue and merits further research.

There remain some important limitations to the portfolio selection approach to natural resource management. In situations where there are competing alternatives with inherently different measures of return, use of the portfolio approach can be complicated by an equivalency problem. For instance, inclusion of the recreational fishing sector in the Florida Gulf Coast into a portfolio selection model like the one presented here is complicated by the non-market nature of recreational benefits. While a selection model could easily be constructed to analyze the risk-return tradeoffs between different recreational activities, one to analyze the tradeoffs between commercial and recreational activities would be much more difficult to build. In essence, it is difficult to compare alternatives whose returns are measured in different units. Construction of equivalency measures between activities that are inherently different is likely to open up new areas of application for the portfolio approach to natural resource management.

Table 3-1. Empirical portfolios in the natural resource management literature

Study	Manager	Assets	Space/Time considerations	Measure of returns	Returns stationary	Constraints
Baldursson and Magnusson (1997)	Fisheries manager	Cod age cohorts	N/A	Profits	Yes	Fish growth and recruitment; fishing costs
Larkin et al. (2003)	Seafood broker Fish Processor Fisheries Manager	Products made from Pacific Whiting and Pollock	Monthly variability	Profits	Yes	Fish population dynamics
Perruso et al. (2005)	Representative vessel	Commercial fish species	N/A	Profits	Yes	Trip limits per species
Koellner and Schmitz (2006)	Range Manager	Plant species in experimental grasslands	N/A	Biomass; Yield in monetary units	N/A	None
Sanchirico et al. (2008)	Fisheries Manager	Commercial fish species	N/A	Revenues	No; Value at Risk Method for covariances	Sustainable fishing levels
Crowe and Parker (2008)	Conservation Planner	Tree seed sources	Adaptation Regions Climate Change Scenarios	Adaptation capacity	Yes	None
Hills et al. (2009)	Coastal Planner	Biomes in the seascape	Spatially defined biomes	Subjective value and risk scale	N/A	None
Radulescu et al. (2010)	Fish Farm Owner	Species in a fish farm	N/A	Profits	Yes	Max. Sust. Yield
Halpern et al. (2011)	Coastal Planner	Commercial fisheries Recreational activities	Spatial planning units	Revenues Trips	Yes	Total effort Spatial closures

Table 3-2. Colombian Pacific Coast species groups, maximum landings in sustainability constraints, and year in which maximum landings were observed

Group	Max. Landings (tons)	Year
Atunes	78025	1997
Berrugate	590	2000
Sardina	28747	1997
Bagres	488	2000
Cojinua	568	2000
Lenguados	171	2001
Lisa	43	2004
Meros	295	2000
Mojarras	101	2004
Pargos	802	2000
Pelada	401	1996
Plumuda	2708.45	2001
Robalo	341	1996
Corvina	347	2006
Sierra	912	1998
Tiburón	2625	2002
Otrospeces	4686	1997
Langosta	9	2001
Camarontigre	2829.65	1997
Cangrejos	865.69	2005
Coliflor	688	2003
camaronblanco	2686	1999
Otrocamaron	910	2004
Jaiba	13	2008
Almejas	10	2000
Calamar	295	1996
Caracol	29	1997
Otromolusco	864	1997

Table 3-3. Measure of inefficiency in the Colombian Pacific Coast

	Returns[a]	Risk[b]
Actual	62.92	275.75
E-1	62.21	148.08
E-2	79.42	273.99
Gross Gain	16.50	127.67
Percent Gain	26.2%	46.3%

[a] Returns are measured in thousand tons
[b] Risk is measured in millions of tons

Table 3-4. Florida Gulf Coast species groups, maximum landings in sustainability constraints, and year in which maximum landings were observed

Group	Max. Landings (tons)	Year	Group	Max. Landings (tons)	Year
Ballyhoo	468.7	1995	Octopus	47	1996
Bluefish	321.2	1988	Eastoyster	1669.9	1987
Catfishes	57.1	1987	Permit	79.7	1991
Cobia	81.2	1996	Flpompano	253	1990
Bluecrab	5792.9	1998	Bluerunner	817.9	1988
Softbluecrab	72.5	2000	Scads	1411.2	1993
Stonecrab	3153.1	1998	Scamp	138.2	1993
Atlcroaker	60	1986	Porgies	299.1	1993
Dolphinfish	480.9	1991	Blkseabass	234.7	1994
Blkdrum	262.7	1986	Sandtrout	83.7	1986
Finfishmeal	3350.3	1992	Spottrout	612.2	1988
Finfishfood	399.7	1987	Sharks	2553.4	1990
Flatfish	106.1	1991	Sheepshead	291.2	1994
Gag	1488.1	2001	Shellfish	756.6	1999
Blkgrouper	616.8	1989	Brownshrimp	1070.8	2006
Redgrouper	4001.4	1989	Pinkshrimp	10774.7	1996
Snowygrouper	119.7	2003	Rockshrimp	2079.1	1992
Warsawgrouper	43.4	1986	Whtshrimp	971.3	2005
Yedgegrouper	450.3	2000	Graysnapper	312.6	1987
Yfingrouper	185.5	1986	Lanesnapper	61.4	1991
Grunts	386.6	1994	Muttonsnapper	164.5	1987
Atlherring	3382.6	1989	Redsnapper	469.2	1986
Hogfish	53	1993	Silksnapper	90.4	1992
Crevjack	1748.3	1990	Vermsnapper	1123.8	2009
Kingwhiting	33.1	1990	Ytailsnapper	994.6	1993
Ladyfish	2629.7	1990	Snappers	171.5	1987
Leatherjackets	169.9	1993	Spot	149.8	1990
Spinylobster	3264.1	1996	Squids	66.2	1998
Slipperlobster	24.9	1994	Swordfish	371.1	1996
Kingmackerel	947.8	1993	Goldtilefish	226	1988
Spmackerel	1616.7	1992	Bigeyetuna	18.1	1989
Menhaden	8613	1987	Blkfintuna	29.1	1990
Mojarras	229.3	1993	Yfintuna	1755.1	1986
Strmullet	10668.3	1989	Wahoo	29	1997
Whtmullet	326	1989			

Table 3-5. Measure of inefficiency in the Florida Gulf Coast

	Returns[a]	Risk[b]
Actual	104.56	198.89
E-1	102.69	110.63
E-2	121.34	198.40
Gross Gain	16.78	88.26
Percent Gain	16%	44.3%

[a] Returns are measured in millions US dollars
[b] Risk is measured in trillions US dollars

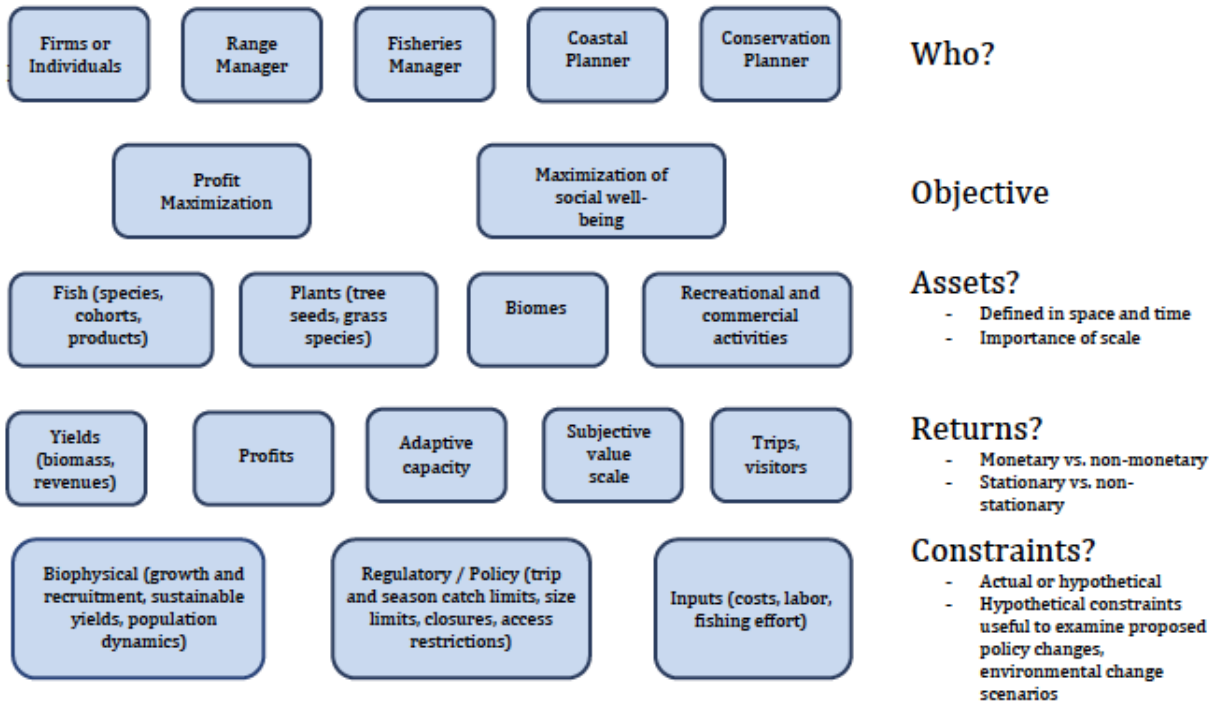

Figure 3-1. Possible answers to the four essential questions for portfolio development

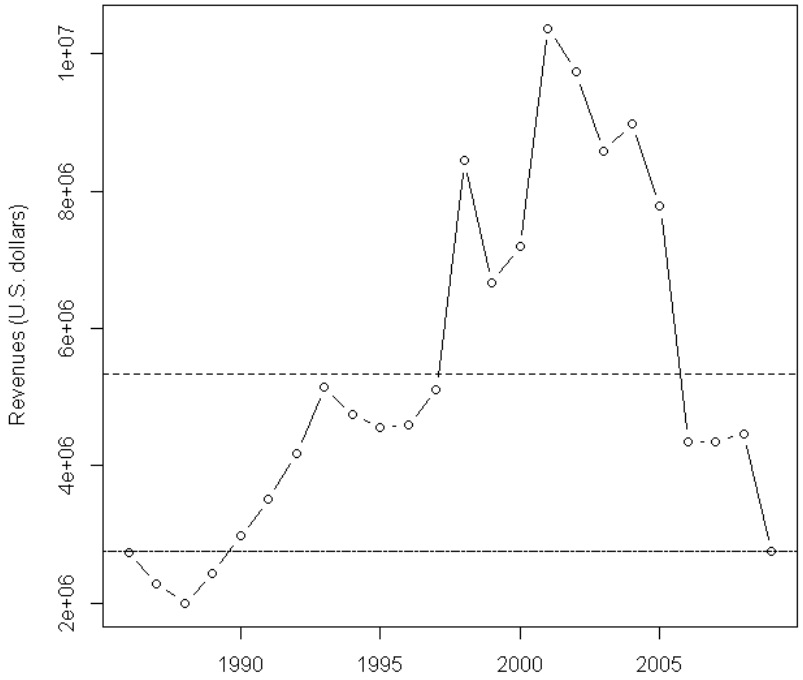

Figure 3-2. Historical returns from Gag grouper (Mycteroperca microlepis) in the Florida Gulf Coast. The dashed line represents the mean returns, while the dotted line represents the ARIMA forecast of returns for the following year.

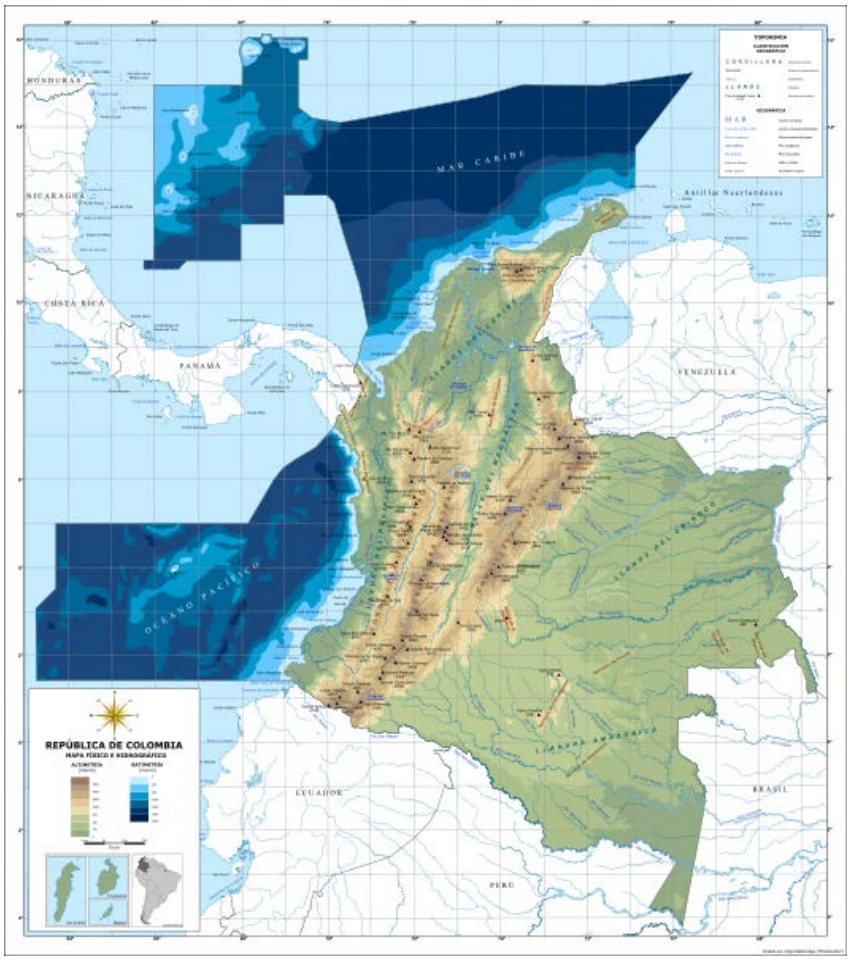

Figure 3-3. Map of Colombia. The Pacific Coast spans south to the border with Ecuador and North to the border with Panama.

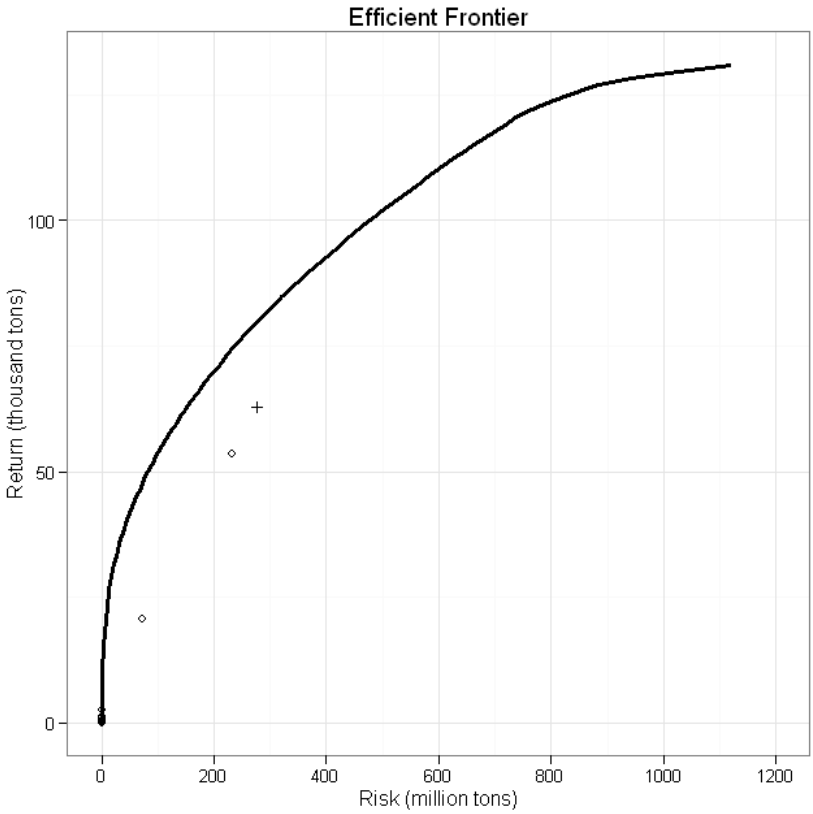

Figure 3-4. Efficient frontier of biomass harvest from 28 groups of marine species in the Colombian Pacific Coast. Circles in the plot represent the return and risk of individual species groups. The cross in the plot represents the current portfolio or combination of harvest rates.

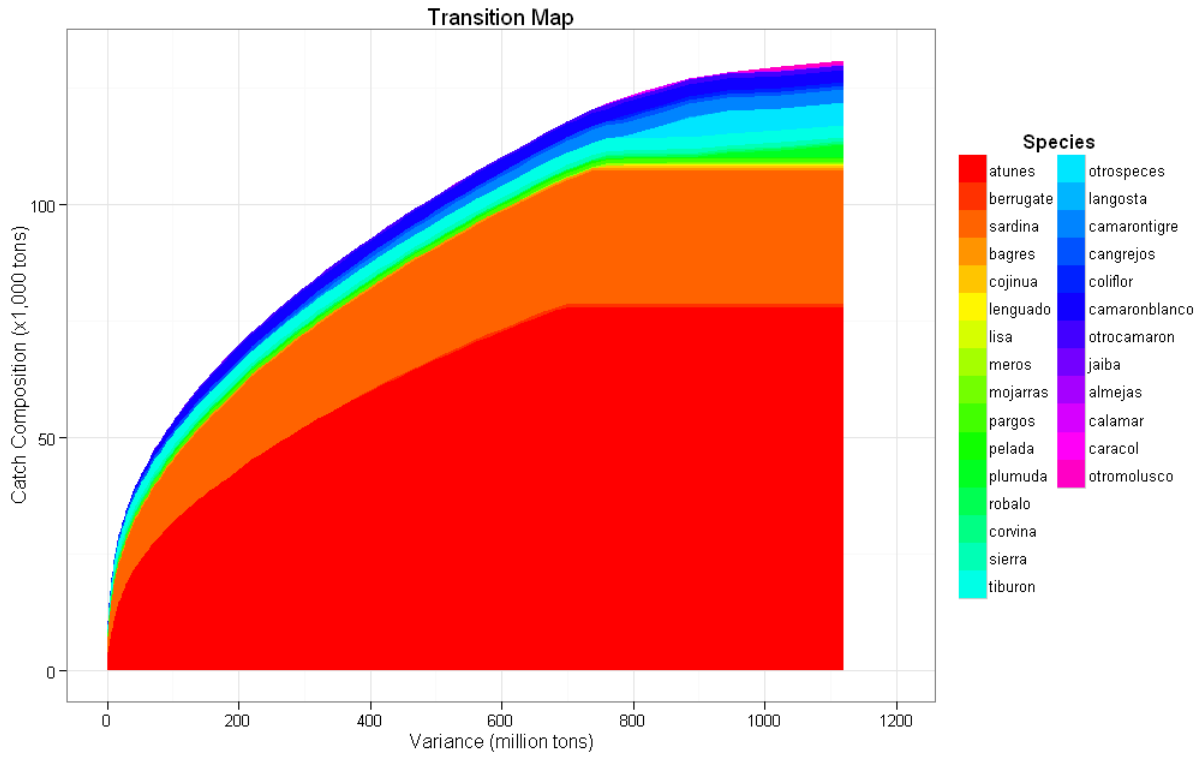

Figure 3-5. Transition map of prescribed harvest policies in the CPC. The curve corresponds with the efficient frontier and the harvest policies for the individual species groups can be traced for each level of allowable risk.

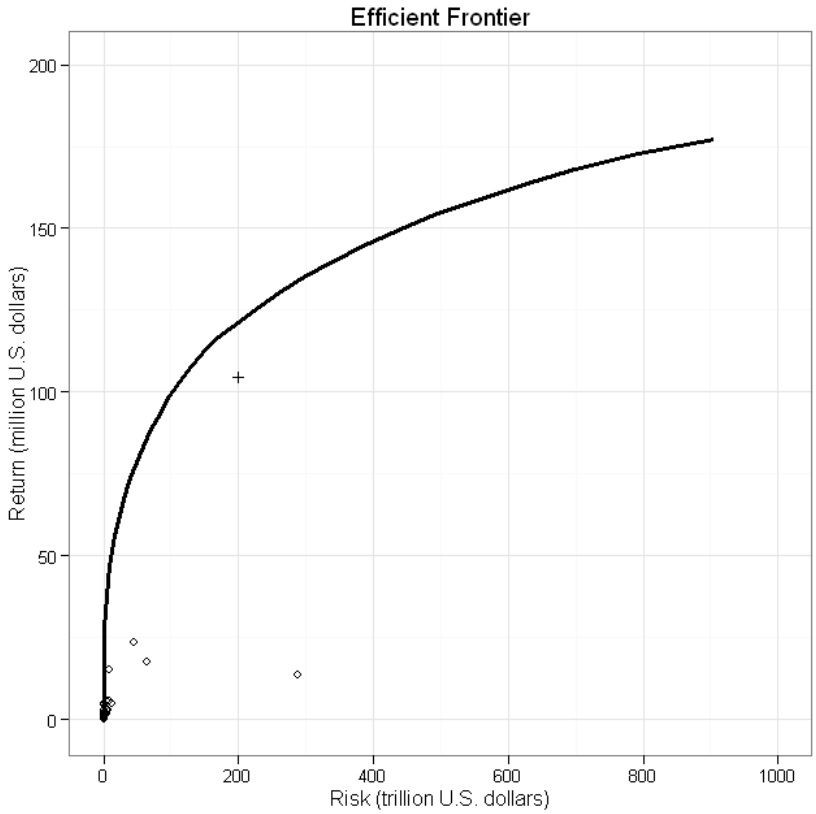

Figure 3-6. Efficient frontier of biomass harvest from 69 groups of marine species in the Florida Gulf Coast. Circles in the plot represent the return and risk of individual species groups. The cross in the plot represents the current portfolio or combination of harvest rates.

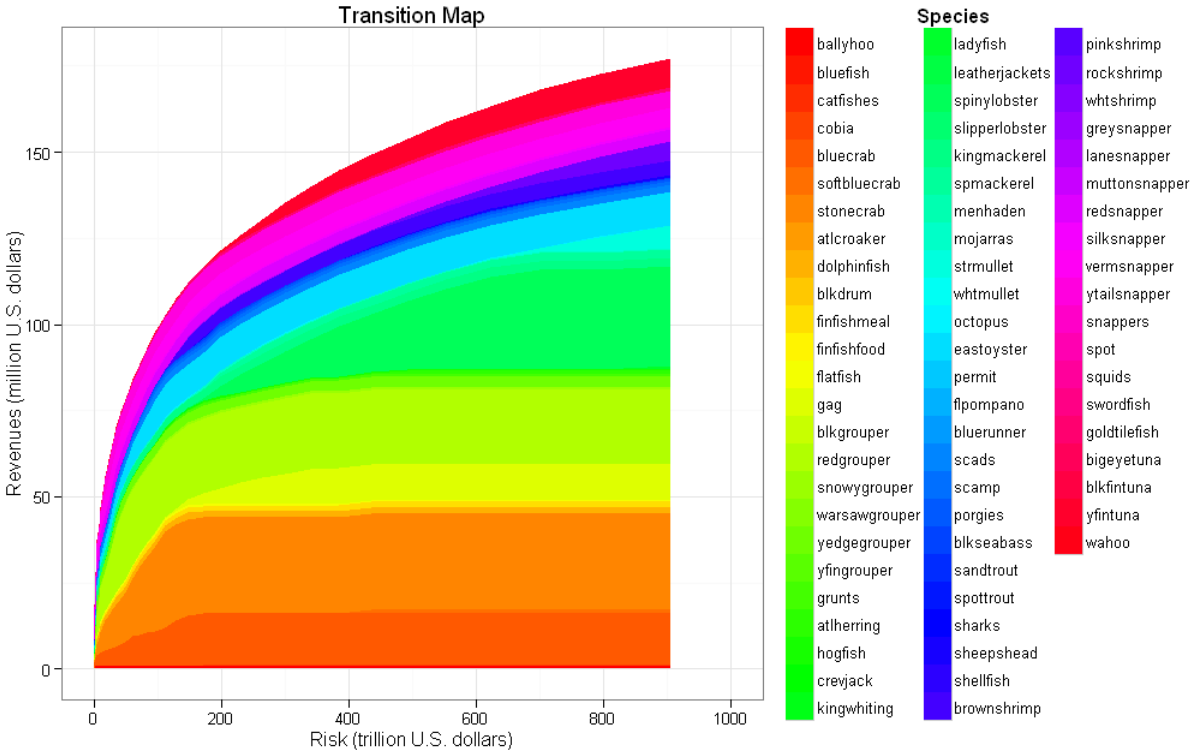

Figure 3-7. Transition map of fishing revenues from prescribed harvest policies in the Florida Gulf Coast. The curve corresponds with the efficient frontier and the expected revenues for the individual species groups when following the prescribed catch policies can be traced for each level of allowable risk.

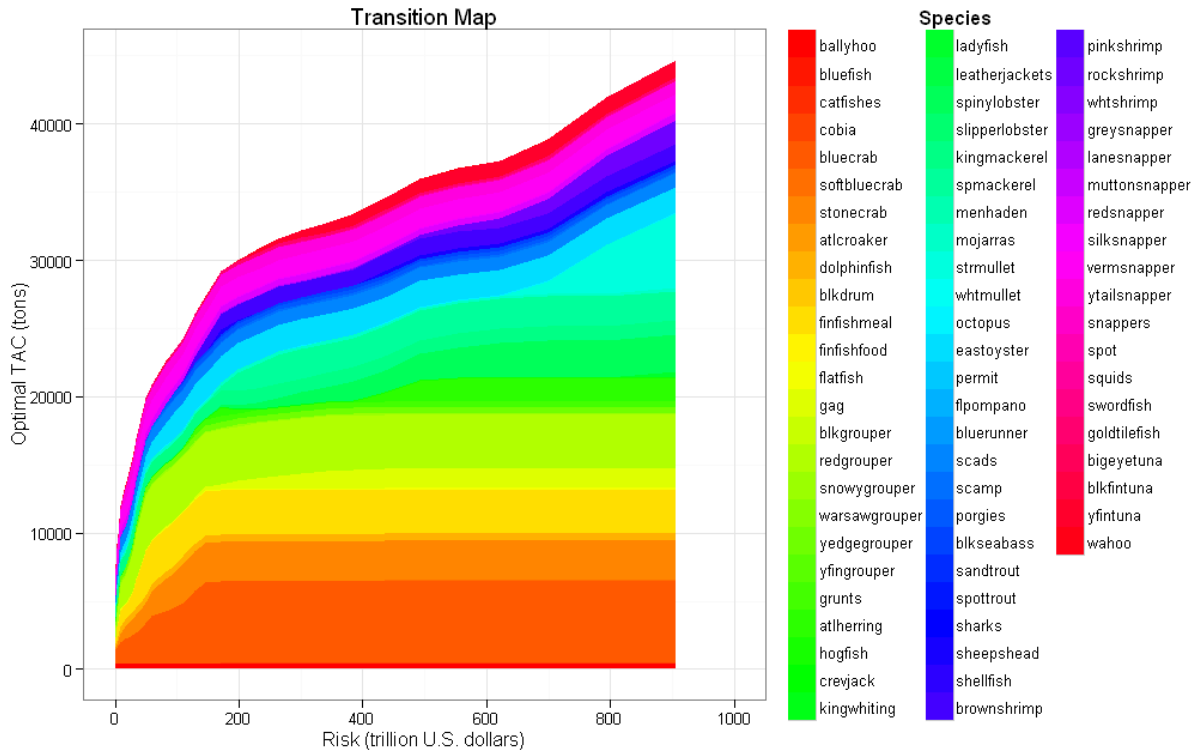

Figure 3-8. Transition map of prescribed harvest policies in the Florida Gulf Coast. The curve is obtained by dividing the expected revenues from each species (Figure 3-7) by the expected price of each species. The individual species groups can be traced for each level of allowable risk.

CHAPTER 4
MODELING IMPACTS OF HUMAN ACTIVITIES ON MARINE ECOSYSTEMS: A STYLIZED APPROACH USING ECOPATH WITH ECOSIM

Introduction

The Ecopath software, as initially conceived by Polovina (1984), was intended as a modeling routine that allowed the estimation of mean annual biomass, production, and consumption for components of an ecosystem. This was accomplished by creating a 'biomass budget box model' in which steady state equilibrium solves simultaneously for the unknown parameters in the system. The main feature was a top-down approach to modeling the ecosystem. Rather than starting from primary production and working its way up to the apex predators, the modeling framework began with the apex predators and other species groups at high trophic levels that were known to exist in the system, and then estimated the amount of primary production required to sustain those populations. Polovina's application to the tropical reef system of the French Frigate Shoals is also notable in that no fishing mortality is included. Therefore, no economic analysis was possible in this early version of Ecopath.

Several advancements in theoretical ecology were included in Christensen and Pauly's (1992) improved version of Ecopath. Notably, measures of ecosystem maturity proposed by Odum (1969) were included to provide some insights into the stability of the ecosystem. Routines to calculate trophic levels, ascendency, trophic aggregation, and a variety of other ecological indices were also included. This version of Ecopath also included the first hints of economic analysis. A routine to calculate direct and indirect impacts of predation, similar to the routines in IMPLAN to calculate direct and indirect economic impacts, was included. Hannon's (1973) interpretation of Leontief's Input-Output framework to model direct and indirect impacts of predation in an

ecosystem provided the basis for this development. Furthermore, the application to the *Schlei Fjord* ecosystem included mortality due to fishing, but no reference was made as to the specifics of the fishing fleet.

The version of the software freely available today (*www.ecopath.org*), *Ecopath with Ecosim* (EwE), includes several improvements and developments that have been added in the nearly 30 years since Polovina's pioneering work. The static, steady-state equilibrium framework of the early Ecopath versions has now been replaced by a temporary mass balance assumption. A dynamic modeling capability known as Ecosim allows exploration of the impacts of fishing and environmental disturbances, as well as optimal fishing policies. Another capability known as Ecospace allows the dynamic models created with Ecosim to be replicated over a spatial grid (Christensen and Walters 2004).

The objective of this Chapter is to explore the capabilities of EwE to perform economic analysis. To do so, a simple hypothetical model of an ecosystem with multiple species groups and multiple harvesting fleets (fisheries) is developed, and the steps required in building such a model are outlined. Special emphasis is given on the economic or financial data requirements for building the model. This model is then used to explore the different routines included in EwE that explicitly deal with the relationship between the fishing fleets and the ecosystem.

Ecopath: A Simple Model of a Tropical Ecosystem

The model used in this exploration is a modified version of that presented in Christensen (2009). As such, the model is meant to reflect historical conditions in the North West Shelf (NWS) of Australia as described by Sainsbury et al. (1993). A flow

diagram of the modified model of the ecosystem, which due to modifications should be considered a hypothetical ecosystem, is presented in Figure 4-1.

Mass Balance

The hypothetical ecosystem is composed of nine species groups: seabirds, piscivores, squid, small fish, benthos, zooplankton, phytoplankton, macro-algae, and detritus. One of the important features of the ecosystem is the habitat interaction that exists between macro-algae and small fish. Small fish find refuge in macro-algae, and so their predation mortality is lower when macro-algae density is high, and vice-versa (Christensen, 2009). The basic input parameters and diet composition matrix are shown in Tables 4-1 and 4-2.

There are three commercial fishing fleets operating in the hypothetical ecosystem. Trawls are the largest fleet as determined by the volume of landings. They target piscivores, which can be sold at a premium price. However, their fishing gear incidentally removes a considerable volume of macro-algae from the ecosystem. This incidental removal is discarded inside the system. On the other hand, fishers using traps also target piscivores, but do so with a minimal impact on the ecosystem, as there are no incidental catches. Finally, jiggers target squid. However, their gear is notoriously detrimental to seabirds, which get caught in the fishing gear and drown while attempting to eat the squid. This incidental bycatch is also discarded inside the system. The landings and discards figures are shown in Tables 4-3 and 4-4.

Applying a forcing function to account for the relationship between small fish and macro-algae as shown by Christensen (2009) concludes the first stage of modeling the hypothetical ecosystem in EwE. Since seabirds also predate on small fish, the forcing function must be applied to the predation mortality that they exert on small fish as well

as that from piscivores and squid. We now have a mass-balanced model of the hypothetical ecosystem.

Economic Input to Mass Balance Stage

As discussed in the previous section, only landings and discards information for each fishing fleet are required to obtain a mass balanced model of the ecosystem. Other information about the fishing fleets is not required to study the ecosystem, but must be added if the user intends to use EwE's capabilities for economic analysis. Inclusion of this kind of information will enrich the outputs obtained from the mass balancing routine, as well as open the possibility of exploring fisheries policy scenarios in Ecosim's dynamic simulations. The types of data that can be used as an input, and the outputs obtained when using this data are described below.

Financial information on cost structure

Different fishing fleets can be expected to have different cost structures depending primarily on the species they target and the gear they use. Furthermore, some fleets may be more profitable than others for a variety of reasons. In theory, the cost structure of a fishing fleet will dictate how fishing effort will respond to changes in relative prices of inputs and outputs, as well as how the fleet may respond to management regulations. EwE allows the user to input financial information about the cost structure and profitability of each fleet. In particular, the percentage of total revenue (total value of the catch) that is required to cover fixed costs, effort related variable costs, sailing related variable costs, and profits in a given year (or the unit of time defined in Ecopath) can be added as an input (Appendix A). The figures are meant to portray the 'average' or 'representative' vessel in the fleet, and each of the cost and profit categories is entered separately (Christensen et al. 2005). The financial

information on cost structure for the three fleets in the hypothetical ecosystem is shown in Table 4-5.

Market and non-market prices

Prices are a critical set of information in most economic activities. The expected market price at which a vessel can sell its catch is a major determinant of fishing decisions. Market prices can fluctuate seasonally, and some fleets may be able to sell their catch at premium prices due to this seasonality. Also, some fleets may operate with highly selective gear that allows them to catch only the largest fish, and may therefore receive a price premium for this selectivity. EwE allows the user to enter a price per unit weight for each species caught by each fleet, allowing different fleets to sell their catch at different prices. This may happen if one gear is better at targeting larger fish (or fish of particular sizes) or if the product can be transported to market fresh rather than frozen, for instance. The price matrix allows the user to enter prices for all species, but only those species that are also represented in the landings matrix of each fleet are taken into account in EwE's calculations. The market price matrix for the hypothetical ecosystem is presented in Table 4-6.

While the most obvious 'value' of an ecosystem is the value of the catch extracted from it (i.e., the total revenue of fishing fleets), an ecosystem and its components may also be valuable in situ for non-extractive uses or non-uses. Some authors have pointed out that one of the key concepts of Ecosystem-Based Management is the complete valuation of all components of the ecosystem, including benefits arising from the existence of non-target species (McLeod et al. 2005). The non-market price matrix in EwE is meant to represent the value of a resource in the ecosystem for non-exploitative uses (Christensen et al. 2005). In the case of the

hypothetical ecosystem, we have given seabirds a non-market value, as we assume that people enjoy watching birds, and some people feel distress by knowing that seabirds die during the operations of jigger vessels. Therefore it is assumed that society receives a benefit when seabirds are conserved, and conversely is negatively affected when seabirds perish due to fishing activities (Appendix B). The non-market value matrix for the hypothetical ecosystem is presented in Table 4-7.

Economic Output of Mass Balancing

Once the economic figures are included in Ecopath, the mass balance procedure calculates the total revenue, cost and profit of each fleet, as well as the value of each species. Let L_{ij} be the landings of species i(i = 1, 2,…, n) by fleet j (j = 1, 2,…, m), and P_{ij} be the price of species i when caught by fleet j. The catch value of species i by fleet j is:

$$CV_{ij} = L_{ij} \cdot P_{ij}. \tag{4-1}$$

Similarly, the total revenue of fleet j is given by:

$$TR_j = \sum_{i=1}^{n} CV_{ij}. \tag{4-2}$$

Now let the percentages from the financial information on the cost structure of each fleet be expressed as proportions, where PFC_j is the proportion of fixed cost, PEC_j the proportion of effort related costs, and PSC_j the proportion of sailing related costs, all for fleet j. The total cost of the fleet can then be expressed as:

$$TC_j = \left[PFC_j + PEC_j + PSC_j\right] \cdot TR_j. \tag{4-3}$$

The total profits of the fleet can similarly be expressed by:

$$TP_j = \left[1 - \left(PFC_j + PEC_j + PSC_j\right)\right] \cdot TR_j. \tag{4-4}$$

Once more, let the non-market price of species *i* be represented by NMP_i, and the biomass of species *i* be represented by B_i. The non-market value of species *i* in the ecosystem can be expressed as

$$NMV_i = B_i \cdot NMP_i. \tag{4-5}$$

The total value of species *i* is given by

$$TV_i = \sum_{j=1}^{m} CV_{ij} + NMV_i. \tag{4-6}$$

And finally, the total economic value of the ecosystem can be expressed as

$$TEV = \sum_{j=1}^{m} TR_j + \sum_{i=1}^{n} NMV_i = \sum_{i=1}^{n} TV_i. \tag{4-7}$$

The mass balance economic output table for the hypothetical ecosystem is shown as Table 4-8.

Ecosim: Time Dynamic Simulation and Policy Optimization

As a software that deals primarily with ecological dynamics, EwE's capacity to conduct 'economic analysis' may not pass the neoclassical economics litmus test (see Holland et al.'s (2010) discussion on what does and does not constitute economic analysis). However, the features available in EwE may prove interesting and useful if one defines fisheries economics very broadly as the study of the interactions between coastal and marine ecosystems and the human beings who use and enjoy them. The Ecosim features that deal with this relationship are outlined in this section.

Fishing Effort Forcing Function

One of the questions concerning this relationship between humans and ecosystems that may be of interest to fisheries managers is the effects in the ecosystem of different fishing rates or levels of fishing effort from the different fleets. The first feature available in Ecosim is a screen that allows the user to create a relative effort

forcing function. As a base (effort = 1), Ecosim uses the fishing mortalities established by the user in the mass balance stage. In our hypothetical ecosystem, for example, a relative effort value of 1 for the trawl fleet removes 0.7 tons per square kilometer of piscivores in one year as landings, as well as 1 and 3 tons per square kilometer of benthos and macro-algae a year as incidental catch, respectively. A doubling in relative effort would double these fishing-attributed mortalities. In essence, the user is allowed to 'draw' a time series of fishing effort for each fleet, taking the mass balance fishing mortalities from Ecopath as the base. Alternatively, the user can specify a time series of relative fishing effort targeted at particular species groups. One can then 'Run Ecosim', and a time series of abundance trends for each species in the ecosystem is calculated and plotted in the same screen. Furthermore, the user can ask Ecosim to produce a series of plots with predicted time series of a variety of ecological indicators by each species group. These plots can be exported as a csv file. Figure 4-2 shows the expected biomass trends of the economically important species groups in the hypothetical ecosystem, if fishing effort of all fleets were to remain at its base value for 20 years.

Bionomic Dynamics: Fleets as Dynamic Predators

An alternative to sketching the relative fishing effort trends is to allow Ecosim to simulate these trends in an open access scenario. To do this, the user must check the 'fleet/effort dynamics' box in the main Ecosim screen. This option simulates fishing effort dynamics using two time scales for fisher response. In the short term, fishing effort can respond to potential income from fishing, but only to a point constrained by the current size of the fleet. In the long term, the investment and depreciation decisions for increasing or decreasing the fleet size (capital capacity to fish) are modeled in a way

analogous to the growth of a biological population. That is, the fleet responds to profits (surplus) by growing in size, and to losses (deficits) by reducing the size of the population.

These responses are represented by two state variables for each fleet *j*. E_{jt} is the current amount of active, searching gear (scaled to 1 as the Ecopath base), and K_{jt} is the fleet effort capacity, such that $E_{jt} \leq K_{jt}$. At each time period *t*, mean income per unit effort is calculated as

$$I_{jt} = \sum_{j=1}^{m} q_{ij} \cdot B_i \cdot P_{ij}, \tag{4-8}$$

Where q_{ij} represents the catchability coefficient for fleet *j* going after species group *i*. A mean profit rate for each fleet is also calculated as

$$PR_{jt} = (I_{jt} - TC_j) \cdot E_{jt}. \tag{4-9}$$

For each time step, the short term effort response for the following time period is predicted as a sigmoid function of income per unit effort and current fleet capacity:

$$E_{jt+1} = \frac{K_{jt} \cdot I_{jt}^{\alpha}}{IH_j^{\alpha} + I_{jt}^{\alpha}}, \tag{4-10}$$

where IH_j represents the income level required for half of fleet *j* to be deployed or enticed to become active (i.e. the income level where $E_{jt} = 0.5K_{jt}$), and α represents a heterogeneity parameter for fishers: high values of α imply that fishers 'see' income opportunity similarly, while low levels imply that fishers deploy their effort at a wide range of income levels (Christensen and Walters, 2004; Christensen et al. 2005).

The parameters IH_j and α can be set by the user and are unique to each fleet, but iterative simulations with the model of the hypothetical ecosystem suggest that these changes are small, and that the system tends to settle at a unique open access or bionomic equilibrium, regardless of changes in the price of fish, profit margins, and

values of the bionomic parameters described above. For comparison, the biomass trends of the economically valuable species in the hypothetical ecosystem are shown in Figure 4-3.

Notable in the bionomic simulations for the hypothetical ecosystem is the growth of the jigger fishery, which ends up driving seabirds to extinction. Recall that the jiggers are assumed to remove seabirds as incidental catch, and the jigger fleet is predicted to grow dramatically. In an effort to manipulate the outcome of the simulation, the price of squid (the target species of the jigger fishery) was reduced dramatically, and the profit margin of the fishery was eliminated. This manipulation did not change the outcome of the simulation. Manipulation of the bionomic parameters IH_j and α changes the time series of effort and biomass, but the end point appears to be the same. These results defy economic theory and basic intuition.

The bionomic dynamics tool appears to be an interesting feature of EwE. However, the conclusions obtained from simple manipulation of the input parameters suggest that this tool can be improved dramatically with some basic economic intuition.

Fishing Policy Search

Invoking the ‘fishing policy search’ option in Ecosim opens a new window that allows entering the number of ‘jobs per catch value’ created by each fishing fleet. While it is possible that some government agencies or fisher groups maintain detailed information on the number of jobs created by each fishing fleet, it is more common to encounter employment statistics for the commercial fishing sector as a whole. The number of jobs created by each fleet can therefore be calculated using the catch value (CV_{ij}) statistic created by the Ecopath mass balance procedure discussed previously.

Recall that the total revenue obtained by each fleet can be obtained by summing over the catch values of the portions caught by each fleet. The total market value of the ecosystem can be calculated as

$$TMV = \sum_{j=1}^{m} TR_j, \tag{4-11}$$

and the proportion of total value that can be attributed to each fleet is therefore

$$PV_j = \frac{TR_j}{TMV}. \tag{4-12}$$

If the total number of jobs created by the commercial fishing sector in the economy is *TJ*, then the jobs per catch value by each fleet can be calculated as

$$jobs_j = TJ \cdot PV_j. \tag{4-13}$$

The jobs by fleet for the hypothetical ecosystem, assuming that commercial fishing creates a total of 300 jobs in this hypothetical economy, is shown in Table 4-9.

To find an optimal fishing policy, the user is allowed to define an objective function to be optimized. This objective can be a combination of net economic value (profits), employment, mandated rebuilding of target species, ecological stability and other index measures. The fishing policy search option in Ecosim uses the Davidson-Fletcher-Powell (DFP) non-linear optimization procedure to iteratively improve an objective function by changing relative fishing rates. The parameter variation scheme used by DFP is known as a ‘conjugate gradient’ method, where alternative parameter values are tested so as to locally approximate the objective function as a quadratic approximation. The DFP is one of the most efficient algorithms for complex, non-linear optimization available (Christensen and Walters, 2004).

Maximizing a simple objective function

The most simple policy optimization option involves defining the weights w_i for an objective function of the form

$$OB = w_1 \sum_{j=1}^{m} TP_j + w_2 \sum_{j=1}^{m} jobs_j + w_3 ER + w_4 ES, \quad (4\text{-}14)$$

where TP_j represents total profits from fleet *j*, *ER* is a mandated rebuilding index that increases as rebuilding targets are met, and *ES* is an ecological stability index similar to those described by Odum (1969). Once the weights are defined, the output from the optimization procedure can be visualized as a table, a trend plot of iterations, and a triangular figure that describes the way the objectives are being met. This procedure allows the 'sole owner' of the ecosystem to define her objectives and use the ecosystem model to define what the best course of action is.

Iteration trends for the objectives and relative effort when maximizing the objective function when $w_1 = 1$ and all other weights are assumed to be zero (profit maximization) in the hypothetical ecosystem are shown in Figures 4-4 and 4-5.

One of the most useful features of EwE's policy optimization routine is that the levels of fishing effort that maximize the objective function defined by the user are automatically sketched into the dynamic model of the ecosystem as an effort forcing function. This allows the user to monitor the biomass and other trends in the ecosystem if the prescribed policy where to be put in place. Biomass trends for the economically valuable species if the profit maximizing policy is followed are shown in Figure 4-6.

Alternative: prevent cost > earnings

A very interesting phenomenon arises in multispecies or ecosystem models of fishing regarding the impacts that one fishery may have on another through the trophic interactions of the target species. Such 'ecosystem externalities' may dictate the sole

owner of the ecosystem to maintain a fleet that operates at a loss if doing so results in an increase of the population of the species targeted by a profitable fleet. The example of the hypothetical ecosystem may serve to illustrate this phenomenon. In our case, the trawling fleet targets piscivores, which eat squid. Furthermore, trawls remove macro-algae as incidental catch, therefore allowing higher predation on small fish by both piscivores and squid. Therefore, the trawl fishery provides a positive ecosystem externality to the jigger fishery by removing some of the squid's predators and by facilitating a higher availability of food for the squid stock. If the trawl fishery was losing money and the squid fishery was still profitable, a sole owner of the ecosystem would want to keep the trawls operating at a loss just to reap the benefits trawlers provide to the jigger fleet through complex ecosystem interactions.

To separate the scenarios in which a sole owner would have control of all the fleets operating in the ecosystem and that in which fleets make independent profit maximization decisions, Ecosim offers the option 'prevent cost > earnings', which limits fleets to operate only at profitable levels. Ecosim also allows the user to visualize the extent of ecosystem externalities with the 'Maximize by Fleet Values' option, which automatically pops up a window with a matrix of ecosystem relationships between fishing fleets. The idea is that such a matrix could be used to estimate the compensation required by different fleets for benefiting or adversely affecting other fleets that operate in the ecosystem.

Maximizing social utility of a risk-averse portfolio

Ecosim also provides the user with an option that could be interpreted as that of maximizing social welfare. The social manager is seen as having an objective function of the form

$$OB = w_1 Log(\sum_{j=1}^{m} TP_j) + w_2 Log(B)S - w_3 V, \quad (4\text{-}15)$$

where the first term in the left-hand side of the equation refers to the profits of all fleets operating in the ecosystem, the second term refers to the 'existence value' of all biomass groups, and the third term is a variance index that increases when the ecosystem is changed from the Ecopath mass balance base (Christensen and Walters 2004). This function therefore attempts to balance profitability of the fleets operating in the ecosystem with negative ecosystem effects that such profit maximization may bring about.

In the hypothetical ecosystem, for instance, maximizing for this risk averse social utility function prescribes a much more conservative policy than that prescribed in the sole owner profit maximization scenario. To maintain an emphasis in profitability of the fisheries, the relative weights chosen were $w_1 = 1$, $w_2 = 0.1$, and $w_3 = 0.1$. The iteration and predicted biomass trends are shown in Figures 4-7, 4-8 and 4-9.

Discussion

While not developed explicitly as a tool for economic analysis, and somewhat lacking in economic theoretical background, EwE is an interesting tool for fisheries modeling and management. If we allow the definition of fisheries economics to be broadly the study of the interaction between marine and coastal ecosystems and the people that use them, then EwE is definitely a tool with a fruitful prospect. The capacity to model trophic interactions that is easily available in EwE is most likely not within the toolkit of most economists, even though the problems studied by fisheries economists are heavily affected by these trophic interactions. A large part of the economic analysis capabilities of EwE rely in simple and straightforward common sense.

The bionomic dynamics routine holds particular promise in integrating economic and ecological models within the EwE framework. As the simple manipulations described here suggest, however, the routine needs improvement. Careful inclusion of bioeconomic theory in this or a similar routine may be the key to successful integration of these models. The fishing policy search routines allow the user to ‘play around’ with different objectives of fisheries management, and in doing so it is easy to examine the inherent tradeoffs between these objectives.

When considering EwE and similar platforms for ecosystem modeling, however, fisheries decision makers must realize that the capacities to conduct analysis of economic and social impacts are very limited. For instance, the cost structure in EwE is always assumed to be linear in parameters, which in turn implies that the marginal cost and productivity of inputs remains constant across all possible levels of fishing effort. This is a problematic assumption that oversimplifies constraints and decision-making at the vessel level. Similarly, fishing effort in EwE does not respond to changes in output prices or input costs. This assumption of exogeneity of fishing behavior is perhaps the biggest shortcoming of the EwE platform when judged from the socio-economic viewpoint.

The exogeneity of fishing effort, which extends to the entire human component in the EwE platform, implies that this software is inappropriate for conducting the wide majority of analyses that fisheries economists perform. For instance, the issues of overcapitalization and capital stuffing, the race for fish, transferrable fishing quotas, among others, cannot be addressed using EwE. Similarly, all issues related to property rights and fishing regulations must be ignored. The first step in addressing this problem

is changing the way in which fishing effort is modeled to make it endogenous to parameters set by the user. In essence, the calibration of an ecosystem model that realistically includes the human component must require at least as much effort in the ecological aspects as in the socio-economic aspects.

It is important to note ease of learning, availability of documentation, and user friendliness of the software as major advantages of using EwE, especially as it relates to building ecosystem models with a diverse suite of ecological features. However, the documentation on conducting economic-type analyses on EwE is not as rich or as clear, and the shortcomings of the platform caused by the exogeneity of fishing effort make it inappropriate for most economic analysis. EwE and its users would definitely benefit from inclusion of economists in the development of successive versions of the software.

Table 4-1. Basic input parameters for the hypothetical model

Group Name	Habitat Area (fraction)	Biomass in habitat area (t/km²)	Prod./ biom. (/year)	Cons./ biom. (/year)	Ecotrophic efficiency
Seabirds	1	1	0.3	1	
Piscivores	1	5	0.3	1	
Small Fish	1	15	1	4	
Squid	1	2	2	10	
Benthos	1	40	5	20	
Zooplankton	1	50	20	80	
Macro-algae	1	5	0.5		1
Phytoplankton	1	100	150		
Detritus	1	100			

Table 4-2. Diet composition matrix

	Prey / Predator	1	2	3	4	5	6
1	Seabirds						
2	Piscivores	0.25					
3	Small Fish	0.5	0.45		0.3		
4	Squid	0.25	0.05	0.05			
5	Benthos		0.5			0.05	
6	Zooplankton			0.95	0.7		
7	Macro-algae						
8	Phytoplankton						1
9	Detritus					0.95	
10	Import						
11	Sum	1	1	1	1	1	1

Table 4-3. Landings in the hypothetical ecosystem (t/km^2)

Group Name	Trawls	Jiggers	Traps	Total
Seabirds				0
Piscivores	0.7		0.4	1.1
Small Fish				0
Squid		0.3		0.3
Benthos				0
Zooplankton				0
Macro-algae				0
Phytoplankton				0
Detritus				0
Sum	0.7	0.3	0.4	1.4

Table 4-4. Discards in the hypothetical ecosystem (t/km^2)

Group Name	Trawls	Jiggers	Traps	Total
Seabirds		0.1		0.1
Piscivores				0
Small Fish				0
Squid				0
Benthos	1			1
Zooplankton				0
Macro-algae	3			3
Phytoplankton				0
Detritus				0
Sum	4	0.1	0	4.1

Table 4-5. Cost structure of the fishing fleets in the hypothetical ecosystem

Name of fleet	Fixed cost (%)	Effort related cost (%)	Sailing related cost (%)	Profit (%)	Total value (%)
Trawls	45	30	15	10	100
Jiggers	45	25	20	10	100
Traps	40	20	35	5	100

Table 4-6. Market prices in the hypothetical ecosystem (hypothetical currency)

Group Name	Trawls	Jiggers	Traps
Seabirds	0	1	1
Piscivores	250	1	250
Small Fish	1	1	1
Squid	1	110	1
Benthos	1	1	1
Zooplankton	1	1	1
Macro-algae	1	1	1
Phytoplankton	1	1	1
Detritus	1	1	1

Table 4-7. Non-market prices in the hypothetical ecosystem (hypothetical currency)

Group Name	Value/unit biomass
Seabirds	100
Piscivores	0
Small Fish	0
Squid	0
Benthos	0
Zooplankton	0
Macro-algae	0
Phytoplankton	0
Detritus	0

Table 4-8. Economic output from the mass balance procedure in Ecopath

Group \ value	Trawls	Jiggers	Traps	Catch value	Non-market value	Total value
Seabirds				0	100	100
Piscivores	175		100	275	0	275
Squid		33		33	0	33
Benthos				0	0	0
Macro-algae				0	0	0
Total value	175	33	100	308	100	408
Total cost	157.5	29.7	95	282.2	-	-
Total profit	17.5	3.3	5	25.8	-	-

Table 4-9. Employment by fleet in the hypothetical ecosystem

Fleet	Catch Value	Proportion	Jobs
Trawls	175	0.568	170.5
Jiggers	33	0.107	32.14
Traps	100	0.325	97.4
Total	308	1	300

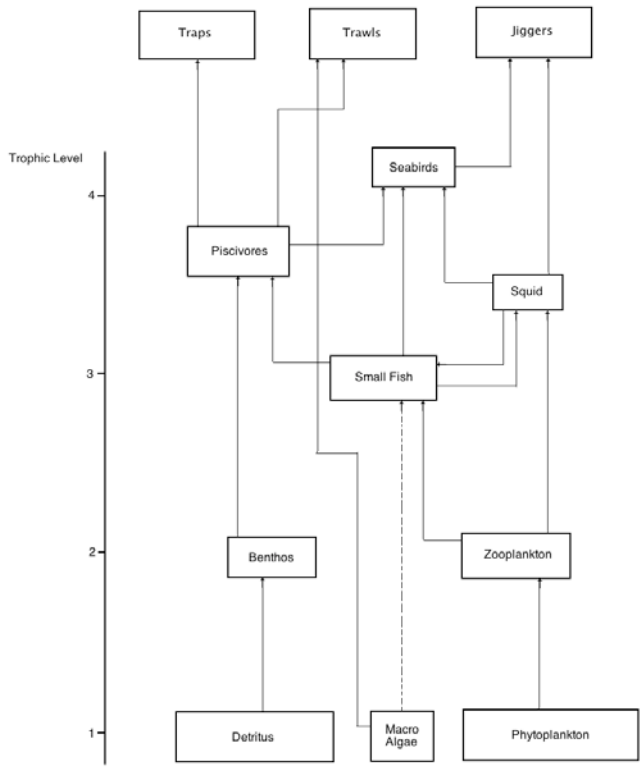

Figure 4-1. Flow chart of the hypothetical ecosystem. Straight lines represent trophic flows, while dashed lines represent habitat interactions.

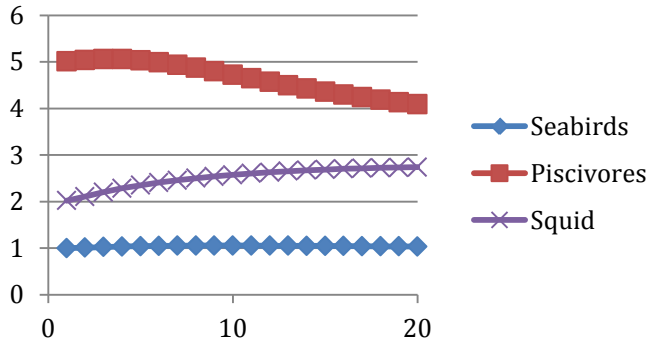

Figure 4-2. Expected biomass trends for economically important species in the hypothetical ecosystem if fishing effort is assumed constant for 20 years

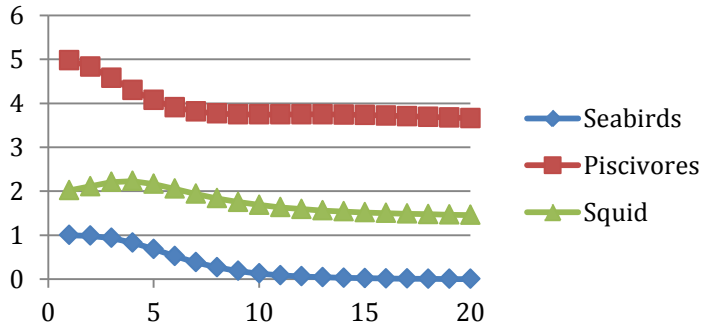

Figure 4-3. Biomass trends in the hypothetical ecosystem when open-access or bionomic dynamics are simulated

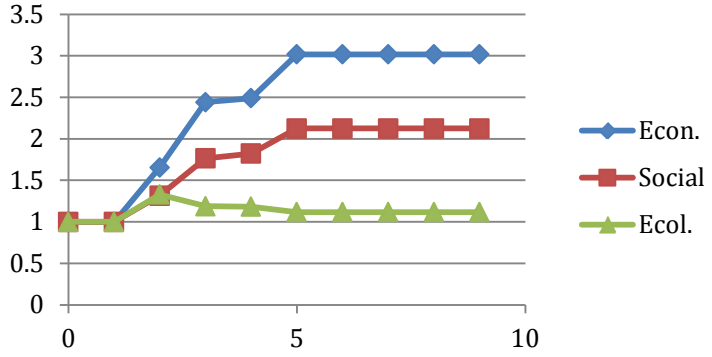

Figure 4-4. Iteration trends of the different objectives when maximizing profits in the hypothetical ecosystem

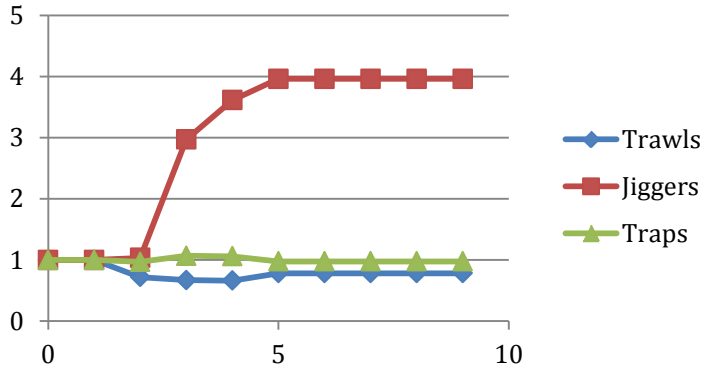

Figure 4-5. Recommended effort trends to allow profit maximization in the hypothetical ecosystem

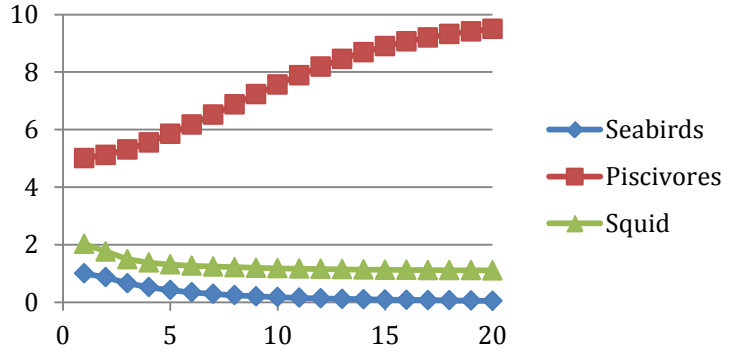

Figure 4-6. Biomass trends in the hypothetical ecosystem if the profit maximizing policy is followed

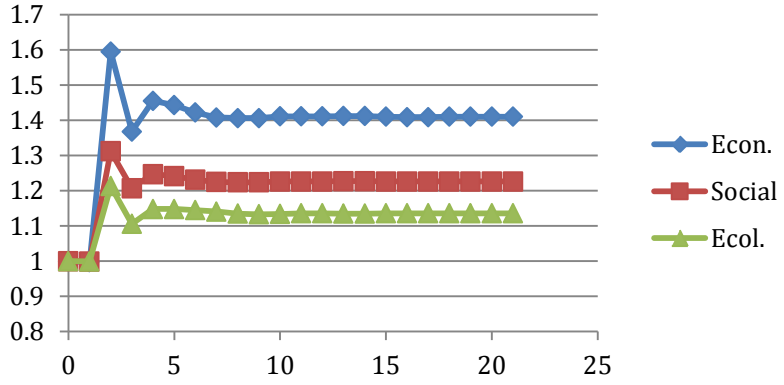

Figure 4-7. Iteration trends of the different objectives when maximizing for risk averse social utility in the hypothetical ecosystem

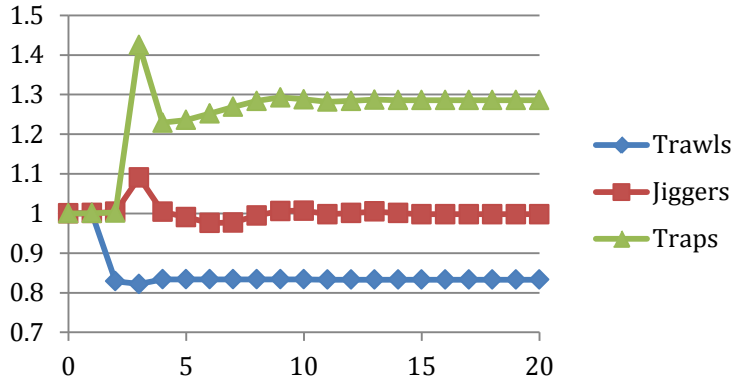

Figure 4-8. Recommended effort trends to allow maximization of the risk averse utility function in the hypothetical ecosystem

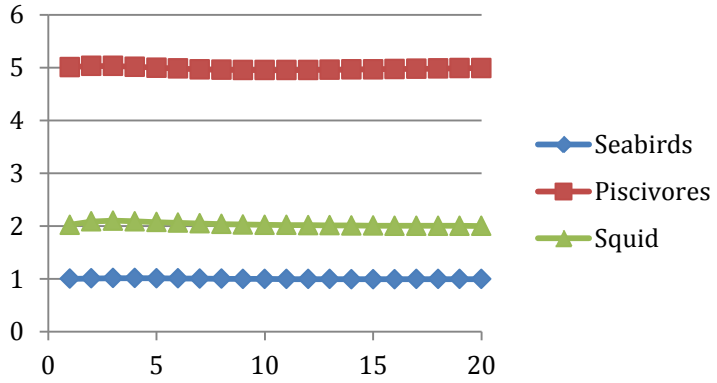

Figure 4-9. Biomass trends in the hypothetical ecosystem if the risk averse social utility maximization policy is followed

CHAPTER 5
CONCLUSIONS

The three essays in this dissertation explore a few of the many emerging issues in mankind's relationship with the natural world, with a particular emphasis on marine resources. In the first essay we explored the issue of water pollution from a major oil spill, the DWH, and its effect on recreational use of marine resources. As the world's population continues to grow and incomes increase, we can expect that recreational demand for marine resources will continue to expand. The same is true of the global demand for energy, and much of it will come from offshore oil drilling or will be transported by sea. The problem of oil spills interfering with recreational use of marine resources, therefore, is likely to be of prime importance in the near future. The methods and analysis developed in that essay, therefore, are likely to maintain relevance and their use is likely to grow.

Similarly, the systematic approach to decision-making in natural resource management developed in the second essay may have its most productive days still ahead. As pressure on our natural resources increases, managers will be forced to make difficult decisions that may require choosing between competing alternatives. Portfolio selection, which has been important in financial decision-making for the past 50 years, may yet prove quite useful in the field of natural resources. The essential questions for portfolio development outlined in the second essay will aid practitioners in the creation of their own portfolio selection models for natural resource management.

Finally, the modeling of entire ecosystems, discussed in the third essay, will continue to grow as a field due to the increased recognition of the importance of ecosystem interactions. While the marine sciences have pioneered this approach, other

disciplines that deal with natural resource management are likely to follow. Integration of economics into these models will likely prove to be a fruitful area of research. The analysis in this essay may help pave the way for a more complete integration of economics and human behavior into EwE and other existing ecosystem models.

APPENDIX A
COMPONENTS OF A VESSEL'S TOTAL OPERATION COSTS

EwE allows the user to enter the percentage of the total value of the catch, or total revenue of a representative vessel in a fishing fleet, that is allocated to the different kinds of fixed and variable costs. Here are some common operating expenses of a fishing vessel, below the EwE cost category to which they should be accounted in:

- Fixed costs
  a) Regular maintenance
  b) Major repairs
  c) Depreciation and capital equipment
  d) Overhead
  e) Insurance
- Effort related variable costs
  a) Bait, tackle, ice, and other supplies
  b) Wages or salary for crew and captain (or share of catch)
  c) Owner's time (if vessel is owner-operated)
- Sailing related variable costs
  a) Boat fuel and oil
- Profits
  a) Whatever money is left, if any, after covering all other expenses. Meant to reflect the return of owning a vessel in a given fishery.

APPENDIX B
TOTAL ECONOMIC VALUE OF AN ECOSYSTEM

The total economic value of an ecosystem is the sum of the following value components (Pearce and Turner 1990):

Use Values

Direct Use Value: Value for actual use or enjoyment of an ecosystem or its components. Values for fishing and other extractive uses of species are examples of direct use. Most commodities traded in markets fall under this category.

Indirect Use Value: Non-consumptive services provided by ecosystems fall under this category. Scenic vistas provided by coastlines and storm mitigation services provided by coastal wetlands are good examples. While these values are sometimes captured in the price of related commodities (i.e., housing), these goods are almost never traded in markets.

Option Value: Represent a preference to preserve an ecosystem for some unspecified use in the future. Conservation of coral reefs and the species associated with them to keep open the option of finding medically valuable species in the future is an example. Extinction of a species, for instance, represents a complete loss of option value.

Non-Use Values

Bequest Value: Preference to conserve an ecosystem or its components for one's heirs or for future generations in general. Conservation of an ecosystem or a species for the sake of one's children or grandchildren is an example of bequest value.

Existence Value: Relates to the satisfaction received by individuals for knowing that an ecosystem or one of its components exists, even though no direct or indirect use is involved.

Treatment of Non-market values in EwE

The current version of EwE assumes that there is a direct linear relationship between biomass of the species group and its non-market price or value, so that a doubling in biomass of a species group results in a doubling of its non-market value (Christensen et al. 2005). However, the relationship between non-market value and extinction is more complex. If extinction is unacceptable from society's point of view, then the non-market value of the last unit harvested before extinction occurs is very high (Clark et al. 2010). EwE's current treatment of non-market values does not account for this social aversion to extinction of species groups. Ecosim can go around this problem by use of the Log Utility optimization option, which makes extinction of a species with non-market value unacceptable.

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BIOGRAPHICAL SKETCH

Sergio Alvarez was born in Manizales, Colombia, in 1982, the year of the dog. He attended Colegio Granadino from kindergarten until graduating high school in 2000. Sergio then moved to South Florida, where he attended Broward Community College and obtained an Associate of Arts degree in agricultural sciences. After that, he came to the University of Florida in Gainesville, where he earned a Bachelor of Arts degree in environmental sciences and completed graduate studies in the Food and Resource Economics (FRE) Department. He holds Master of Science and PhD degrees in natural resource economics.

Sergio is interested in the interaction between mankind and nature in general, but his graduate research focused mostly on fisheries issues. Some specific areas where he has conducted research include choice modeling, non-market valuation, ecosystem and bioeconomic modeling. Besides fisheries, Sergio is interested in protected area management and the conservation of biodiversity.

Sergio has been married to Cassie since 2008, and they try to coexist with a German Shepherd, miniature Collie mix named Rumi and a black cat named Malinche. He enjoys outdoor activities, and has recently developed a special interest in kayak and canoe fishing, which he does mainly for research purposes.