

AN ABSTRACT OF THE DISSERTATION OF

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Researchers rely on bioeconomic models to guide research and generate fishery management advice for commercial fisheries. Due partly to a paradigm shift towards ecosystem based fishery management, increasing complexity in the characteristics of the problems has meant that bioeconomic simulation models are becoming more prevalent in the fisheries literature. However in many of these models the economic behavior of fishermen is either omitted, or incorporated using a model that is not based on an economic theory of human behavior. This dissertation comprises three essays that make contributions to advancing the art and science of bioeconomic simulation modeling. The first essay illustrates how a model of fisherman behavior can be incorporated into a bioeconomic harvest-control-rule assessment model of a complex multi-species, multi-fleet fishery. Insights for rebuilding stocks based on different assessment techniques and fleet strategic behavior are discussed. The second essay introduces a novel method for distributing fishing effort across space and time in bioeconomic simulation models based on game theory. A comparison between this method and more traditional methods for modeling fleet fishing behavior are analyzed and the implications and the relative strengths of the game theoretic approach discussed. The third essay describes a bioeconomic simulation model of the Oregon Dungeness crab fishery. A novel application of duration analysis to describe the in-season exit behavior of fishermen is combined with a zero-inflated Poisson model to determine how fishing effort is allocated by different fleets under alternative fishery conditions. A stock dynamics model is then incorporated into a Monte Carlo simulation to assess how changes in season closure dates affect the amount of discard mortality in the fishery, and how these changes affect operating profits in the fishery.

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Bioeconomic Simulation Modeling of Fisheries: Three Essays

by
Christopher Inju Cusack

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Christopher Inju Cusack, Author

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CONTRIBUTION OF AUTHORS

Chapter 2 was co-authored with Linsey Arnold, Dr Selina Heppell, Dr Michael Harte, and Dr Gilbert Sylvia. Ms Arnold and Dr Heppell helped to design and build the biological component of the model and Drs Sylvia and Harte helped with the economic component. All authors helped to edit the final manuscript.

Chapter 3 was co-authored with Dr David Sampson. The original idea for the Nash equilibrium method for distributing fishing effort spatially was Dr Sampson's. Dr Sampson also helped in the editing and design of the manuscript.

Chapter 4 was co-authored with Dr Sylvia, Noelle Yochum, and Shannon Davis. Dr Sylvia pointed me towards duration modeling and provided oversight for the entire paper. Ms Yochum helped in the conceptual design of the biological component of the model and Mr Davis acquired the data used in the analysis and provided much needed input into the workings of the West Coast fishery.

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1. INTRODUCTION

Fisheries management in the United States has historically been centered on a single objective—managing and conserving the biological stock. In parallel, a significant amount of effort has been exerted in developing biological modeling techniques, collecting and analyzing data, and disseminating model results to the scientific and policy-making communities, all focused on describing the behavior and population dynamics of the biological resource. However, over the last several decades there has been a gradual paradigm shift in fisheries management—the adoption of an ecosystem based approach which includes the human dimension (Essington and Punt 2011; Gaichas 2008; Botsford, Castilla, and Peterson 1997). As well as wider ecological impacts, economic efficiency concerns and the distribution of economic impacts among various sectors of the economy have become more important than in the past. The response to these concerns has been manifested in, among other things, the increased use of property rights systems in fisheries and fishery management plans that give social, economic, and ecological considerations more weight (PFMC 2016). Along with this revised focus is a need to increase investment in economic research into fisheries, including the development of economic theory, modeling techniques, and greater collection of data that can be applied in such models. The rationale for including economic considerations in fishery management decisions is that fishery management systems exist precisely because of economic influences on fisheries and the ecosystems they are a part of. People derive benefits from fishing that in some cases can be measured, such as a commercial fishing vessel’s ex-vessel revenue, or a consumer’s seafood consumption, but in many other cases cannot, such as the utility gained from the satisfaction of seeing a fish stock protected. Analyzing and predicting the behavior of fishermen necessarily calls for an economic framework. Even if the goal of some individuals is solely to protect particular components of the marine ecosystem, these concerns arise because of anthropogenic influences. Economics is therefore a critical tool for informing the public, fishermen, and fishery managers when decisions on how to make best use of a resource, and what that best use is, need to be made.

The application of economic theory and methods to fisheries problems has a rich and varied history, starting with the seminal works of Gordon (1954), Schaefer (1954), and Scott (1955). Since then, significant progress has been made in determining and studying the main causes of the major fishery problems of our time, such as the common property nature of fisheries leading to economic inefficiency through capital stuffing and supply gluts, which lead to processing and other value chain inefficiencies. This progress has been paralleled in the biological and ecological disciplines, especially in the development of knowledge regarding the reproductive and growth capacity of fishes, and how these processes are affected by

population pressures caused by fishing, or greater environmental influences. An important recent example of this is the discovery that older female rockfishes, which sometimes live more than 100 years, have a disproportionately beneficial influence on reproductive success than younger animals (Berkeley et al. 2004). If a goal of fishery management is population sustainability, removing an older fish from a population therefore has different implications for reaching this goal than removing a younger one. However, without modeling the component of the fishery system that determines which individual is removed, the ability to form management advice that can translate into real world progress towards sustainability is limited. Examples such as this are widespread, but even so fishery issues are rarely examined using an interdisciplinary framework.

Bioeconomic models of fisheries are important: fish and fishermen interact in ways that are complex and not intuitive to fishery managers. Bioeconomic models are not new; for example, the early works of Gordon (1954) and Schaefer (1954) included both biological and economic components and significant progress has been made in exploring fisheries through analytical models. For example, Sanchirico and Wilen (1999) and Sanchirico and Wilen (2005) showed that the equilibrium characterizing a spatial bio-economic fishery system is as dependent on economic parameters as stock characteristics. Sanchirico and Wilen (2001) show that the ability of a marine reserve to create value depends as much on assumptions regarding economic behavior and parameters as biological factors. Despite the importance of simultaneously considering economic and biological processes in fishery models, this practice is not pervasive in fisheries science (Carruthers et al. 2014), and in cases where economic factors are included in the analysis, the biological component is generally given much greater attention in terms of both data input and rigor of analysis (van Putten et al. 2012; Barclay 2012). Nevertheless, bioeconomic models that combine the salient components of fisheries in order to investigate the potential impacts of management actions have become increasingly numerous. While analytical fisheries models are important in gaining key insights over a global range of parameter values can be derived from closed form solutions, these models quickly become intractable as the number of parameters and dimensions increase. This limitation, and the need to perform policy analysis for complex real world situations has shifted the analysis of fishery systems using numerical optimization and simulation techniques (Pelletier and Mahévas 2005a; Powers and Abeare 2009).

In many fishery bioeconomic simulation models, fishing effort is assumed to be determined exogenously to the model (van Putten et al. 2012), and in ways that are not supported by microeconomic theory and/or econometric analysis (Dalton and Ralston 2004). This occurs despite the aspiration of the analyst to realistically represent fishermen behavior. Even so, bioeconomic simulation models have become

increasingly complex over the last several decades, partly due to advances in modeling and computation techniques, and the need to explore new, more complex issues as our knowledge of fishery systems improves. While this complexity comes at a cost, the interpretability of results quickly becomes difficult as the number of model inputs increases. Incorporating a realistic level of detail into models provides a framework with which to explore alternative hypotheses about the fishery (Hilborn and Walters 1987), and encourages new ways of thinking about the interaction between fishermen and the resource they depend on. Bioeconomic simulation models that incorporate a realistic level of detail in both the bioeconomic and economic components are therefore useful tools to encourage thinking and foster learning about the interactions between fishermen and the stock and provide directions for future research in both the biological and economic disciplines.

Three broad issues in modeling fisheries that have important implications for fishery management are addressed in this set of essays: 1) multi-species interactions, 2) spatial interactions, and 3) population process interactions. Multi-species interactions occur, for example, when several species are either targeted or caught incidentally. While management measures may focus on each species separately, fishermen treat the species as a catch complex. In these cases, a management action that is established in the interests of a single species may have effects on other species in the fishery that are often not well understood and are potentially undesirable (Salas and Gaertner 2004). In many cases the behavior of fishermen is ignored or poorly modeled and the impacts of management measures are difficult to predict without considering realistic fisherman and fish behavior simultaneously (Wilens et al. 2002; Fulton et al. 2011).

Spatial interactions occur when the behavior of fishermen and/or fish stocks have a spatial component that at least partly determines population processes, catch, and profit in the fishery. As a simple example, if the price of older female rockfish is higher than that of younger fish in our previous discussion, and these fish are found in particular fishing areas, effective policy advice can only be reliably formed by simultaneously considering biological and economic factors. In general, fishermen's behavior determines the spatial pattern of fishing mortality in a fishery, and this behavior depends on economic factors (Wilens et al. 2002). Population process interactions occur when some aspects of the behavior of the fish population interact either temporally or spatially with harvesters. For example crustaceans, as part of their growth processes, are in a softshell state for some periods during a year. Being in this state has implications for the price that fishermen receive for harvesting the animal, which in turn affects fishing behavior. Models that can examine these interactions in order to inform policy makers are necessarily bioeconomic in nature. These bioeconomic considerations form the basis for the material in the research which follows.

This thesis consists of three essays that describe endeavors to make contributions to the existing fisheries bioeconomic literature. All essays are based on bioeconomic fisheries simulation models that were designed in order to examine contemporary issues in fisheries research. The first essay illustrates the utility of integrating economics into a model that assesses the performance of a data-poor harvest control strategy, an area of research that traditionally does not take fishermen behavior into account. The model is applied retrospectively to a complex, multi-species fishery in order to demonstrate how the economics of a complex fishery may be incorporated into biological models, and to gain economic insights about the challenges inherent in rebuilding stocks using alternative harvest control rules. The second essay makes a contribution to the examination of spatial interactions in fisheries by presenting a novel method, based on the tenets of game theory, of spatially distributing fishing effort in bioeconomic simulation models. This method is then compared to several contemporary methods for distributing effort in such models. The third essay describes the design and implementation of a simulation model of the Oregon Dungeness crab fishery in order to examine the potential interactions between moulted crab which are in a soft shell state, and the temporal distribution of fishing effort in the fishery. The first application of an economic duration model to the in-season exit behavior of fishermen is combined with a bioeconomic representation of the Oregon Dungeness crab fishery using a Monte Carlo simulation framework designed to evaluate the potential impacts of adjusting the season closure date in the fishery.

2. COMBINING FISHERIES MANAGEMENT EVALUATION WITH FISHERMAN BEHAVIOR: A RETROSPECTIVE ANALYSIS OF A U.S. WEST COAST ROCKFISH

2.1 Abstract

The effects of a management action that reduces the total allowable catch of a single species in a multi-species fishery often has unpredictable consequences on the economics of the fishery. These potentially important effects can be explored using bioeconomic models that couple biological processes with a representation of fleet behavior that together determine expected biological and economic impacts that may result from a management change. When analyzing or testing fishery assessment methods or management tools it is important to account for economic incentives that drive fleet behavior, as fisherman behavior ultimately determines the level and distributions of mortality in a fishery. We applied a bioeconomic simulation framework to a complex multi-species fishery in order to illustrate that including a realistic economic component to a fisheries assessment model can provide important management and policy insights. We used a retrospective approach to take advantage of the available historical data on fleet behavior and economics, thereby reducing the guess-work inherent in predictions of human behavior in traditional forward-looking modeling approaches. We employed a novel method of characterizing the historical structure of the U.S. west coast groundfish trawl fleet and analyzed changes in fishing behavior that could have resulted from a changing catch constraint on a single species, canary rockfish (*Sebastes pinniger*). We categorized the range of fishing behavior that affected canary rockfish using different fishing ‘strategies’, each one varying in hypothetical effect on canary rockfish mortality by age and sex, as well as other species’ catch composition. Because each mixed stock fishing strategy utilizes different gear types and fishing locations, the canary rockfish selection-at-age varies across strategies, which in turn affects the age composition of the catch. Biological information from the age-structured assessment model created allowable catch, but the actual catch and its age structure each year were determined by the optimum catch strategies from the economic model. These values often differed from the expected biomass and age structure of the catch that was predicted by the biological model alone, and were fed back into the assessment model for each annual update. While the retrospective model results are somewhat speculative, we showed that catch limits informed by data-rich and data-deficient single-stock assessment techniques led to potentially beneficial fishing behavior for many species within a multi-species fishery, but had detrimental effects on two currently overfished species in the same stock complex. We also demonstrated that a ‘data moderate’ assessment technique (DB-SRA) resulted in foregone operating profits on the order

of \$5.5 million, not including the management and monitoring costs of implementing the assessment method. Incorporating simple fleet behaviors into assessment simulations can help identify optimum and likely fishing strategies when resources are constrained, and should be considered in evaluation of alternative management strategies.

2.2 Introduction

Fisheries assessment and management in the United States is centered on biologically-based performance measures. While these measures are essential for the long-term sustainability of the fisheries resource, they do not address important social and economic factors (Sylvia and Enriquez 1994) or wider ecological considerations (Essington and Punt 2011; Gaichas 2008; Botsford, Castilla, and Peterson 1997). The Magnuson-Stevens Fishery Conservation and Management Act (MSFCMA; NOAA 2007), mandates an integrated consideration of both biological and socio-economic factors in fisheries-related decision making. However, it does not provide guidance on the extent to which these different factors have to be taken into account, especially when setting total allowable catches (TACs), or designing stock rebuilding plans in the case of overfished species (Larkin et al. 2006). Even when economic factors are included in analyses, such as bio-economic fishery management models, the biological component is generally given much greater attention than economic factors in terms of both data and rigor of analysis (van Putten et al. 2012; Barclay 2012).

Although including multi-species considerations in fishery models increases their complexity, multi-species models are necessary to transition towards ecosystem-based fisheries management (Plagányi et al. 2014; Essington and Punt 2011; Field and Francis 2006; Cochrane 1999). However, the impacts of management measures in multi-species fisheries are difficult to predict without explicitly considering fisherman behavior (Wilens et al. 2002; Fulton et al. 2011). Although many models allow for interactions between multiple species, e.g. Punt et al. (2010), accounting for interactions between the multiple species in a biological model and fleet behavior predicated on economic theory is not as common. Bioeconomic modeling is an approach that allows us to meet biological management goals while simultaneously taking social and economic factors into consideration (Larkin et al. 2011). Bioeconomic models are particularly well suited for shedding light on the impacts of alternative management scenarios on a fishery. Fish and fishermen interact in ways that are often not intuitive to fishery managers, and models that illustrate these interactions are essential for implementing responsible fishery management plans (van Putten et al. 2012; Pelletier and Mahévas 2005; Hilborn and Walters 1987). For example, when setting TACs for a single

species in a multi-species fishery, the complex interactions between fishermen and the portfolio of harvest options is often neglected (Pelletier et al. 2009). As a result, a management action established to achieve optimal yield of a single species may have effects on other species in the fishery that are often not well understood and are potentially undesirable (Salas and Gaertner 2004). For example, Mackinson, Sumaila, and Pitcher (1997) showed that ignoring fishermen's targeting behavior for pelagic schooling fishes caused significant under-predictions of stock depletion rates, significantly increasing the risk of stock collapse above that expected by fisheries managers. In analytical models, Sanchirico and Wilen (1999) and Sanchirico and Wilen (2005) demonstrated that the equilibrium characterizing a spatial bio-economic fishery system is as dependent on economic parameters as stock characteristics. Sanchirico and Wilen (2001) show that the ability of a marine reserve to create value depends as much on assumptions regarding economic factors and economic behavior as biological factors. For example, the level of fishing effort in multi-species fisheries can remain high, and fishing profitable, even if one or more of the stocks are nearing depletion (Burgess, Polasky, and Tilman 2013). Despite these examples, the consideration of social and economic factors in fisheries management models is not widespread (Carruthers et al. 2014).

The importance of including social and economic factors in models for fisheries management is highlighted by a number of Management Strategy Evaluations (MSEs; Butterworth and Punt 1999; Holland, Bentley, and Lallemand 2005; Smith et al. 2009; Dichmont et al. 2010). However, most studies either do not include a *behavioral* economic component, or specify it in such a way that may not recognize the interactions between physical fishery characteristics and fishermen. For example, in an MSE of a range of harvest limits for the Australian northern prawn fishery, Wang and Wang (2012) assume that the number of fishing days per year is fixed, and that a fixed proportion is allocated to the different prawn fisheries. Dichmont et al. (2006) were among the first to include effort dynamics due to input controls (effort limits) in a MSE with fleet targeting behavior changing relative to endogenous fishery biomass. In an MSE of rock lobster in New Zealand, fleet size changed in response to both catch and catch limits in the fishery, but effort per vessel remained constant (Holland, Bentley, and Lallemand 2005). Maravelias, Pantazi, and Maynou (2014) evaluated alternative fishing input restrictions (effort and trawl net mesh size) in a Mediterranean trawl fishery, but the authors used a fixed level of effort and did not model how vessels would react to these management measures. Punt et al. (2010) include fixed and variable costs of fishing in a MSE of the Australian northern prawn fishery, as well as price fluctuations due to changes in size composition of the prawn populations. However, fishing effort is treated as a variable in a calculation to maximize the net present value of the fishery, and not as a behavioral component of the model.

Implementation uncertainty is one model component that potentially represents the behavioral response of fishermen to a management action, for example, the uncertainty of whether actual catch in the fishery will fall short of, meet, or exceed the catch limit set by managers. Implementation uncertainty is commonly blamed for the failure of management actions to achieve their stated biological goals (Cochrane 1999; Levontin et al. 2011), however it is not always easily incorporated into assessment models. For example, Punt and Ralston (2007) conducted an MSE of alternative rebuilding rules for Pacific rockfish species and set model catch equal to the policy recommendation. Cooke (1999), in a comparison of various harvest control rules, assumed that catch in the model is exactly equal to the catch limit set by the assessment model, although the author implements an upper bound on effort. When implementation uncertainty *is* incorporated into simulation models it is normally done by specifying an error term with an associated probability distribution (Punt, Dorn, and Haltuch 2008). Simulation exercises that incorporate a range of possible fishing effort levels or catches in this fashion can be useful for comparing the theoretical performance of alternative assessment techniques. However, we argue that a reason for including implementation error in these situations is to compensate for not including a behavioral model that explains how implementation error is produced. Whatever the management strategy or assessment technique being evaluated, models are designed to be applied in the real world- where fishermen behave in ways that may not be accurately represented by implementation error based on a distributional assumption. In the case of evaluating stock assessment techniques, it is also possible that fishermen's behavioral response to management actions will interact with assessment methods, changing the results of the comparison (Carruthers et al. 2014).

Considerations of implementation uncertainty and fishermen/fleet behavior are of particular importance in the evaluation of alternative methods for designating total allowable catch (TAC). With the majority of the world's fisheries in a data-deficient state, where little or no information that can be used to formulate a prediction of stock status exists (Costello et al. 2012), data-intensive stock assessment methods which are generally catch-at-age models fit to fishery-dependent and independent data, are not feasible for a large number of fisheries (Smith et al. 2009). As a result there has been much recent interest in the development and testing of data-deficient methods for setting acceptable catch limits (Dick and MacCall 2011; Wetzel and Punt 2011; Carruthers et al. 2014; Arnold and Heppell 2015). However, most of the evaluations of data-deficient methods do not incorporate a model to describe the dynamics of fisherman behavior as described by fishing effort, even though the spatial and temporal distribution of effort in a fishery defines the pattern of fishing mortality (Wilen et al. 2002). Fisherman behavior has been largely ignored in the evaluation of fishery assessment techniques (Plagányi et al. 2014). The complexity of assessments and their reviews prior

to advising management requires enormous time and effort; thus, it is not too surprising that economic data and changes in fishing behavior have not been fully incorporated into the assessment process.

Due to the complexity of many fisheries, bioeconomic models often take a forward-looking simulation-based approach, e.g. Dichmont et al. (2006), with a range of alternative scenarios projected under different environmental or economic conditions. But retrospective analyses can also be a useful way to examine how the interplay of fish and fisheries might have changed if alternative management strategies had been employed. For example, Marsden, Martell, and Sumaila (2009) analyzed how the profitability of the Fraser river sockeye fishery could have changed with the implementation of several different control rules. Martell, Walters, and Hilborn (2008) conducted a retrospective analysis of what could have happened in the Bristol Bay and Fraser river sockeye fisheries given current knowledge of the mean stock-recruitment relationships and variation in past recruitment. The main advantage of using a retrospective approach is that we know with relative certainty what *did* happen in a fishery, and can use that as a benchmark to compare what might have happened under different conditions (Arnold and Heppell 2015). Although there is often a high degree of uncertainty regarding stock biomass and distribution, the fisheries catch by year and economic variables such as fish prices, fuel prices, and revenues and costs are all known (albeit with a certain degree of observation error). This provides the researcher with a set of pseudo-experimental conditions under which the potential effects of management actions can be evaluated in order to inform future management.

We set out to explore the integration of behavior, economics, and biology in the management of a multi-species fishery with a retrospective bio-economic model that captures known elements of the past as data to inform current management scenarios. We analyzed fleet behavior in response to a data-rich management scenario and a data-deficient management scenario. Our goal is to illustrate one method of incorporating fleet dynamics into biological models that is simple to implement and based on sound economic theory. With historical data on fleet behavior in the U.S. west coast groundfish trawl fishery, we applied two management scenarios to the canary rockfish stock (*Sebastes pinniger*), a data-rich and data-deficient scenario. We chose canary rockfish due to its historical importance to the fishery and severe decline leading to an overfished designation in the 1990s and constraining effect on the multi-species groundfish trawl fishery for more than two decades.

2.2.1 RETROSPECTIVE CASE STUDY: CANARY ROCKFISH

The U.S. west coast groundfish trawl fishery (hereafter groundfish fishery) is complex, and over its history has included thousands of vessels of different gear types. Spatial and temporal variability in the distribution of fishing effort is high, harvesting more than 90 species of groundfish as either a targeted fishery, as by-catch, or incidental catch. Long-lived rockfish species are particularly important in the fishery, not only because of their economic market values, but also because of historic overfishing (PFMC 2011). Rebuilding plans for some species have resulted in significantly reduced catch limits that affect multiple fisheries. Because rockfish are caught by fishermen targeting a range of species using a variety of gears, the effect of a constraining catch limit has had serious impacts on the groundfish fishery (Field and Francis 2006). These impacts have led to changes in fishing strategies and targeting behavior, but those effects have not been fully examined.

Historical catches of canary rockfish reached 5500 metric tons in the early 1980s. The history of exploitation has been characterized by a period of overfishing followed by stock collapse and the implementation of a rebuilding plan in the early 2000s (Stewart 2009). A revision of rockfish productivity estimates, declining catches of rockfish species, and reauthorization of the Magnuson Act as the Sustainable Fisheries Act of 1996 (NOAA 1996), led to tightening controls on trawl vessels. However, by 2000 the fishery was in a state of ‘disaster’ (Hanna 2001). Several species of rockfish were designated as overfished and stringent rules were adopted in an effort to rebuild these stocks. These included bocaccio rockfish (*Sebastes paucispinis*), yelloweye rockfish (*Sebastes ruberrimus*), widow rockfish (*Sebastes entomelas*), darkblotched rockfish (*Sebastes crameri*), cowcod (*Sebastes levis*), and Pacific Ocean perch (*Sebastes alutus*). During the rebuilding period, canary rockfish was a highly constraining species in the fishery; low catch limits coupled with their harvest by alternative fleets and gear types has compelled fishermen to actively avoid canary rockfish in the fear that reaching the catch limit would cause the fishery to be shut down. Currently, a transferable quota system for groundfish trawl fisheries requires strict bycatch limits by vessel, which continues to affect fishing strategies.

The more than 90 species that are included in the Groundfish Fishery Management Plan (FMP; PFMC 2016) are required by the Magnuson-Stevens Act to have annual catch limits (ACL) established using the ‘best scientific advice’ Given the data requirements, human expertise, and time requirements necessary to conduct full stock assessments that estimate management reference points, including the ACL, less than 40% of the 90+ groundfish species included in the FMP have been fully assessed. Under current budgetary

restrictions approximately eight stock assessments are completed each assessment cycle, in addition to updates for overfished stocks that are managed under rebuilding plans.

2.2 Materials and Methods

The bio-economic model consisted of a population dynamics model of canary rockfish and an economic model simulating fleet behavior. The bio-economic model follows an iterative process that passes total allowable catch (TAC) from the population dynamics model to an economic model that calculates actual catch, accounting for fleet behavior, and passes actual catch back to the population dynamics model on a yearly time step (Fig. 2.1). The economic component was parameterized on historical fleet data such as revenues, costs, fleet capacity and fleet structure. The biological model begins in the year 1980 with the canary rockfish stock at levels estimated by the 2009 stock assessment (Stewart 2009). The population was projected forward through 2006 under a data-rich management scenario (DR) and a data-moderate management scenario (DM). In addition to the DR and DM management scenarios, a base case simulation was conducted keeping canary catch per trip and TAC at historical levels.

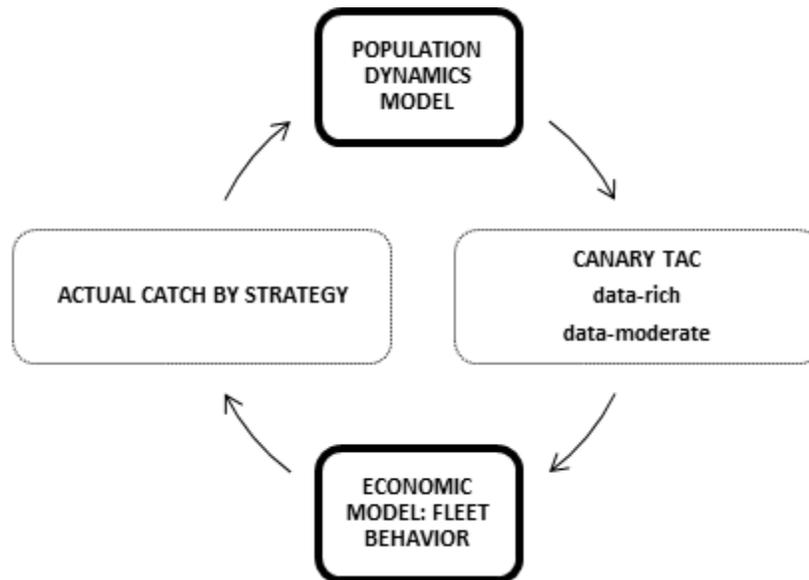


Figure 2.1 Iterative process of the bio-economic model. For each year, Total Allowable Catch (TAC) was calculated from the population dynamics model and passed to the economic model. Actual catch was calculated by the economics model and passed back to the population dynamics model.

2.2.1 POPULATION DYNAMICS MODEL

The population dynamics model is age- and sex-structured with recruitment defined by the Beverton-Holt (Beverton and Holt 1957) form of the stock-recruitment relationship:

$$N_{y+1,s,a} = \begin{cases} 0.5R_{y+1} & \text{if } a = 0 \\ N_{y,s,a-1} e^{-(M_{s,a-1} + \sum_{STG} S_{s,a-1,STG} F_{y,STG})} & \text{if } 1 \leq a < x \\ N_{y,s,x-1} e^{-(M_{s,a-1} + \sum_{STG} S_{s,a-1,STG} F_{y,STG})} + N_{y,s,x} e^{-(M_{s,a} + \sum_{STG} S_{s,a-1,STG} F_{y,STG})} & \text{if } a = x \end{cases} \quad \text{Eq. 2.1}$$

Where $N_{y,s,a}$ is the number of fish of sex s and age a at the start of year y ; x is the maximum age in the model, treated as a plus group (an age cohort accounting for all fish of age x and higher); $M_{s,a}$ is the instantaneous rate of natural mortality for fish of sex s and age a , assumed constant through time; $S_{s,a,STG}$ is the selectivity of the fishing strategy (STG) on fish of sex s and age a . Strategies are categories of fishing behavior that are based on gear type, fishing depth, and target species and are discussed fully in section 2.2.2. Selectivity is assumed constant through time, but varies by fishing strategy. F_y is the fully selected fishing mortality rate in year y and R_y is recruitment during year y :

$$R_y = \frac{4hR_0SB_y}{SB_0(1-h) + (5h-1)SB_y} (e^{-0.5\sigma_R^2 + Rdev_y}) \quad \text{Eq. 2.2}$$

Where h is the steepness of the stock-recruit curve (the fraction of unfished recruitment, R_0 , expected when spawning biomass, SB , is 20% of unfished spawning biomass, SB_0). Sigma R, σ_R , and the recruitment deviation in year y , $Rdev_y$, are error terms for each year defined by the 2009 stock assessment (Stewart 2009). SB_y is the spawning biomass in year y defined by the sum of mature female biomass from age 2 to the plus group, a_{max} :

$$SB_y = \sum_{a=2}^{a_{max}} p_a N_{fem,a} w_{fem,a} \quad \text{Eq. 2.3}$$

Where $N_{fem,a}$ is the number of females at age a , $w_{fem,a}$ is the sex-specific weight-at-age, and p_a is the proportion mature at each age, characterized by a logistic equation:

$$p_a = \frac{1}{1 + \exp(-\theta(a - a_{50}))} \quad Eq. 2.4$$

Where a_{50} is the age at which 50% of the females are mature and θ is 4x the slope of the maturity curve at a_{50} . Weight-at-age is an allometric function of length-at-age defined by:

$$w_a = XL_a^Y \quad Eq. 2.5$$

Length-at-age (L_a) is defined by the Von Bertalanffy growth model:

$$L_a = L_{inf} * (1 - e^{-k(a-a_0)}) \quad Eq. 2.6$$

Where L_{inf} is the average asymptotic length, k is the growth coefficient and a_0 is the theoretical age at zero length. Population and life history parameter values used in the simulation were taken from the most recent stock assessment of canary rockfish (Stewart 2009), and are given in Table 2.1.

Table 2.1: Input Parameters for the Population Dynamics Model

Parameter	Value		Description
<i>Population</i>			
R_0	3,335		unfished recruitment
SB_0	25,574		unfished spawning stock biomass
h	0.511		stock recruit curve steepness
σ_R	0.5		recruitment deviation
<i>Life History</i>			
	Female	Male	
M	0.6 ages < 7	0.06	natural mortality
a_{50}	8		age at which 50% of females are mature
θ	0.25		4x slope of maturity curve at a_{50}
X	0.000016		parameter for weight at age
Y	3.03		parameter for weight at age
L_{inf}	60	52	average asymptotic length
K	0.131	0.170	growth coefficient
a_0	0.102	0.202	age at zero length

Catch in year y was calculated using the Baranov catch equation (Baranov 1918) to determine the catch at age, sex, and strategy such that:

$$C_y = \sum_a \sum_s \sum_{STG} N_{a,s} \left(\frac{\sum_{STG} S_{a,s,STG} F_{STG}}{M + \sum_{STG} S_{a,s,STG} F_{STG}} \right) (1 - e^{-(M + \sum_{STG} S_{a,s,STG} F_{STG})}) \quad Eq. 2.7$$

Equation 2.7 was incorporated into the objective function in an optimization model that searched for the values of F_{STG} resulting in a value of C_y equal to the total catch passed from the economic model. The model was constrained to values of F for each strategy that resulted in a catch-per-strategy equal to the proportions given by the economic model.

2.2.1.1 Management Scenarios

Two management scenarios, one where fishery independent, age-structured data were available on an annual basis (the ‘data-rich’ scenario) and the other where only an estimate of stock size was available on an annual basis (the ‘data-moderate’ scenario), were used to calculate the total allowable catch (TAC) passed to the economic model. The data-rich scenario is modeled on the harvest control rule (HCR) defined by the Pacific Fisheries Management Council (PFMC) for groundfish TAC. This HCR sets catch based on estimates of current spawning biomass, SB_y , and unfished spawning biomass, SB_0 , following the formulation described in Punt and Ralston (2007):

$$\tilde{C}_y = \begin{cases} 0 & \text{if } \frac{SB_y}{B_0} < \alpha \\ \frac{\beta SB_0}{SB_y} * \frac{(SB_y - \alpha)}{(\beta - \alpha)} * C(F_{MSY})_y & \text{if } \alpha \leq \frac{SB_y}{SB_0} < \beta \\ C(F_{MSY})_y & \text{if } \frac{SB_y}{SB_0} \geq \beta \end{cases} \quad Eq. 2.8$$

Where β is the threshold reference point and α is the stock size below which target catch is 0. In this study, the alpha and beta parameters were set to 0.10 and 0.40, respectively, following management practice on the U.S west coast (PFMC 2016). Above the threshold reference point, expected catch is determined by a proxy of the fishing mortality rate that produces maximum sustainable yield, F_{MSY} . The expected catch for year y corresponding to a fishing mortality rate of F_{MSY} is calculated as:

$$C(F_{MSY})_y = \sum_s \sum_a w_{s,a} N_{y,s,a} \frac{S_{s,a} F_{MSY}}{(M_{s,a} + S_{s,a} F_{MSY})} (1 - e^{-(M_{s,a} + S_{s,a} F_{MSY})}) \quad Eq. 2.9$$

The F_{MSY} proxy used in this study was the constant fishing mortality rate that reduces the lifetime egg production, LEP , of a stock to $x\%$ of that in the unfished condition, $F_{x\%}$ (Clark 1991, 2002). Consistent with the PFMC F_{MSY} proxy for rockfish defined in the 2011 Fishery Management Plan (PFMC 2011) we chose

$F_{50\%}$. LEP is a function of the proportion mature at age, p_a , the relative fecundity at age, Φ_a , and female survival from age 1 to age a , such that:

$$LEP = \frac{\sum_{a=0}^{amax} \exp(-(M \cdot a + \sum_{a=0}^a F_a)) \cdot \Phi_a \cdot p_a}{\sum_{a=0}^{amax} \exp(-M \cdot a) \cdot \Phi_a \cdot p_a} \quad Eq. 2.10$$

For the data-moderate scenario, the TAC was defined by the overfishing limit (OFL) calculated by Depletion-Based Stock Reduction Analysis (DB-SRA; Dick and MacCall 2011). DB-SRA generates probability distributions of the maximum sustainable yield (MSY) and was implemented in this study using a delay-difference production model:

$$B_t = B_{t-1} + P(B_{t-a}) - C_{t-1} \quad Eq. 2.11$$

Where B_t is biomass at time t , P is latent annual production (based on a preceding parental biomass), and a is the age at reproductive maturity. The latent production function used in this analysis is the alternative hybrid Schaefer-PTF model developed by Dick and MacCall (2011) that approximates a Beverton-Holt stock-recruitment relationship without restricting peak productivity to one-half of the unfished biomass. DB-SRA requires the catch time series and five input parameters: (1) an estimate of stock status, (2) the biomass at MSY relative to the unfished state (B_{MSY}/K), (3) the ratio of F_{MSY} to M , (4) M , and (5) the age of 50% maturity.

2.2.2 ECONOMIC MODEL

The economic model simulated changes in historical fishing behavior in response to an annually varying constraint (TAC of canary rockfish) on a multi-species fishery. Fleet behavior defined the difference between the TAC and the actual catch, creating a more realistic evaluation of assessment scenarios than assuming actual catch is equal to the value of the constraint, or setting the difference between TAC and catch with an error term. The interaction of the economic model with the biological model through differential selectivities also caused differences in the age structure of the removal from the population. Because different fleets also had different selectivities due to where and how they fish, the actual catch could have a different age structure than expected from a purely biological model. The major challenge in this modeling exercise was determining how best to model the complex U.S. west coast trawl fishery in a way that preserved the historical structure of the fishing fleet while allowing the model to respond to changes in the TAC for canary rockfish, without markedly increasing overall model complexity.

Historically, the U.S. west coast trawl fleet was composed of thousands of vessels, differing in size and horsepower, with significant heterogeneity in fishing behavior. Using vessel-level fish ticket information collected by the west coast states and maintained by the Pacific States Marine Fisheries Commission (PSMFC), we defined six mutually exclusive fishing strategies (Table 2.2) that encompassed the entire range of fishing behavior displayed by the west coast trawl fleet during the modeling period, and which are similar to those used by Babcock and Pikitch (2000). These strategies are defined using the gear type indicated on the fish ticket, and the species composition of the catch. We assumed that a single fish ticket corresponded to one ‘trip’ and assigned a ‘strategy’ to every fish ticket collected within the modeling period. Our strategies are somewhat analogous to the concept of ‘métiers’ discussed by Ulrich et al. (2002), which categorize fishing behavior in terms of a target species and area fished.

Table 2.2: Fishing strategy definitions for the economic model

Code	Strategy	Description	Notes
DT	Dover/Thornyhead /Sablefish (DTS complex)	If a fish ticket record shows "any other trawl" gear is used and DTS \geq 33% revenues for the trip.	Deep water fishing on the continental slope
SR	shelf rockfish	If a fish ticket record shows "any other trawl" gear is used and DTS $<$ 33% revenues and rockfish complex $>$ 50% revenue	Shallow water fishing with roller gear on rocky habitat
PW	Pacific whiting	If a fish ticket record shows "midwater trawl" gear is used and whiting \geq 50% revenue for the trip	Mid-water trawling, no roller gear, exceedingly low bycatch
PY	pelagic rockfish	If a fish ticket record shows "midwater trawl" gear is used and whiting $<$ 50% revenue for the trip	Mid-water trawling for pelagic rockfish species
SH	shrimp	If a fish ticket record shows any "shrimp trawl" gear is used.	Small mesh size nets on mud/sand bottoms, often shallow water.
NF	nearshore mixed species	If a fish ticket record shows "any other trawl" gear is used and DTS $<$ 33% revenues and rockfish complex $<$ 50% revenue.	Main targets are roundfish and flatfish-bottom trawl gear used, often with small roller gear.

Examination of the data showed that some vessels exclusively pursued one strategy in a given year, while others switched between strategies throughout the year. In order to impose a historical structure on the

model, we created ‘sub-fleets’ composed of all vessels in the fishery that pursued a particular set of strategies in a given year. For example, vessels which pursued the DT strategy exclusively were grouped into a sub-fleet, and vessels that pursued only strategies DT, SR, and PY in a given year were grouped into another sub-fleet. With a possible number of combinations in each year of 720 (6!), a maximum of 38 sub-fleets in 1994, and a minimum of 21 sub-fleets in 2006 characterized the fleet. Using vessel logbook data from 1987 to 2006 (the years in which logbook data were available) we calculated average length of trip (measured in days) by strategy in each year. For the years 1981-1986 (in which logbook data were unavailable) we used the average of the trip lengths in 1987 and 1988 as an estimate. The capacity of each sub-fleet in each year (y), defined as number of trip days, was calculated as:

$$Capacity_{fy} = 1.05 \cdot \sum_{j=1}^{J=6} Number\ of\ trips\ made_{jy} \times Length\ of\ trip\ (days)_{jy} \quad Eq. 2.12$$

Where j is strategy and f is sub-fleet. Our capacity calculation assumed that vessels would exert a maximum effort equal to what was observed historically, while allowing total effort to increase by a nominal 5% in each year. This assumption precludes the ability of vessels to exert a total amount of effort much beyond historical levels.

2.2.2.1 Selectivity-by-Strategy

In addition to gear type, target species, and catch composition, strategies are associated with different selectivity curves for canary rockfish. Selectivity curves are used in the equations for survival (Eq. 2.1), and catch (Eq. 2.7) to account for differential fishing mortality by age. Since each strategy was defined by different gear types and fishing depths, and the depth distribution and vulnerability to gear of canary rockfish is age-specific, the selectivity curves vary by strategy according to the hypothesized vulnerability of canary rockfish to a strategy. The DT, PY, and SR strategies were defined by asymptotic selectivity based on the selectivity curve of the Oregon trawl fleet, as defined by the 2009 assessment (Stewart 2009). The PW strategy was also asymptotic and based on the at-sea whiting selectivity curve in the 2009 assessment. The highly domed-shape selectivity curve of the NF strategy was based on the southern California trawl fleet selectivity curve (Stewart 2009). Finally, the SH strategy was defined by an exponential-logistic selectivity curve:

$$S_a = \frac{\exp[\gamma\alpha(\beta - a)]}{1 - \gamma[1 - \exp[\alpha(\beta S - a)]]} \quad Eq. 2.13$$

Where $1/\alpha$ is the scale, β the peak, and γ is the shape parameter. Alpha (female: 2.0, male: 2.1) beta (female: 5, male: 5) and gamma (female: 0.2, male: 0.14) were chosen to create a hypothetical, biologically realistic, curve describing the selectivity of canary rockfish to the shrimp fishery. Given that a shrimp trawl operates with fine mesh nets over soft bottom, and young canary rockfish settle in shallower water before moving deeper (Love, Yoklavich, and Thorsteinson 2002), the younger age classes are more likely available to the shrimp trawl vessels. Selectivity time blocks were used to model management actions that required gear modifications, specifically, footrope restrictions which removed the bottom trawl fleet from high-relief rocky habitat. Selectivity is assumed constant through time for the PW, DT, PY, NF, and SH strategies. Selectivity for the SR strategy switches from asymptotic to dome-shaped in 1995 and changes again in 2000 (figure 1). Time blocks for the SR strategy are based on the 2009 canary rockfish stock assessment (Stewart 2009).

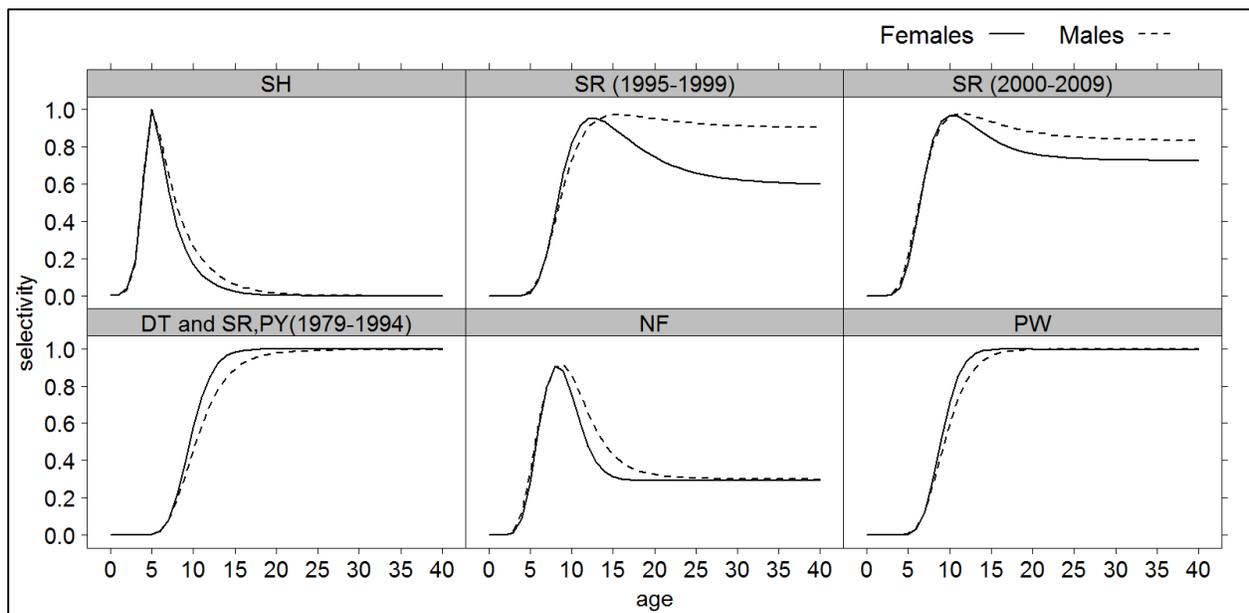


Figure 2.2: Canary rockfish selectivity curves by strategy. Males (dotted line) and female rockfish (solid line).

All species caught in the fishery were assigned to 11 species groups (Table 2.3). Canary rockfish formed its own species group and all other species were formed into groups of economic and strategy-specific relevance. For example, the Dover sole/Thorny-head rockfish/Sablefish (DTS) complex was composed of these three species and is a common target group for trawlers in the west coast fishery. This complex made up a significant portion of the catch in the DT strategy. Pacific whiting and shrimp are main targets for

pelagic trawlers and shrimp trawlers respectively and make up the majority of catch in the PW and SH strategies.

Table 2.3: Species groupings for the economic model

Code	Species
CAN	Canary rockfish
DTS	Dover sole, Thornyheads, Sablefish
OFF	All other flatfish
ORF	All other rockfish
OOF	All other roundfish
SHS	Sharks and skates
PWH	Pacific whiting
SHR	Shrimp
PEL	Pelagic species
HMS	Highly migratory species
OTH	All other species

Using fish ticket revenue data in each year we calculated average annual price per species group by dividing total revenues per species group by delivered weight. We found significant differences in species group prices between strategies, possibly due to 1) a different mix of species caught in each strategy which leads to price differentials 2) different volumes of species delivered, 3) seasonal market conditions, or 4) perceived quality differences in the catch between strategies. We calculated catch per trip of each species group as the trip average of the total catch by strategy in each year, and revenue per strategy trip was calculated as the product of this and the calculated price by species group, which included strategy-specific differences.

2.2.2.2 Economic model output: actual catch

For the economic model to return actual catch to the biological model, we had to define the historical relationship between canary rockfish biomass and catch rates in the fishery. We estimated log-log

transformed linear regressions for the relationship between observed catch (from fish ticket data) and total biomass (as estimated in the 2009 stock assessment for canary rockfish (Stewart 2009)). We conducted separate regressions for the DT, SR, PY, and NF strategies (j). Canary catch was extremely low in the SH and PW strategies and we assumed that catch in these strategies did not change with canary stock status. The estimating equations took the form:

$$\ln[\text{canary catch per trip}_j] = \beta_{1j} + \beta_{2j} \ln[\text{canary biomass}] + \varepsilon_j \quad \text{Eq. 2.16}$$

The results of these regressions are shown in Table 4. In the simulation we used the beta coefficients and estimates of canary rockfish biomass derived from the biological model to calculate canary rockfish catch per trip in each year for each strategy. Catch per trip of the other 10 species groups were assumed to remain at historical levels. The actual catch of canary rockfish was calculated as the product of catch per trip by strategy (kg) and the level of effort exerted (trips).

Table 2.4: Regression coefficients used to estimate actual catch per trip by strategy.

Strategy	β_1 (CONSTANT)	β_2 (lnBIOMASS)
DT	2.2478	0.3277 *
SR	3.3517 *	.3734 *
PY	-17.021 *	2.0102 *
NF	-1.2576	.5216 *

* indicates significance at 5% level.

The purpose of the economic model was not to arrive at a perfectly accurate retrospective estimation of fleet profitability, but rather to evaluate changes in fishing behavior due to the constraints on harvest of a single species in a multi-species fishery. We did not include a detailed measure of fleet profitability (e.g., fixed costs) with which we could evaluate welfare effects. We did, however, include a proxy for variable costs. In deciding on a particular fishing strategy at any point in time, profit-maximizing fishermen will decide on the action that maximizes vessel profits, and in doing so maximizes crew share, which is normally paid on the lay system (PSMFC 1999). While crew compensation is the main component of variable cost, we did not include a measure of it as vessel behavior is hypothesized to respond to changes in net revenue over alternative strategies, of which crew share is a simple proportion. The second largest component of variable costs, which we hypothesized may have an effect on fishermen's choice of strategy, is fuel costs

(an average of 13% of total variable costs) (PSMFC 1999). Fuel costs vary according to the length of time that the vessel takes to make a trip, how far away from port the vessel fishes, and the particular activity that the vessel is engaged. To calculate average fuel consumption per trip, we used data on average gallons of fuel consumed per hour by fishing activity from an economic survey conducted by the Pacific States Marine Fisheries Commission (PSMFC 1999). Of the vessels in the survey, fuel consumption averaged 13.15 gallons per hour while trawling, 11.06 gallons per hour while shrimping, 11.58 gallons per hour while steaming fully loaded, and 9.96 gallons per hour while steaming empty. Using vessel logbook data on length of trip by strategy, we assumed that a vessel's trip time was spent equally between trawling (or shrimping in the SH strategy), steaming-fully loaded, and steaming-empty. We then combined average fuel consumption per trip by strategy with a price series of average cost of #2 diesel fuel in U.S. west coast ports from 1981 to 2006 (EIA 2009) to arrive at an estimate of fuel consumption per trip by fishing strategy.

As our model was a short-run model of fleet behavior, and entry and exit into the fishery were effectively captured in our time series data on fleet capacity, we did not include entry/exit behavior endogenously in the model. The implicit assumption is that the change in the stock status and availability to the fishermen of canary rockfish would not have affected a fisherman's entry or exit decision within a particular year. As a result, fixed costs were not included in the model. Using our calculated historical prices, trip fuel costs, and estimates of actual catch per trip, we conducted an optimization procedure in each year using GAMS (GAMS Development Corporation.2013), in which the decision variable was the number of trips made in each strategy by sub-fleet. The objective function for each year, y , is:

$$Max_x(NET\ REVENUE) = \sum_{f=1}^F \left(\left(\sum_{j=1}^J X_{fjy} \cdot \sum_{i=1}^N R_{ijy} \right) - \left(\sum_{j=1}^J X_{jfy} \cdot B_{jfy} \right) \right) \quad Eq. 2.17$$

Where i =species, j =strategy, f =sub-fleet, X_{jf} is the number of trips made per sub-fleet in each strategy, R_{ij} is revenue per trip for each species per strategy, and B_{jf} is fuel cost per trip per strategy.

Equation 2.17 was maximized subject to constraints on catch (equation 2.18) and effort (equation 2.19), which varied according to sub-fleet:

$$\sum_{f=1}^F \sum_{j=1}^J X_{jfy} \cdot C_{ijy} \leq E_{iy} \quad \forall i, y \quad Eq. 2.18$$

And

$$\sum_{j=1}^J X_{jfy} \cdot D_{jy} \leq G_{fy} \quad \forall f, y \quad \text{Eq. 2.19}$$

Where C_{ij} is catch per trip by species in each strategy, E_i is TAC by species group, D_j is length of trip by strategy, and G_f is the historical capacity of each sub-fleet. Note that while effort could not exceed that observed historically, it was free to vary below that limit.

The fishery was modeled from a sole owner perspective that allowed us to arrive at an outcome that provided a ‘best-case’ scenario with which to evaluate possible changes to the fishery. As well as capacity constraints (canary rockfish TAC) on the sub-fleets in each year, sub-fleets were limited to a maximum allowable catch of various species. We relaxed the constraints on the “sharks and skates” (SHS), “pelagic” (PEL), “highly migratory” (HMS), and “other species” (OTH) species groups, by setting these TACs to levels that would not be reached before other species became constraining in the model. These species groups have not historically been subject to catch limits. As Pacific whiting and shrimp were the main drivers of catch in the PW and SH strategies, and canary rockfish were rarely present in these catches, we set the TACS for these species equal to the amount of fish actually caught historically. Canary rockfish was a significant component of the catch in all other strategies and in order to allow some flexibility in the model we increased TACs for DTS, OFF, ORF, and OOF species groups by 5% above actual historical catch. We therefore treated historical catches as pseudo catch-limits in our model, albeit with flexibility built-in.

2.3 Results

2.3.1 MODELED CATCH

Under the DR and DM management scenarios, canary rockfish TACs were set far below the level of catch observed historically from 1981-1993, with an initial decrease of 43% and 64%, respectively (Fig. 2.3). After this initial period, TACs increased above the level observed historically, and remained above the historical catch as the modeled canary population never became overfished. The DM scenario was more restrictive than the DR scenario during the first 10 years of the modeling period, but this relationship reversed thereafter. Canary rockfish catches were generally equal to the TAC until 2000, and then fell below the TAC level thereafter due to other species in the model becoming constraining on fishing effort.

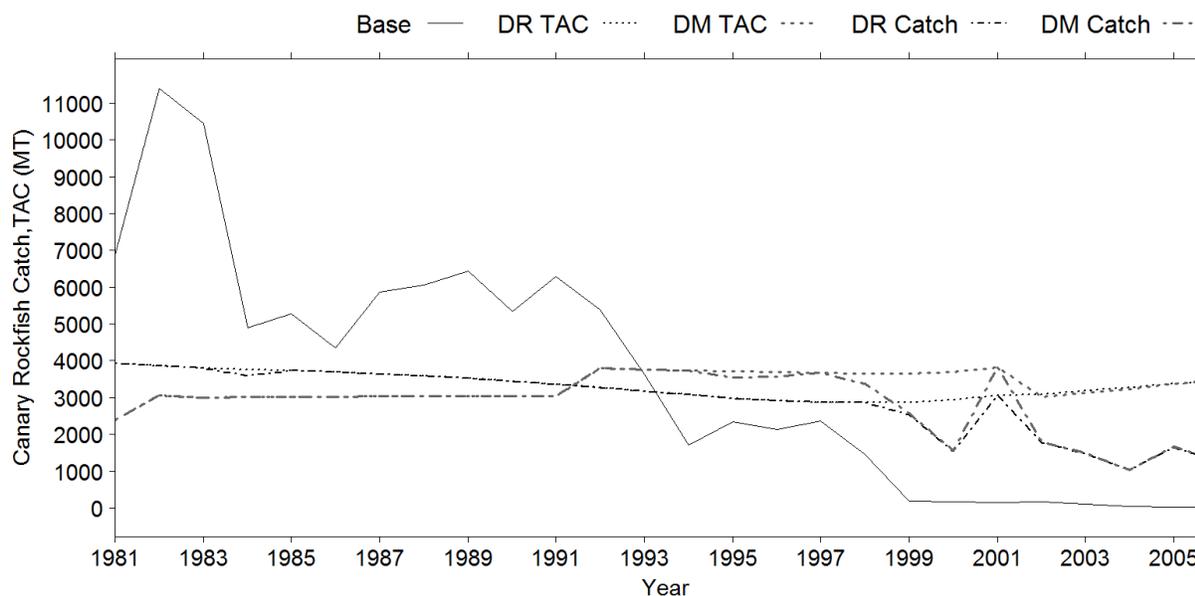


Figure 2.3: Canary rockfish TACs and modeled catch.

2.3.2 FLEET BEHAVIOR

To maximize total fishery profits, fleets switched between strategies depending on historical prices, catch rates of all species groups, and the constraints on catch of species groups. A fundamental pattern emerged: when canary TACs were reduced to levels significantly below historical catches, fleets exerted increased levels of effort in the pelagic rockfish (PY) strategy and decreased effort in the shelf rockfish (SR) strategy (Fig. 2.4). Switching behavior was not as evident (although still present) between the other strategies, and effort levels in these strategies remained largely the same as historical levels. The non-SR and PY strategies were associated with significantly lower catch rates of canary rockfish and were less affected by changes in the catch limits for this species.

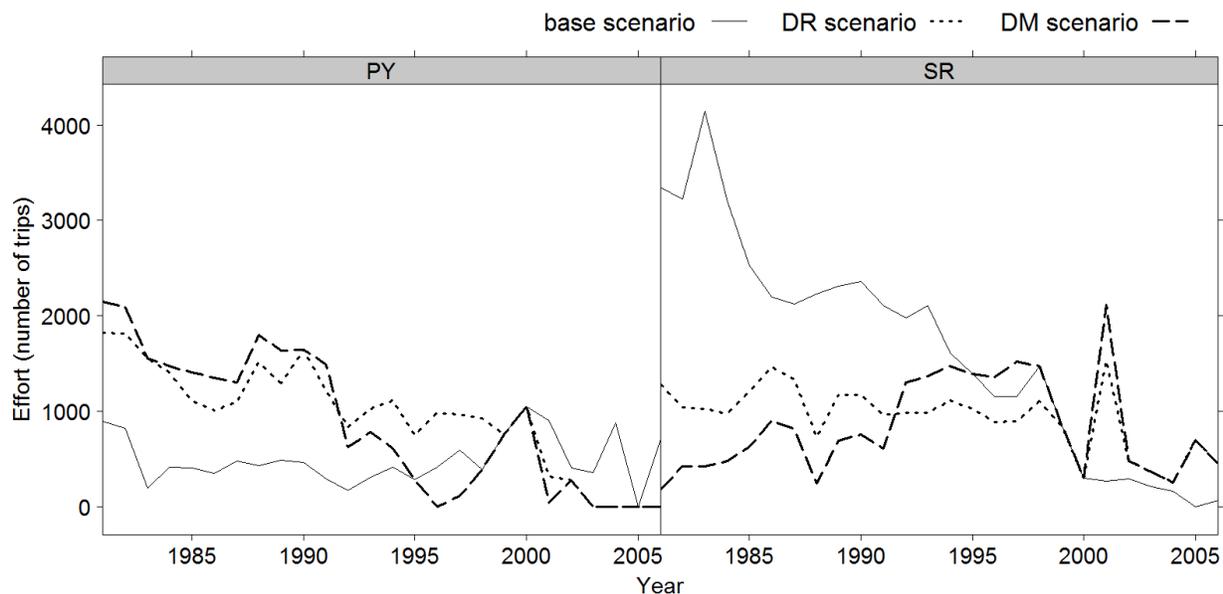


Figure 2.4: Number of fishing trips (effort) per strategy.

2.3.3 OPERATING PROFITS

As a result of the reduced TACs and catches through the 1990s, model-generated operating profits were far below the level observed historically during this time period (Fig. 2.5). After 1998, due to a combination of increased TACs and increased catch per trip of canary rockfish, operating profits increased above the level observed historically, and remained there for the remainder of the simulation period. At a 5% discount rate, and looking retrospectively at the cumulative value of the operating profits in the fishery, the historical value in the west coast trawl fishery from the base simulation was calculated as \$943.63 million. Under DR and DM assessments, that value was reduced to \$928.57 million and \$923.1 million, respectively. This represents a discounted difference of \$15.06 million for the DR scenario, and \$20.53 million for the DM scenario, or 1.6% and 2.2%, respectively.

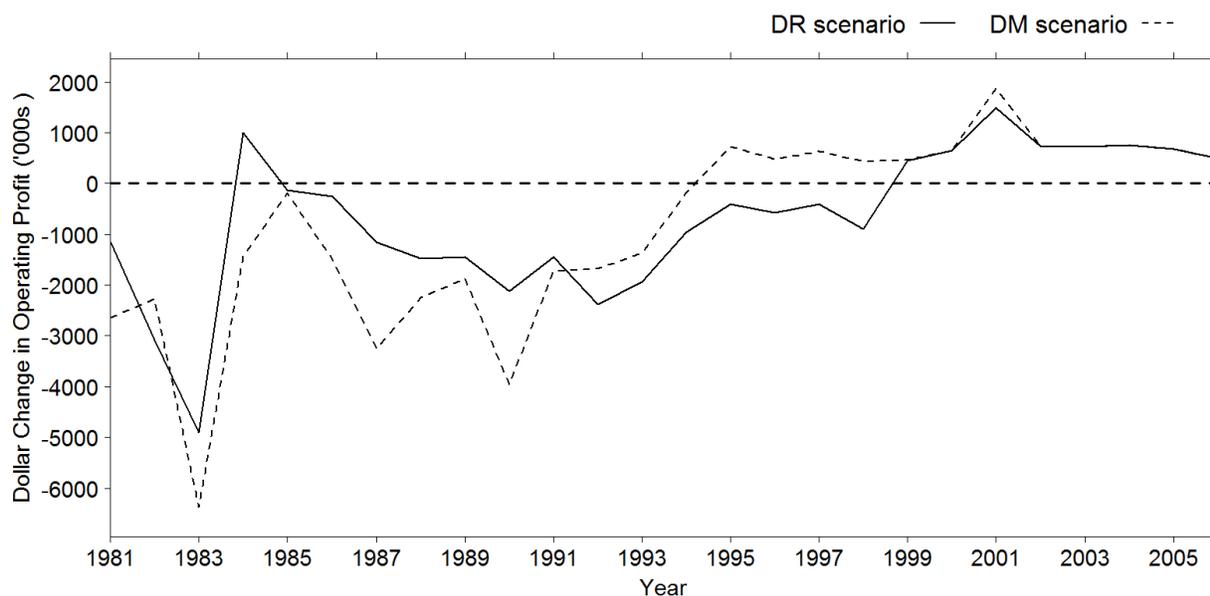


Figure 2.5: Change in operating profits (the difference between total revenues and variable costs) relative to historical profits for the data-rich and data-moderate scenarios. The dashed line represents the level of operating profits calculated using the base scenario

2.3.4 MARGINAL VALUES

In our model canary rockfish TACs were constraining on the fleet from 1981-1999 for the two management scenarios, and until 2006 for the base scenario (Fig. 2.6). The marginal value of canary rockfish for each management scenario, is interpreted as the value to the objective function (total fishery operating profits) of relaxing the catch constraint on canary rockfish by a marginal amount. In the base run, canary rockfish are extremely constraining towards the latter end of the modeling period with a maximum marginal value of \$22.19 in 2004 (Fig. 2.6). In each of the management scenarios, canary rockfish were a constraining species in the model until 1999, after which other species became constraining (Fig. 2.7). As a result, modeled catches of canary rockfish failed to reach the level of the TAC in these later years.

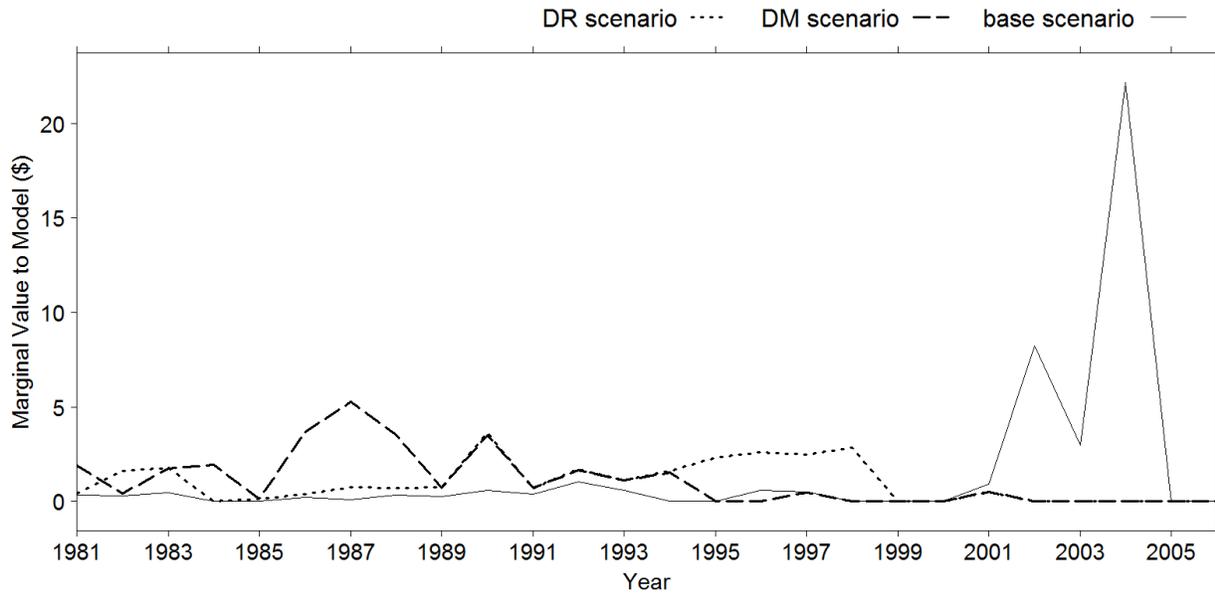


Figure 2.6: Marginal value of canary rockfish for each management scenario. The marginal value represents the value to the objective function (total fleet operating profits) of relaxing the catch constraint on canary rockfish by one kg.

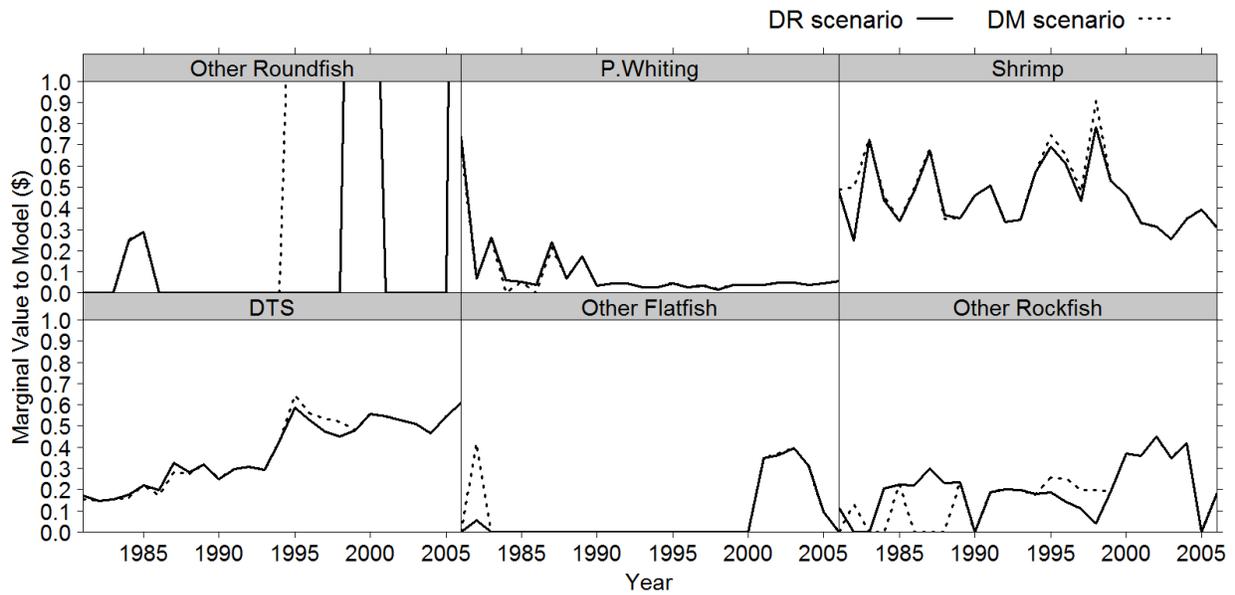


Figure 2.7: Marginal values of Other Species Groups in the Model. Marginal values for the ‘Other Roundfish’ group were in the \$2-\$5 range between 1995 and 2005.

2.4 Discussion

Our bioeconomic model illustrates how an economic model of fishing behavior can be incorporated into an assessment evaluation model. We also demonstrate a method for representing the behavior of heterogeneous fishermen in a complex, multi-species fishery based on their portfolios of multiple strategies. Our results showed that under two management scenarios (based on the 40-10 and DB-SRA models), the stock status of canary rockfish could have remained at a level that was above the management target. Total operating profits in the fishery for all species, however, would likely have decreased significantly throughout the modeled time period due to the constraining nature of decreasing allowable catches of canary rockfish. In addition, altered targeting behavior of fishermen could have had potentially serious consequences for other stocks in the fishery. Our model shows that fishermen are likely to have changed their behavior significantly, and in such a way that would have significant impacts on the other stocks in the fishery, including currently other overfished stocks. The main switching behavior that occurred under both alternative management scenarios was between the shelf rockfish (SR) strategy and the pelagic rockfish (PY) strategy. The main component of catch in both the SR and PY strategies was the rockfish (ORF) complex, although catches of canary rockfish were almost exclusively higher in the SR strategy than the PY strategy. The pelagic stocks of rockfish, which are mainly composed of yellowtail rockfish (*Sebastes flavidus*) and widow rockfish (*Sebastes entomelas*) (two species that are or recently have been subject to rebuilding plans), would have been exposed to more fishing pressure. Decreased pressure in the SR strategy has important implications for pressure exerted on species associated with this strategy. Many of the species designated as overfished in the early 2000s by the Pacific Fisheries Management Council (PFMC) have historically been caught by fishermen employing this strategy. These species include the Pacific ocean perch (*Sebastes alutus*), yelloweye rockfish (*Sebastes ruberrimus*), bocaccio rockfish (*Sebastes paucispinis*), darkblotched rockfish (*Sebastes crameri*), yellowtail rockfish (*Sebastes flavidus*), cowcod (*Sebastes levis*), and lingcod (*Ophiodon elongatus*). Our results suggest that decreasing the binding TAC for canary rockfish would have meant decreased pressure on a number of species that were designated as overfished in the early 2000s, while increasing pressure on others.

We showed that after a period when canary rockfish catches (and TACs) would have been far below their historical levels, eventually harvest could have superseded the historical catch. This pattern of lower, less variable catch followed by steadily increasing catches in the later part of the modeling period translated into operating profits that followed the same pattern. While operating profits were shown to gradually supersede the level observed historically, profits were significantly lower in the early stages of the modeling

period. From a retrospective perspective, and given a 5% discount rate, the foregone value of operating profits (revenues minus fuel costs) in the fishery between 1981 and 2006 amounted to \$15.06 million for the 40-10 scenario, and \$20.53 million for the DB-SRA scenario, or 1.6 and 2.2% of total discounted profits, respectively. This was due to the decreased TACs for canary rockfish in the early stages of the simulation which caused vessels to switch from the relatively profitable SR strategy to the less profitable PY strategy. In addition, total effort levels in the fishery decreased significantly relative to historical levels between 1981 and 1985 due to the constraining nature of the canary TAC. Total effort was reduced by an average of 3.3% for the 40-10 scenario, and 5% for the DB-SRA scenario during this early time period. After this initial period, total effort levels agreed relatively well with historical levels and changes in operating profits were due mainly to switching behavior, illustrating the potential flexibility that fishermen have in responding to catch constraints.

In terms of discounted future value of operating profits, the 40-10 harvest control rule out-performed the DB-SRA method. However, without accounting for the difference in costs of completing assessments and management actions under the two scenarios, it is unclear which scenario would have resulted in higher benefits to the fishery. The 40-10 harvest control rule relies on a more accurate estimate of stock status in each year. These estimates are generally derived from complex assessment models that make use of both fishery independent data (mainly collected through an annual west coast trawl survey), and fishery dependent data (such as catch and effort data). Currently, full stock assessments are conducted for approximately 8 species per year due to resource constraints. DB-SRA is classified as a ‘data-poor’ method, and relies on a time-series of fisheries catch as the main input, although initial estimates of stock status and biological parameters are required. Given that no fisheries independent data are required for implementation of DB-SRA, it is relatively less expensive than a 40-10 approach that requires full assessments. Depending on the costs of assessments, our results suggest that a DB-SRA approach could be more economically efficient than other TAC-setting approaches that require full stock assessments.

Maintaining a healthy population of canary rockfish would have meant significant changes to the fishery starting in 1981. Management capabilities of state and federal agencies in the early 1980s were in a development phase- strict enforcement of catch limits and the prevention of discarding would have proven difficult. In addition, stock assessment techniques were still being developed and there was limited knowledge of the life history of rockfish species. As is true for any model that attempts to capture the salient features of a complex fisheries system, the assumptions restrict the applicability of our results and conclusions that we may draw from them (Carruthers et al. 2014). For example, trip limits for canary

rockfish were not instituted until the mid-1990s, although trip limits for the *Sebastes* complex (of which canary are a component) were introduced starting in the mid- 1980s. These trips limits changed frequently in response to many factors such as in-season catch rates and assessments. Modeling how these trip limits were set in response to these factors was an unrealistic task and as a result we imposed a fleet-wide TAC which served as the maximum amount of each species that each vessel could catch. In estimating the relationship between catch per trip of canary rockfish and the biomass of the stock, we used the best available estimate of stock biomass through time. These estimates were derived from the most recent stock assessment for this species (Stewart 2009). Whereas catch, revenue, and effort data are observable and are known with certainty (minus measurement error), stock status at any moment in time is not. Fish are not directly observable and any information regarding the status of the stock has to be inferred from fitted population dynamics models based on samples from the population. Estimates of the status of the canary population are thus likely to be uncertain. Catch and revenue data are also subject to reliability issues. Although the trend through time is one of greater collection of data on a species level, in the early years of the modeling period estimates of individual species catch were restricted to a few commercially important species. Catch reconstructions based on species composition sampling conducted by state agencies make up a significant portion of historical catch by-species-data. However, given these caveats, our model does illustrate implications of managing one species in a multi-species fishery.

The capacity constraint that we employed- in which sub-fleets were restricted to the ‘mix’ of strategies and total effort levels consistent with historical patterns allowed a historical structure to be imposed on the model. This method may prove useful for characterizing fishing fleets in future work. The main assumption in using this approach was that the influence of a changing TAC of only one species would not be enough to cause significant capacity changes in the fishery in a given year. In addition, we assumed that within a year, vessels that historically did not target a particular ‘strategy’ would not change their targeting behavior due to a change in the TAC of canary rockfish. Employing these assumptions allowed us to examine potential fishing fleet behavior in a way that preserved the historical characteristics of the west coast trawl fleet.

The U.S. west coast trawl fishery is extremely complex with many heterogeneous vessels, a substantial geographic range, and many species. Modeling this type of complex fishery is a challenge and requires some simplifying assumptions. In some ways the retrospective approach simplified this task because instead of predicting variables such as fish prices, fuel costs, and fleet size and structure into the future, these variables were available from publicly accessible databases and were known with a relative amount of

certainty. What was left was to predict how fishermen *would have* made decisions when faced with a change in fishery conditions, such as an initial reduction in the allowable catch of a currently overfished rockfish species. This task is arguably easier than predicting how fishermen would make decisions in the future given the high levels of uncertainty surrounding many aspects of the fishery. As such, a retrospective approach has value in predicting the effects of management actions in complex fisheries situations, a value which may then potentially be used to inform future management. However, any results gleaned from a retrospective analysis may have limited applicability to current fisheries management in that our results do not tell us what the best course of action is, and what we are left with are useful insights on how a fishery may potentially respond to management actions.

2.5 CONCLUSION

The effects of a management action that reduces the total allowable catch of a single species in a multi-species fishery often has unpredictable consequences on the economics of the fishery. We have explored a retrospective approach to modeling a complex multi-species fishery and showed that historical data can be used to reduce the number of ‘predictions’ that must be made compared to a traditional ‘forward looking’ approach. We employed a novel fleet-strategy method of characterizing the historical structure of the west coast groundfish trawl fleet and used this structure to analyze the potential changes in fishermen behavior that could have occurred due to changing catch constraints for canary rockfish. While it is difficult to state precisely what ‘would have happened’, we showed that starting from a time when it was considered a healthy stock, if canary rockfish had been managed using two contemporary methods for setting fisheries catch limits, fishing behavior is likely to have changed in such a way that would have had potentially beneficial stock effects on many threatened rockfish species commonly caught in a ‘shelf-rockfish’ strategy, and potentially detrimental effects on two other species that are currently subject to rebuilding plans. Finally, we demonstrated that if the DB-SRA method had been used to set canary TACs throughout the simulation period, instead of the 40-10 method, foregone operating profits are likely to have been on the order ~2% of actual operating profits, not including the management and monitoring costs of implementing each method. As DB-SRA is likely a less expensive option than conducting full, data-rich, assessments, further research examining the full cost of conducting stock assessments could shed light on the relative economic benefits of these two approaches.

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3. METHODS FOR THE SPATIAL DISTRIBUTION OF FISHING EFFORT IN BIOECONOMIC SIMULATION MODELS: A COMPARISON

3.1 Introduction

Bioeconomic models that combine the salient components of fisheries in order to investigate the economic and biological impacts of management actions have become increasingly common over the last several decades (Larkin et al. 2011). Gordon (1954) and Schaefer (1954) were the early pioneers of this field, depicting a single-species fishery targeted by a homogeneous fleet, and at static bioeconomic equilibrium. In the sixty years since these seminal papers were published, a significant literature has developed on integrated biological and economic fishery models (see Prellezo et al. (2012) and Knowler (2002) for reviews). In the development of these integrated models, relatively little attention has been paid to the subject of fisherman behavior and fleet dynamics, while far more attention has been paid to describing the spatial and temporal dynamics of fish stocks (van Putten et al. 2012; Pelletier and Mahévas 2005a). In most fishery bioeconomic simulation models, fishing effort is assumed to be determined exogenously to the model (van Putten et al. 2012), and in ways that are not supported by microeconomic theory and/or econometric analysis (Dalton and Ralston 2004).

Many authors have emphasized that understanding harvester response in fisheries is critical for managing fisheries in ways that provide both economic and ecological benefits and avoid unintended management outcomes e.g. (Holland and Sutinen 1999; Hilborn and Walters 1987; Marchal et al. 2013; Fulton et al. 2011; Salas and Gaertner 2004). These authors have emphasized the importance of including spatial interactions between the fisherman and the stock in fishery models. Models that assume that fishing effort is spatially distributed in relation only to biological factors such as stock abundance, and that do not take economic factors into account, may lead to erroneous results in predicting the pattern of fishing mortality. The pattern of fishing mortality (on both temporal and spatial scales) depends on fishermen's short term effort decisions (Sampson 1991; Pelletier and Magal 1996; Wilen et al. 2002a; Pelletier and Mahévas 2005a). As a simple example, if a fish stock at the beginning of a fishing season is homogeneously distributed across several areas, vessels will tend to favor those areas closer to port *ceteris paribus*, as costs involved with travelling to and from the fishing grounds are lower. Disregarding spatial behavior in this simple example leads to over-predicting fishing effort in areas that are farther away from port, and under-predicting impacts on stock biomass in areas that are closer to port. In perhaps the seminal paper on this topic, Sanchirico and Wilen (2005) show that the optimal management of a fish stock depends on the ability to

distribute fishing effort over space and time in ways that recognize and integrate spatial biological processes such as dispersion, and factors that affect the spatial distribution of profits, such as area population levels. Spatial fishery models have also shed light on the welfare implications of spatially delineating fishing rights in a rights based management system. For example, Costello and Deacon (2007) show how non-spatial rights may constitute incomplete ownership of the resource, and how the spatial delineation of fishing rights can alleviate inefficiencies that arise from inter-vessel competition for high-valued patches. In addition to economic and social implications, understanding the spatial behavior of fishermen is also important for informing fishery managers on the status of the stock they are managing. The use of fishery dependent data (such as Catch per Unit Effort (CPUE)) in informing stock assessments is widespread, and often the only biomass indicator when fishery independent surveys are not undertaken. Failure to take the spatial behavior of fishermen into account leads to problems in relating CPUE to a measure of stock abundance (Gillis 2003; Gillis, Peterman, and Tyler 1993). For example, the movement of vessels from areas in which stock abundance has been depleted to areas where abundance is still high keeps CPUE high even though the overall stock level is being reduced (Hilborn and Walters 1987). In response to this issue some authors have suggested that the spatial distribution of fishing effort is a better predictor of stock distribution than CPUE (Gillis, Peterman, and Tyler 1993). Failure to accurately predict how the level and the distribution of fishing effort will change as a result of a management decision therefore has potentially serious implications for policy analysis.

Because of the increased recognition of the importance of space in fisheries, the explicit treatment of spatial interactions in fishery models, while not new e.g. Caddy (1975), has seen a significant increase in recent years (Pelletier and Mahévas 2005a; Sanchirico and Wilen 2005; Powers and Abeare 2009). While analytical models of spatial fishery processes are important, especially for gleaning important results about a theoretical system, they become intractable fairly quickly when the number of dimensions increases (stocks, age classes, spatial areas, time periods). For example, Tahvonen (2009) develops a two age class model to show how age-structure and endogenous recruitment influence the optimal steady state population and harvest of the resource. Skonhøft, Vestergaard, and Quaas (2012) develop an age-structured model of a fishery where two fishing fleets target two different age classes of the stock, with one cohort not yet recruited into the fishery and investigate optimal harvesting under different assumptions regarding fleet fishing selectivity. The number of results these authors glean from the model is limited, however, as understanding the interactions of the economic and biological forces at work in the model proved difficult. Instead, the authors show that optimal harvesting essentially depends on the various biological and

economic parameters in the model. These considerations, and the need to perform policy analysis for complex real world situations has limited the use of analytical models. Bioeconomic fishery systems are now generally analyzed using simulation techniques (Pelletier and Mahévas 2005a; Powers and Abeare 2009).

Bioeconomic simulation models have become increasingly complex due to advances in modeling and computation techniques. This complexity, however, comes at a cost since the interpretability of results quickly becomes difficult as the number of model inputs increases (Hilborn and Walters 1987) and sensitivity analyses quickly become impractical given the number and range of parameter values (Marchal et al. 2013). Unlike in analytical models, general results that apply over the full range of parameter values cannot be derived easily from simulation models where no explicit mathematical statement is evaluated as a closed form solution. However, one of the main advantages of simulation models is that they encourage exploration of alternative hypotheses -- something that is true even for very simple simulation models (Hilborn and Walters 1987). Bioeconomic fishery simulation models generally require an endogenous calculation of the level and spatial distribution of effort exerted in a fishery. In many of these models the *level* of effort is either set at: 1) historically observed values (e.g. (Kaplan, Holland, and Fulton 2014; Walters and Bonfil 1999), 2) at a user-defined constant level (e.g. Mahévas and Pelletier (2004), or 3) at a management-prescribed level (such as the effort required to attain a target fishing mortality rate e.g. (Holland and Herrera 2012). The *distribution* of effort is then determined according to a rule or algorithm that prescribes how effort should be distributed according to stock, fleet, and other characteristics. Methods that have been used to distribute effort spatially in bioeconomic fisheries models include the gravity model e.g. Caddy (1975), models based on the Ideal Free Distribution (IFD) (e.g. Powers and Abeare (2009)), models based on the Random Utility Model (RUM) framework (e.g. Holland and Sutinen (1999)), the sequential model (e.g. Hilborn and Walters (1987)), arbitrary-type methods such as distributing effort equally among areas (e.g. Pelletier and Magal (1996); Mahévas and Pelletier (2004)), and game theoretic models (e.g. White and Costello (2011); Holland and Herrera (2012)). However, most bioeconomic simulation models rely on very simplistic methods for distributing fishing effort (Pelletier and Mahévas 2005a). Whatever the method of distributing fishing effort between areas, at a fundamental level they all aspire to realistically represent fishermen's spatial effort decisions, often in response to changes in fishery conditions.

Economic theory predicts that the spatial distribution of fishing effort will be determined by the expected net returns of fishing in different locations (Gordon 1954). The theory is that if fishermen are homogeneous

and have perfect information, when net returns (including the costs of moving) are higher in alternative locations, vessels will move between grounds until profit rates are equal across grounds (Holland and Sutinen 2000). The basic intuition is that fishermen will change their effort distribution until the marginal net benefit of doing so falls to zero, which results in equalized marginal net revenues between areas. However, the assumptions underlying this theory are easily violated in real life situations and a variety of factors can impact the spatial distribution of fishing effort (Pelletier and Mahévas 2005a). Individual vessel heterogeneity (such as a vessel's physical characteristics (e.g. size, horsepower), and fishermen's attitudes, abilities, and habitual behavior) interact with conditions in the fishery (such as weather, the distribution of other vessels' effort, and the heterogeneous distribution of the resource in relation to port location) and result in violations of the predictions of Gordon's theory (Pelletier and Mahévas 2005a; Holland and Sutinen 1999; Abrahams and Healey 1990; Caddy 1975). Predicting the spatial distribution of effort in a fishery is therefore no simple task and is often a source of uncertainty for fishery managers and policy makers (Dalton and Ralston 2004).

This economic theory for how fishermen distribute effort over space has a parallel in the theory of the Ideal Free Distribution (IFD) (after Fretwell and Calver (1969)), which derives from the ecological literature on foraging theory. The IFD provides a testable null hypothesis for how fishermen distribute themselves in space (Gillis, Peterman, and Tyler 1993). While originally applied to describe the spatial distribution of birds in their habitat, when applied in a fishery setting the theory predicts that if 1) fishermen are of equal 'fitness', 2) interference competition between fishermen exists, 3) movement costs are zero, and 4) information on resource and fishermen's distribution is unrestricted, vessels will move between areas until the average net revenue per unit effort is equalized between areas (Gillis, van der Lee, and Walters 2012). Recently there has been increasing interest in applying models based on the theory of the IFD to fishery situations, although rarely in a computational bioeconomic framework (Gillis 2003; Gillis, Peterman, and Tyler 1993; Powers and Abeare 2009; van der Lee et al. 2014; Gillis, van der Lee, and Walters 2012; Abernethy et al. 2007).

In the classical formulation of the theory, and in the cases in the literature where it has been applied to fisheries, the strategic interaction that gives rise to the IFD is a result of interference competition between agents. Competition between fishermen can take two forms- interference competition and exploitation competition (Boyce 1992; Gillis and Peterman 1998). Interference competition occurs as a result of the reduction in fishing success due to physical interactions between fishing vessels and/or their gear, as well as impacts on fish stock behavior; however the underlying processes giving rise to it are poorly understood

(Rijnsdorp et al. 2011; van Putten et al. 2012). For example, Dalton and Ralston (2004) find evidence of vessel crowding externalities in an econometric analysis of a subset of the California groundfish trawl fleet but do not describe how it occurs. Interference competition can occur in all fisheries, but is thought to be prevalent in fisheries where the resource is renewing (generally through fish movement) throughout a fishing period, or in geographically small fishery areas. This type of competition occurs, for example, in the Prince William Sound salmon purse seine fisheries in Alaska. In these fisheries, fishermen have a tendency to set their nets near geographic features, such as a point, that may concentrate the flow of salmon interacting with the gear. In some cases fishermen wait several hours for a turn at fishing the ‘point’.

Exploitation competition, on the other hand, occurs when the fishery resource is locally depleted by the impact of fishing gears, which affects the catch rate for other vessels in the fishery. Exploitation competition, apart from being a logical process in all fisheries where catch is taken, is thought to be especially prevalent in fisheries where the resource is non-renewing during a fishing period; for example in sedentary abalone and geoduck fisheries (Gillis and Peterman 1998). Both exploitation and interference competition are likely to exist in most fisheries, but the difficulty in distinguishing between the two types of competition will remain a continuing problem until increased levels of information regarding the spatial distribution, abundance, and behavior of both fish stocks and fishing vessels are generated (Gillis and Peterman 1998; Gillis 2003). For example, if a fishery resource is non-renewing during a single time period, catch rates may increase in an area after a decrease in the number of vessels fishing due to reduced interference competition. However, if the resource is renewing during a time period, catch rates could increase with a decrease in the number of vessels fishing even in the absence of interference competition. In general, if catch rates are observed to decline with an increase in fishing effort in an area it is an extremely difficult task to ascertain whether the reduction in catch rates is a function of gear and vessel interactions, or the localized depletion of the resource. In many cases both processes may be at work (Gillis and Peterman 1998).

The application of the IFD to fisheries has been criticized as too simplistic (Holland and Sutinen 1999) or inadequately justified (Abernethy et al. 2007; Allen and McGlade 1986). In addition its inclusion in an operational simulation model is complicated by the fact that the theory of the IFD does not make any assumptions regarding *how* the distribution is attained (Wilson 1982). However, empirical evidence of its appearance has been presented in cases where the assumptions that underpin the theory have been relaxed (Gillis, van der Lee, and Walters 2012). The IFD has been shown to constitute a Nash equilibrium (Nash 1951), a situation where all ‘players’ in a game of strategic interaction (in our case competition between

fishermen) cannot be made better off by deviating from the IFD (Quijano and Passino 2007). It is therefore intuitively appealing to economists. In addition, in situations when the various assumptions hold, the end predictions of the IFD and Gordon's economic theory are the same -- that average net revenue (or profit) per unit effort are equalized among areas in which fishing occurs. What is different is how this distribution is achieved- the IFD relies on interference competition between vessels, while Gordon's theory relies on exploitation competition.

The purposes of this paper are as follows. First, we discuss the theoretical basis and review the practical applications of several of the most common methods for distributing effort in spatially explicit bioeconomic simulation models. Second, we introduce a game theoretic method (the 'Baranov-Nash' (B-N) model) for resolving the spatial distribution of fishing effort in a bioeconomic simulation model. The method is based on the well-known Baranov catch equation (Baranov 1918), the assumption that competition exists between vessels, and that a Nash Equilibrium (NE) spatial distribution of fishing effort can arise. An algorithm for solving the model and tests for NE existence under effort and catch constraints are provided. Third, given the often ad hoc decision of choice of sub-model with which to distribute fishing effort, and the fact that it is not clear how the predictions made by each type of model differ, we simulate the short term effort distributions that result from their use in a simple stylized model of a fishery and compare these to the predictions of the B-N model. We simulate a simple model of a fishery to examine the predictions of each model under different economic and biological conditions, and determine the conditions under which systematic differences exist.

3.1.1 CURRENT METHODS FOR DISTRIBUTING FISHING EFFORT IN BIOECONOMIC SIMULATION MODELS

Apart from distributing effort evenly across space, several methods that have been applied in bioeconomic simulation models exist. All of the methods for distributing fishing effort in simulation models that are discussed calculate the *distribution* of fishing effort in a model. The *level* of fishing effort is not endogenous to any of the frameworks explored. A separate calculation or assumption on fishing effort level must be made, often on the basis of an exogenous input from the user (e.g. (Ulrich et al. 2007; Hilborn and Walters 1987)).

3.1.1.1 Gravity Model

The gravity model, while employed previously in recreational site choice models (see Hunt (2005) for a discussion), was originally employed in the fisheries literature by Caddy (1975). The gravity model provides a mechanism for distributing fishing effort between areas in a fishery in proportion to the relative ‘attractiveness’ of each area. The general form of the model is:

$$p_i = \frac{a_i}{\sum_j a_j} \quad \text{Eq. 3.1}$$

Where p_i is the proportion of effort in fishing ground i (of j grounds), and a_i is the attractiveness of that ground. Attractiveness is generally linked to expected net revenue or expected catch of fishing in that ground. For example, Walters and Bonfil (1999) included a gravity model in a spatial fisheries assessment model for the British Columbia trawl fleet in order to test possible spatial management measures. They modeled a single fleet and defined the proportion of effort in each ground to be equal to relative average gross income per unit effort on each ground, weighted by the costs of fishing in each ground. Seijo and Caddy (2008) utilized the proportion of the previous period’s profits in each area to allocate effort in a bioeconomic metapopulation simulation model. Walters, Hilborn, and Parrish (2007) use a gravity model to distribute fishing effort in a bioeconomic simulation model designed to assess the effectiveness of the design of marine protected areas where attractiveness is measured by the logarithm of stock size in each area, and prices and costs of fishing are not included. ECOSPACE, a spatially explicit simulation model for policy evaluation (Walters, Pauly, and Christensen (1999)), also utilize the basic gravity model to spatially distribute fishing effort, where fishing effort is distributed in proportion to relative net revenue rates among areas.

Some authors have observed that fishing effort appears to be more concentrated than what the basic gravity model predicts (Pelletier and Mahévas 2005a). In addition, the basic model does not take into account factors such as information flow between fishermen, so the basic model has been augmented in various ways. For example, Caddy (1975) re-weighted the measure of attractiveness by incorporating information on historical habits. Walters et al. (1993) amended the basic gravity model to include a parameter describing relative distance from port, and included a ‘concentration parameter’ to increase the attractiveness of the already attractive areas. For high values of the concentration parameter, the model approximates the sequential model (see next section). The gravity model has been amended in other ways. Allen and McGlade (1986) modified the attractiveness parameter to incorporate information exchange between fishers. The

authors re-specified the attractiveness parameter as the exponent of the product of expected net rate of return and an information quality parameter. Exponentiating this product also results in a high concentration of effort into more attractive areas.

The gravity model, and variations of it, are attractive because of its simplicity and have been widely used, even though it has been criticized as not founded on any theory of fisherman behavior (Hunt 2005), and its progenitor in the fisheries literature states in the original paper that “*this approach to the sub-allocation of effort is artificial although perhaps more reasonable than assuming that effort and abundance are independently distributed*” (Caddy 1975, pg.1314). The literature suggests that the gravity model has not been tested using fisheries data.

3.1.1.2 Random Utility and Discrete Choice Models

Random utility models (RUMs) based on McFadden’s (McFadden 1973) discrete choice framework have been relatively successful at identifying the factors that influence fishermen’s decision on where and when to fish, and at providing estimates of each factor’s importance (van der Lee et al. (2014)). The motivation for this class of models is the idea that fishermen will choose to fish in a particular discrete area if his or her expected utility from fishing in that area exceeds that of the other areas. Utility for each individual, i , of fishing in area j , is composed of an observable component (V_{ij}), generally linked to the expected monetary benefit of fishing as well as other factors, and an unobservable component (ε_{ij}) :

$$U_{ij} = \beta X_{ij} + \varepsilon_{ij} \quad \text{Eq. 3.2}$$

The observable component of utility is generally specified as a linear combination of explanatory variables and a vector of parameters (β) that may be specific to an individual (i) or a choice (j). In the multinomial logit model only individual specific characteristics are modeled, while choice specific attributes are included in the conditional logit model. The nested logit model is useful in cases where the random component of utility is potentially correlated within particular groups of alternatives (Holland and Sutinen 1999; Wilen et al. 2002a). Another variation of the logit model is the mixed logit model, which allows for both individual and choice-specific variables (see van der Lee et al. (2014) for an example of its application to a fishery situation). These models have been extensively discussed in the literature. For a good overview of discrete choice models based on the RUM framework see Train (2009).

While the assumptions regarding model structure vary between the different manifestations of the multinomial logit model, when included in a bioeconomic simulation model the choice probabilities that are the output of the regression analysis need to be translated into a distribution of fishing effort among areas. This is generally conducted by multiplying the choice probabilities of fishing in a particular area (which sum to unity over all areas), by a total level of effort to be distributed in a time period. For example, Holland (2000) estimates a nested logit model where fishermen first choose a fishery and zone combination (nest), and then choose an area within that nest, as part of a bioeconomic simulation model to explore possible economic and ecological effects of imposing permanent marine sanctuaries on Georges Bank, New England. The calculated probabilities of vessels participating in each fishery/area were then multiplied by an observed total effort level to derive a spatial distribution of fishing effort in the model. Andersen et al. (2010) estimate the parameters of a conditional logit model and incorporate these parameters into a gravity model- type of effort distribution model where effort is distributed in proportion to the relative probabilities of fishing in each area. The utility of fishing in each area (represented using a combination of value per unit effort and past effort levels) was used as a measure of ‘attractiveness’ instead of an abundance measure. Hutton et al. (2004) apply a conditional logit model to estimate how factors such as value per unit effort, trip length, and catch affect the probability of vessels fishing in a particular area. These results were then combined into a simulation model of fleet behavior where displaced effort (from area closures) was redistributed according to the relative benefits of fishing in each area- in much the same way as in the gravity model.

Using discrete choice statistical models to identify and measure the factors that affect a fisherman’s spatial location choice and then to include these predictions in bioeconomic simulation models allows the spatial distribution of effort to be empirically grounded, rather than to be based only on *ad hoc* descriptions of fishing behavior (Hutton et al. 2004). However, there are situations where this class of methods is undesirable and other methods may be preferred. Including an econometric model into a simulation model can sometimes be subject to mismatches in modeling scale and data limitations (Ulrich et al. 2007). The definition of areas using biological considerations (such as benthic substrate type or current system characteristics) may not naturally synchronize with area definition from an econometric standpoint, which should represent, as closely as possible, actual choices that a fisherman makes (Holland and Sutinen 1999). For example, Hutton et al. (2004) found that after estimating their well-specified RUM, only some of the results could be incorporated into the overall simulation model due to mismatches between the estimating and simulation model scales. Ulrich et al. (2007) find similar restrictions when designing a generic spatial

bioeconomic simulation model for evaluating management measures. Short term effort is distributed by multiplying calculated choice probabilities by an overall effort level. However, the set of explanatory variables that could be included in the model inputs was restricted by the fact that biological information was available at a much coarser scale than information on fleet behavior. These scale considerations forced the authors to use a reduced set of explanatory variables to generate bioeconomic model predictions.

Parameters estimated using data for a particular fishery over a specific time period reflect the behavior of fishermen over that particular time period and fishery, and are based on the economic, social, and biological structure of the fishery at the time. Economists believe that an advantage of using econometric models based on behavioral micro-economic models is that the response of individuals to policies can be predicted even if the policies were not in place during the period modeled (Wilén et al. 2002b; Hutton et al. 2004). While the performance of these models in such a situation is likely to be better than using average behavior in an unrelated fishery situation, and the direction (sign) of the results may be found to be consistent with economic theory, the magnitude of the parameter estimates may not be easily generalizable to other fisheries or even for the same fishery in the future. Given that utilizing any model for policy reform is often contentious in fisheries, structural changes such as management system changes, stock characteristics, or fleet characteristics will determine the model's predictive capabilities.

3.1.1.3 Sequential Model

The sequential model of spatial effort allocation (Hilborn and Walters 1987), takes a different approach to the gravity and RUM models in that effort is allocated spatially in a series of sub-time-steps. For example, if a gravity model were to allocate effort on an annual basis, the sequential model would split this annual time step into numerous smaller time steps in which an effort distribution calculation is conducted. The basic structure of the model is that at the beginning of each time step, a fleet's available effort (in that time step) is allocated to the area where the net revenue rate is highest. Between time steps, abundance, and hence net revenue rates, are updated, and effort is distributed with the updated area-specific net revenue rates for the next period. In one application of the use of the sequential model, Tanaka, Tanaka, and Hasegawa (1991) modified the model to accommodate multiple heterogeneous fleets in order to simulate how fishermen made effort distribution decisions in a bioeconomic model of a flatfish fishery. They found that their estimates of effort distribution in the fishery were significantly correlated with actual observations. Although further examples of its use in fisheries bioeconomic models are rare, Stouten et al. (2008) utilize a sequential-type model in a simulation model of Belgian fleet dynamics. Abstracting away from stock

dynamics, they allocate effort for portions of the fleet within a time period to the area with the highest catch per unit effort for that fleet.

While the sequential model has not been extensively applied in a simulation setting, perhaps as a result of a perceived added complexity compared to the gravity model, it has an intuitive appeal in that it is based on the idea that, unlike the gravity model, individual fishing vessels maximize expected profits when distributing fishing effort.

3.1.1.4 Game Theoretic Models and the Ideal Free Distribution

Game theory is a mathematical tool for analyzing strategic interaction, which occurs when all agents in a model are affected by the actions of all other agents (Sumaila 1999). Earlier fishery studies focused mainly on deriving analytical results in relatively simple cooperative and non-cooperative games (Munro 1979; Levhari and Mirman 1980; Dockner, Feichtinger, and Mehlmann 1989). For example, Dockner, Feichtinger, and Mehlmann (1989) represent the fishery resource as a single homogenous biomass and examine the market externality created when the price of fish depends on the quantity of fish supplied and the fishermen act as an oligopoly. Clark (1980) considers a limited access fishery as an n person, non-zero sum game to examine the dynamic stock externality created when a single population of fish is exploited by a finite number of fishers. In his seminal paper, Munro (1979) examined the optimal management of a trans-boundary resource jointly owned by two states, and how differences in discount rates, consumer preferences, and fishing effort costs can affect the strategic responses of the resource owners. Bischi and Kopel (2002) model a commercial fishery as a duopoly to study the effects on a population of fish over time of economic variables. They find that higher fishing costs increase the likelihood of a large stock size. In all of these cases simplifying assumptions regarding the structure of space, dynamics of effort, and the representation of the biological resource were necessary in order to achieve analytical results, which are generally difficult to derive for game theoretic models (Levhari and Mirman 1980). More recently, White and Costello (2011) incorporate a game theoretic component into a bioeconomic model of the size of Territorial Use Right for Fishing (TURF) in relation to the scale of stock dispersal. The strategic aspect of the problem related to choosing a harvest level that would maximize an agent's yield given the harvest (and thus impact on dispersal) of the other agents in the fishery. The authors compared this non-cooperative solution to the sole owner scenario and found that, strategic responses by fishermen, represented by the simultaneous maximization of each fisherman's profit, in the non-cooperative solution reduced fishery yield. Holland and Herrera (2012) distribute effort in a bioeconomic simulation model of a theoretical

spatial fishery by equalizing marginal net revenue rates subject to catch constraints. The authors use a modified Baranov equation in their model which incorporates exploitation competition.

Although game theoretic models are particularly intuitive for incorporation into bioeconomic frameworks (van Putten et al. 2012), relatively little progress has been made in this area in incorporating game theoretic components into bioeconomic simulation models. One example is Merino, Maynou, and García-Olivares (2007), who construct a model of the red shrimp fishery in Spain. The authors model a single fleet that is heterogeneous in catchabilities and model the amounts of effort each vessel exerts in a fishing season in a non-cooperative Nash equilibrium versus a cooperative sole-owner solution. They found that vessels with higher catchability coefficients exerted more effort than other vessels in the sole-owner solution, while in the Nash equilibrium everyone's effort was equal.

IFD models predict the distribution of agents in an environment, but do not describe how these patterns arise (Cosner 2005). Its inclusion as a component of a dynamic bioeconomic model is therefore difficult. Perhaps the closest application of the IFD in a computational bioeconomic model is made by Powers and Abeare (2009). These authors develop a class of simulation models based on IFD assumptions where the suitability of an area decreases as the number of vessels fishing in that area increases. An equilibrium distribution of effort was then resolved, assuming that catch rates declined with an increase in fishing effort, and the results applied in a model of spatial area closures in the Gulf of Mexico and Atlantic Ocean. While the model was built under the assumption of interference competition between vessels, if the form of competition was assumed to be exploitation the same results would have been generated.

Operationalizing the principles of game theory and the concept of the Nash equilibrium in spatial fishery models is intuitively appealing; maximizing each vessel or fleet's profits given the actions of all fishermen may be more realistic than either maximizing fishery-wide profit or distributing effort in other ways, such as with the gravity model. One of the fundamental equations of fisheries science provides a mechanism for doing so. The Baranov catch equation (Baranov 1918) is perhaps the most used equation that relates catch to effort in fisheries modeling (Quinn 2003), and is a useful construct for incorporating a game theoretic component into fisheries models. The equation gives catch as a function of a population size at the beginning of the time period and instantaneous rates of fishing (F) and natural mortality (M) which are assumed constant over time (Xiao 2005). While the assumptions of constant F and M are violated in many real world situations, the Baranov equation has been shown to be a relatively good approximation even when these assumptions are violated (Liu, Heino, and Hilborn 2013). Importantly, another assumption of

this equation is that the catch rate is a function of all effort in a fishery -- when effort increases, *ceteris paribus*, catch rate decreases. The mechanism for this is stock exploitation -- the more effort applied to a fishery in time, the higher the catch, resulting in fewer fish in future time periods to exploit. This mechanism can also be interpreted as the strategic interaction that is a component of all game theoretic models where the optimal level and distribution of effort for an individual vessel depends on the actions of all other vessels in the fishery. In the next section we present our “Baranov-Nash” model for spatially distributing fishing effort in integrated bioeconomic simulation models.

3.2 Baranov-Nash Model

The model is structured spatially with $j=1, \dots, J$ areas that are treated independently within a time period. Time periods are discrete and no movement of fish occurs in or out of areas within a time period. This is similar to the meta-population approach to describing the spatial structure of fish populations (Gilpin and Ilkka 1997), with inter-relationships (migration, diffusion) between local populations resolved between, and not during, time periods. There can be any number of species (K_j) in each area. Predator-prey relationships and other interactions do not occur within a time period. There are $i=1, \dots, I$ fleets, where a fleet is made up of one or more vessels with identical fishing technology and variable costs.

Strategic interaction in this model is derived from the Baranov catch equation (Baranov 1918). Given a positive catchability coefficient (q_i), rate of natural mortality (M_j), and biomass (N_j), the first partial derivative of the catch function with respect to own effort is positive, while the first partial derivative of catch with respect to other fleets' effort is negative, implying that effort is a strategic substitute (Hicks, Horrace, and Schnier 2012). The catchability coefficient (q_i) represents the relationship between the fleet specific fishing mortality rate and the effort exerted by that fleet. The catchability coefficient can account for differences in the type of gear employed by a fleet, as well as a fleet's relative fishing efficiency. The natural mortality rate (M_j) and biomass (N_j) are area-specific and fixed within each time period. The Baranov equation can be applied to spatially structured populations if we assume that the distribution within each area is homogenous (Caddy 1975).

Catch (C_{ijk}) of species k for fleet i in area j in a given time period is:

$$C_{ijk} = \frac{q_{ik} \cdot f_{ij}}{M_{jk} + \sum_{i=1}^I q_{ik} \cdot f_{ij}} N_{jk} \left[1 - \exp(-M_{jk} - \sum_{i=1}^I q_{ik} \cdot f_{ij}) \right] \quad \text{Eq. 3.3}$$

The net revenue function (π_{ij}) is the product of price (p_k) and catch for each species, less the costs of fishing. Here, the variable costs of fishing (v_{ij}) are fleet and area specific, and are incurred linearly with effort (f_{ij}). Fleet specific differences in costs may represent distance from a fleet's homeport to a particular area, vessel size, engine efficiency, crew size, and other costs.

The net revenue function (π_{ij}) for fleet i in area j is:

$$\pi_{ij} = \sum_{k=1}^K C_{ijk} \cdot p_k - f_{ij} \cdot v_{ij} \quad \text{Eq. 3.4}$$

We assume that each fleet is a profit maximizer and takes the actions of all fleets into account when making its decision on the level and distribution of fishing effort to exert. In addition, each fleet possesses perfect information of the distribution of the resource, as well as the costs and catchability coefficients of the other fleets. At the beginning of a time period each fleet makes a decision on the level and distribution of fishing effort to exert. This is a one shot, simultaneous move game implying that the distribution, size, and characteristics of fish stocks are known *ex ante*. While we employ the assumption that harvesters have perfect information on the distribution of the resource as well as the technological capabilities of the other harvesters, our formulation allows vessels to be differentiated, and heterogeneous variable costs of fishing to be explicitly incorporated into the model.

In the absence of constraints on effort or catch, each fleet's objective function is:

$$\max_{f_i} \sum_{j=1}^J \pi_{ij}(f_i, f_{-i}) \quad \text{Eq. 3.5}$$

Where: f_i is the focal fleet's effort vector and f_{-i} represents all other fleet's effort vectors.

The first order conditions are:

$$\frac{\partial \pi_{i1}}{\partial f_{i1}} = \dots = \frac{\partial \pi_{ij}}{\partial f_{ij}} = 0 \quad \forall j : f_{ij} > 0 \quad \text{Eq. 3.6}$$

A Nash equilibrium in this model is collection of $I \times J \times I$ vectors (f^*) of feasible effort levels such that if any fleet were to deviate from this solution, that fleet would not be made better off by such a change:

$$\varphi_i(f^*) = \max_{y_i} \{\varphi_i(f_1^o, \dots, y_i, \dots, f_n^o) | \varphi_i(f_1^o, \dots, y_i, \dots, f_n^o) \in R\} \quad Eq. 3.7$$

Where R is the set of real numbers.

In the unconstrained case, the first own partial derivatives of each fleet's net revenue function with respect to effort (evaluated at f^*) are identically zero in those areas where a positive level of effort is exerted. In areas where a fleet exerts no effort, these derivatives are non-positive. In a strictly concave, n-player game such as this, a unique Nash equilibrium has been shown to exist (Rosen 1965). Given that each area in our model is independent it follows naturally that a unique unconstrained Nash equilibrium exists in each area. The Nash equilibrium point in our model represents a spatial distribution of fishing effort that is determined in advance of any fishing activities, and from which no fleet has an *a priori* incentive to deviate.

In practice, effort is an inherently bounded variable. Measured in fishing days, the maximum effort that a vessel can exert in a year is 365, and negative effort values are not feasible. A constraint on effort will be necessary in most cases in order to bound the model within a realistic value space. In addition many fisheries are managed using constraints on the amount of fish available for harvest. These constraints can either be in the form of Total Allowable Catches (TACs) that operate on the fleet as a whole, or as individual catch limits as are the case in Individual Fishing Quota (IFQ) fisheries. We will focus on individual limits on effort and catch.

In the case of a fleet-specific constraint on the maximum amount of effort to be exerted (E_i), we can represent the objective of fleet i as the Lagrangian:

$$\mathcal{L}_i(f, \lambda_i) = \sum_{j=1}^J \pi_{ij}(f_i, f_{-i}) - \lambda_i \left(\sum_{j=1}^J f_{ij} - E_i \right) \quad Eq. 3.8$$

With first order conditions:

$$\frac{\partial \mathcal{L}_i}{\partial f_i} = \frac{\partial \pi_{ij}}{\partial f_{ij}} - \lambda_i = 0 \quad \forall j$$

$$\lambda_i \frac{\partial \mathcal{L}}{\partial \lambda_i} = \lambda_i [\sum_{j=1}^J f_{ij} - E_i] = 0 \quad Eq. 3.9$$

$$\frac{\partial \mathcal{L}_i}{\partial \lambda_i} = \sum_{j=1}^J f_{ij} - E_i \leq 0 \quad \forall i$$

$$\lambda_i \geq 0 \quad \forall i$$

At an effort constrained equilibrium, each fleet's first own partial derivatives of their net revenue functions with respect to effort are equalized across areas in which they exert some effort. For areas in which no effort is exerted by a fleet, the first own partial derivatives are no greater in value than those representing areas where effort is exerted. Intuitively, the allocation of effort between areas can't be improved upon if the constraint is binding, and the marginal benefit of exerting effort is equal among areas.

In the case where fleet- and species-specific catch constraints exist (denoted H_{ik}), the Lagrangian function for each fleet is:

$$\mathcal{L}_i(f, \mu_{ik}) = \sum_{j=1}^J \pi_{ij}(f_i, f_{-i}) - \mu_{i1} \left(\sum_{j=1}^J C_{ij1} - H_{i1} \right) - \dots - \mu_{iK} \left(\sum_{j=1}^J C_{ijK} - H_{iK} \right) \quad Eq. 3.10$$

With first order conditions:

$$\frac{\partial \mathcal{L}_i}{\partial f_{ij}} = 0 \quad \forall j$$

$$\mu_{i1} \left[\sum_{j=1}^J C_{ij1} - H_{i1} \right] = \dots = \mu_{iK} \left[\sum_{j=1}^J C_{ijK} - H_{iK} \right] = 0 \quad Eq. 3.11$$

$$\frac{\partial \mathcal{L}_i}{\partial \mu_{ik}} = \sum_{j=1}^J C_{ijk} - H_{ik} \leq 0 \quad \forall k$$

$$\mu_{ik} \geq 0 \quad \forall k$$

A catch constrained Nash equilibrium is a collection of $I \times J \times 1$ vectors (f_c^*) of feasible effort levels such that if any fleet were to deviate from this solution, that fleet would not be made better off by such a change:

$$\varphi_i(f_c^*) =$$

$$\max_{y_i} \{ \varphi_i(f_1^o, \dots, y_i, \dots, f_I^o) | \varphi_i(f_1^o, \dots, y_i, \dots, f_n^o) \in R; (C(f_1^o), \dots, C(y_i), \dots, C(f_n^o)) \in D \} \quad \text{Eq. 3.12}$$

Where D is the catch constraint set and R is the set of real numbers.

Apart from the trivial case where two species are binding at the same time, in general only one of the μ_{ik} will be greater than zero, reflecting one binding species in a fisherman's catch portfolio. At a catch constrained Nash equilibrium the Lagrangian multipliers on the binding species are equalized across those areas where effort is exerted. Intuitively, this reflects the idea that the marginal net benefit of relaxing the constraint on catch is equal across areas, and that a fleet cannot improve their situation by re-allocating effort.

3.2.1. SOLUTION METHOD

Solving for equilibrium points in this model is carried out by iterating the effort distributions of each fleet until there is no change in the total distribution of effort. The process is detailed below:

Iterative Process for resolving an equilibrium spatial distribution of effort (I fleets, J areas):

Step 1: Assign a vector of initial effort levels to each of the *I* fleets.

Step 2: Starting with fleet 1 maximize net revenue given initial effort distribution of all other fleets, and subject to any constraints on effort or catch. The result is an optimal level of effort for fleet 1 given the initial effort levels of all other fleets. Update the effort vector with these optimal values.

Step 3: Repeat for the other *I-1* fleets, updating each fleet's effort vector.

Step 4: Repeat steps 2-3 until the *stopping rule* (see below) is met.

Step 5: Check the resulting distribution of effort using *equilibrium tests* (see below).

Stopping Rule:

Although the stopping rule can be absolute or relative, and apply to changes in any of the effort-dependent functions in the model (such as catch or net revenue), we suggest using a relative change in effort rule that

determines whether a distribution is ‘close enough’ to the final equilibrium distribution. For fleet i , area j , and iteration s , the stopping rule is:

$$if: \max \left(\left(\left| \frac{f_{i,j,s} - f_{i,j,s-1}}{f_{i,j,s-1}} \right| \forall i, j \right) \right) \leq rtol : STOP \quad Eq. 3.13$$

In other words, if the maximum of the absolute relative differences in effort levels between two iterations satisfies a user-defined relative tolerance ($rtol$) level, then a candidate equilibrium point has been reached. In general, given computational time, there is a tradeoff between the size of $rtol$, and the precision with which an equilibrium is described.

3.2.2. EQUILIBRIUM TESTS:

After a candidate equilibrium point has been reached, a test can be carried out to determine if that point is a Nash equilibrium. These tests depend on whether the problem is unconstrained, effort constrained, or catch constrained.

3.2.2.1 Unconstrained equilibrium test

An unconstrained equilibrium is characterized by a distribution of effort that no fleet has an incentive to deviate from. Intuitively, if there is a positive marginal net benefit to exerting an additional unit of effort in any area, the system is not in equilibrium. For fleet i , and area j , the following conditions should be met:

$$\frac{\partial \pi_{ij}}{\partial f_{ij}} = 0 \quad \forall (i, j: f_{ij} > 0) \quad Eq. 3.14$$

And

$$\frac{\partial \pi_{ij}}{\partial f_{ij}} \leq 0 \quad \forall j: f_{ij} = 0 \quad Eq. 3.15$$

3.2.2.2 Effort constrained equilibrium test:

In an effort-constrained equilibrium, each fleet’s effort distribution is such that there is no net benefit to re-allocating effort between areas, subject to the constraint on a fleet’s total effort. This situation is characterized by the first derivatives of the net revenue function being equalized among areas for each fleet. This rule only applies for a fleet in those areas where a positive level of effort is applied. In the areas where

a fleet does not exert effort, the first own derivatives of the net revenue function are less than the values in the areas where effort is exerted. An effort constrained equilibrium satisfies the following conditions:

$$\text{for each fleet } i, \quad \frac{\partial \pi_{im}}{\partial f_m} = \frac{\partial \pi_{in}}{\partial f_n} \quad \forall \text{ areas } m, n: f_m, f_n > 0 \quad \text{Eq. 3.16}$$

, and

$$\text{for each fleet } i, \quad \frac{\partial \pi_s}{\partial f_s} \leq \frac{\partial \pi_p}{\partial f_p} \quad \forall \text{ areas } s: f_s = 0, \forall \text{ areas } p: f_p > 0 \quad \text{Eq. 3.17}$$

3.2.2.3 Catch constrained equilibrium test:

In a catch constrained equilibrium where one or more species are constraining on the final effort distribution of all fleets, the species-specific Lagrangian multipliers reflect the contribution to a fleet's net revenue of relaxing the constraint by a marginal unit. If a constraint is binding, the multipliers associated with this constraint will be equalized across areas in which a fleet exerts effort. If the constraint is not binding, or if no effort is exerted by a fleet in a particular area, the associated multipliers may not be equalized across areas, and will be lesser in value than those representing binding combinations. Intuitively, this reflects the fact that at a Nash equilibrium no fleet can adjust their effort distribution and levels for gain, while satisfying their constraints. For fleets i , areas j , and species k , the Lagrangian multiplier is calculated as the ratio of marginal net revenue to marginal catch:

$$\mu_{ijk} = \frac{\frac{\partial \pi_{ij}}{\partial f_{ij}}}{\frac{\partial C_{ijk}}{\partial f_{ij}}} \quad \text{Eq. 3.18}$$

For each constraining species k , a catch constrained equilibrium satisfies the following conditions:

$$\text{for each fleet } i, \quad \mu_{ijk} = \mu_{ilk} \quad \forall \text{ areas } j, l \text{ such that } f_{ij}, f_{il} > 0 \quad \text{Eq. 3.19}$$

The equilibrium distribution of effort that characterizes the solution to the model is such that there are no potential gains to any fleet from deviating from their equilibrium strategy. For a unique equilibrium we require that each fleet is, at least slightly, differentiated in terms of catchability and/or variable costs of fishing. If two fleets were exactly the same, their effort distributions and levels would also be the same, and a unique equilibrium would be impossible to ascertain. Rosen (1965) showed that if the joint strategy

space in a concave, n-player game is convex and compact, and if each player's payoff function is continuous, and concave throughout the strategy space, an equilibrium exists. In a theoretical development of a class of models where location decisions are based on individual and choice specific characteristics, Bayer and Timmins (2005) show that a unique equilibrium can only be guaranteed in the presence of a congestion effect, which is analogous to our case of effort being a strategic substitute. The most relevant proof of equilibrium uniqueness is presented in Laye and Laye (2008). The authors show that in a multi-market Cournot competition game with linear demand in each market, and capacity constraints that operate over several markets, a unique equilibrium exists. This situation is analogous to our model setup, with 'markets' relating to fishery areas, and 'capacity constraints' analogous to constraints on the total amount of fishing effort exerted across areas. While a proof of equilibrium uniqueness is beyond the scope of this paper, extensive sensitivity analyses have, so far, failed to uncover a single case of multiple equilibria in the model.

3.3 Model Comparisons

In this section we conduct a numerical comparison of several methods for spatially distributing effort in bioeconomic simulation models. We compare the Baranov-Nash model, the sequential model (Hilborn and Walters 1987), the gravity model (Caddy 1975), and a model of a sole owner fishery where total fishery profits are maximized. We do not include a RUM in the comparison, due to the operational similarities between the gravity model and the RUM when applied in bioeconomic simulations, and the difficulty in conducting an empirical comparison of all methods. We also do not include an IFD model as a computational framework that describes how the IFD is formed is lacking. Instead, we will examine the conditions under which the manifestation of an IFD (equalized average net revenues between areas) may be predicted by the models in the comparison. The setting is a hypothetical single-species fishery with 2 fishing fleets and 3 fishing areas- one close to port, one far from port, and one area in between. In order to focus on the short term distribution of effort we simplify the biological component of the model and do not represent recruitment or growth. Each area has an equal biomass of fish to start the season, and the rate of natural mortality is not area-specific. We assume that there is no movement of fish and all fleets have perfect information regarding the technology of the other fleets as well as the variable costs of fishing. Fleets are composed of a group of 10 homogenous vessels Fishing effort is distributed on a weekly basis in a 52 week season and fishing effort is measured in the number of days each fleet fishes. We bound effort for each fleet to be non-negative and capped at the number of days in the week multiplied by the number of vessels in the fleet. We first investigate differences in the spatial distributions of effort predicted by each of the three

models in a base parameterization where the fleets are identical. We then determine how model predictions are affected by different assumptions regarding model parameters and variables. We then examine how model predictions are affected when fleets are heterogeneous in fishing power, and in cost structure. All simulations are conducted in R (R Core Team 2015).

3.3.1 STOCK

The stock is assumed to be subjected to two processes- natural mortality and fishing mortality. No growth, recruitment, or movement between areas occurs within the season. Stock size at the end of time t in area j is:

$$N_{j,t} = N_{j,t-1} \left(\exp(-(M_{j,t} + F_{j,t})) \right) \quad \text{Eq. 3.20}$$

Where $N_{j,t-1}$ is the stock size at the end of time $t-1$ in area j , $M_{j,t}$ is the instantaneous (weekly) rate of natural mortality in time t and area j , and $F_{j,t}$ is the instantaneous rate of fishing mortality in time t and area j .

The instantaneous rate of fishing mortality, $F_{j,t}$, is the product of a catchability coefficient, q_i , and effort, f_{ijt} , summed over the fleets, i :

$$F_{j,t} = \sum_{i=1}^2 q_i f_{ijt} \quad \text{Eq. 3.21}$$

Note that catchability is fleet specific but constant over time and space, while the effort exerted by each fleet i , can vary over time and space. Catch, C , for each fleet depends on the stock size in each time period, the amount of effort each fleet exerts in each area, and the amount of effort the other fleet exerts:

$$C_{ikt} = \frac{q_i \cdot f_{ijt}}{M_j + \sum_{i=1}^2 q_i \cdot f_{ijt}} N_{jt} \left[1 - \exp(-M_j - \sum_{i=1}^2 q_i \cdot f_{ijt}) \right] \quad \text{Eq. 3.22}$$

Defining Z_{jt} as the instantaneous rate of total mortality for the portion of the stock in area j at time t as:

$$Z_{jt} = M_j + \sum_{i=1}^2 q_i \cdot f_{ijt} \quad \text{Eq. 3.23}$$

And the survival rate, S_{jt} , as:

$$S_{jt} = \exp(-Z_{jt}) \quad \text{Eq. 3.24}$$

The first derivative of C_{ijt} with respect to fleet i 's effort, which depends on other fleets' effort in the fishery, can be shown to equal:

$$\frac{\partial C_{ijt}}{\partial f_{ijt}} = N_{jt} \cdot \frac{q_i}{Z_{jt}} \left[1 - S_{jt} - \frac{F_{jt}}{Z_{jt}} + \frac{F_{jt}}{Z_{jt}} \cdot S_{jt} + F_{jt} \cdot S_{jt} \right] \quad \text{Eq. 3.25}$$

Net revenue (NR) in each time period is price, p , multiplied by catch minus costs, with costs entering as a constant cost per day fishing, v_i :

$$NR_{ijt} = p \cdot C_{ijt} - f_{ijt} \cdot v_i \quad \text{Eq. 3.26}$$

The first partial derivative of NR_{ijt} with respect to fleet i 's effort is then:

$$\frac{\partial NR_{ijt}}{\partial f_{ijt}} = p \cdot \frac{\partial C_{ijt}}{\partial f_{ijt}} - v_i \quad \text{Eq. 3.27}$$

3.3.2 MODELS AS IMPLEMENTED IN THE SIMULATION

The **Baranov-Nash model** is implemented using the following algorithm:

1. Assign a vector of initial effort levels to each fleet corresponding to each area
2. Maximize NR for fleet 1 subject to the constraint that total effort must be non-negative and can't exceed the maximum effort constraint. Update the effort vector for fleet 1.
3. Repeat step 2 for fleet 2.
4. Repeat steps 2 and 3 until the maximum absolute change in effort for all areas for both fleets is less than .0001, which is the relative tolerance level we define for the comparisons.
5. Check that the resulting distribution of effort is a constrained Nash equilibrium by checking that the first derivatives are equalized across all areas where a positive level of effort is exerted, and for each fleet (equation 3.28):

$$\frac{\partial NR_{ijt}}{\partial f_{ijt}} = \frac{\partial NR_{ijt}}{\partial f_{ijt}} \quad \forall \text{ areas } j \text{ and fleets } i: f_{ijt} > 0 \quad \text{Eq. 3.28}$$

For the **gravity model** we define the ‘attractiveness’ of an area for a fleet as the marginal net revenue in that area (at zero effort) at the beginning of the time period. Relative attractiveness is attractiveness divided by the sum of marginal net revenues for that fleet over all areas. If marginal net revenue for a fleet in an area is negative that area is not included in the attractiveness calculation and effort is set to zero. Relative attractiveness of each area is then multiplied by the fleet’s upper constraint on effort to arrive at that fleet’s effort distribution:

$$f_{ijt} = E_{it} \cdot \frac{\frac{\partial NR_{ijt}}{\partial f_{ijt}}}{\sum_{j=1}^3 \frac{\partial NR_{ijt}}{\partial f_{ijt}}} \quad \forall j, i: \frac{\partial \pi_{ijt}}{\partial f_{ijt}} \geq 0 \quad Eq. 3.29$$

The **sequential model** that we use in the comparisons assigns all available effort for a fleet during a sub-time period to the area where that fleet’s first derivative of net revenue (Eq. 3.27) is highest. The derivative is evaluated before effort is exerted, i.e. at zero effort levels. Effort for the area with the highest marginal net revenue is set to the effort limit, while effort in the other areas is set to zero. For the simulations, the weekly time period is split into 7 day periods which is the level that the sequential model makes effort calculations. Daily effort predictions are then aggregated into weekly statistics to facilitate the comparisons.

The **sole owner model** maximizes the sum of net revenue for both fleets with the constraint that each fleet’s effort in each time period cannot exceed an effort limit, E_k . The Lagrangian to be maximized is:

$$\max \mathcal{L}_t(f_{ijt}, \lambda_{ijt}) = (\sum_{i=1}^2 p \cdot C_{ijt} - f_{ijt} \cdot v_i) - \lambda_1 (\sum_{j=1}^J f_{j1t} - E_1) - \lambda_2 (\sum_{j=1}^J f_{j2t} - E_2) \quad Eq. 3.30$$

Where C_{ijt} is shown in equation 3.22. Note that the first derivative of C_{ijt} with respect to own effort is positive. In terms of other fleets’ effort the effect is negative. The Kuhn-Tucker conditions are:

$$\begin{aligned} \frac{\partial \mathcal{L}_t(\cdot)}{\partial f_{1jt}} &= p \frac{\partial C_{1jt}}{\partial f_{1jt}} + p \frac{\partial C_{2jt}}{\partial f_{1jt}} - v_1 - \lambda_1 = 0 \\ \frac{\partial \mathcal{L}_t(\cdot)}{\partial f_{2jt}} &= p \frac{\partial C_{1jt}}{\partial f_{2jt}} + p \frac{\partial C_{2jt}}{\partial f_{2jt}} - v_2 - \lambda_2 = 0 \\ \lambda_i \frac{\partial \mathcal{L}}{\partial \lambda_i} &= \lambda_i [\sum_{j=1}^J f_{ijt} - E_i] = 0 \quad , \quad i = 1,2 \end{aligned} \quad Eqs. 3.31$$

$$\frac{\partial \mathcal{L}_t}{\partial \lambda_i} = \sum_{j=1}^J f_{ijt} - E_i \leq 0, \quad i = 1,2$$

$$\lambda_i \geq 0, \quad i = 1,2$$

The first derivative of the objective function for the sole owner model includes both the positive marginal impact on a fleet's net revenue function of increasing that fleet's effort in an area, as well as the negative marginal impact on that fleet's net revenue function of increasing the *other* fleet's effort in that area. The necessary first order conditions for the B-N model, in comparison, only include the positive marginal impact of a fleet increasing its effort in an area. The impact of the other fleet's effort on net revenue in the B-N model is incorporated in the iterative solution technique.

3.3.3 BASE PARAMETERS

While many different parameter values were explored we chose a set of base parameters such that even if all effort was concentrated in one area for the entire season, net revenue rates would still be positive at the end of the season, i.e. stocks would not be depleted to a level where it was not profitable to fish in a given area. This could be induced in the model by decreasing starting stock size, increasing costs, increasing catchability, increasing natural mortality, or increasing the weekly effort limit. Base parameters are shown in table 3.1:

Table 3.1: Base set of parameters used in the simulations

Variables	Area 1	Area 2	Area 3	Fleet 1 values	Fleet 2 values
Starting stock size by area (tons)	60,000	60,000	60,000		
Natural mortality per week	.04	.04	.04		
Parameters					
Catchability by fleet				.00025	.00025
Cost per fishing day by area	\$100	\$150	\$200	same	same
Price of fish per ton				\$200	\$200
Effort limit per week period				70 days	70 days

3.4 Results

The predictions of the gravity model conform to general findings in the literature -- effort is spread out among all areas throughout the season. The only difference between areas at the beginning of each season

is costs of fishing, and the ‘attractiveness’ of each area in this model is defined at a vector of zero effort levels. Therefore the impact of changes in the value of parameters on the gravity model predictions depends on that parameter’s effect on marginal revenue in each area (the first term on the right hand side of equation 3.32), on that area’s relative attractiveness to the other areas in the model. When areas and fleets are homogenous, marginal revenue increases with an increase in each of stock size, catchability, and price and increases in the relative values of these parameters relative to area costs will cause the gravity model to predict a more even distribution of fishing effort over areas. This is due to differences in attractiveness (a_j) between areas diminishing. An increase in the effort limit does not affect marginal revenue directly, but rather through a dynamic stock depletion effect. As effort in an area is increased, the stock is depleted more than it would have been with a lower effort limit. This lowers the available stock in the next time period, and causes the gravity model to concentrate effort more in low cost areas as the season progresses, even with no differences in the exploitation rate between areas.

$$a_j = \frac{\partial NR_{ijt}}{\partial f_{ijt}} = p \cdot N_{jt} \cdot \frac{q_i}{M_j} [1 - \exp(-M_j)] - v_{ij} \quad Eq. 3.32$$

Equation 3.32 is also evaluated in the sequential model although in this model all of a fleet’s effort for a single sub-period (in our case a fishing day) is allocated to the area with the highest attractiveness, a_j . The sequential model therefore does not take other fleets’ predicted behavior into account directly. The fact that the sequential decision is made 7 times in the space of a week (compared to once for the other models) means that dynamic stock depletion effects are implicitly taken into account- the attractiveness of each area, after each day’s mortality has occurred is re-evaluated on a daily basis, which alludes to a brute force profit maximization procedure.

The sole owner model maximizes total fleet profit in each time period by adjusting the distribution of effort over all areas without regard to whether or not this distribution is optimal for each individual fleet. Equation 3.33 illustrates the necessary first order conditions for maximum fleet profit in each time period. The positive effect on each fleet’s marginal revenue of (1) is balanced against the negative effect on the other fleet’s marginal revenue of exerting effort (2).

$$\frac{\partial \mathcal{L}_t(\cdot)}{\partial f_{ijt}} = p \frac{\partial C_{1jt}}{\partial f_{ijt}} (1) + p \frac{\partial C_{2jt}}{\partial f_{ijt}} (2) - v_i - \lambda_i = 0 \quad Eq. 3.33$$

In contrast the B-N model follows an algorithm where each fleet's optimal distribution is calculated by explicitly taking the other fleet's best response (*BR*) into account (equation 3.34). A fleet's best response in this case is a fleet's effort distribution that results in maximum net revenue given the effort distribution of the other fleet. Fleets are therefore treated as individual profit maximizers and not overall profit maximizers as in the sole owner scenario.

$$\frac{\partial \mathcal{L}_t(\cdot)}{\partial f_{1jt}} = p \frac{\partial C_{1jt}(f_2(BR))}{\partial f_{1jt}} - v_1 - \lambda_1 = 0 \quad \text{Eq. 3.34}$$

3.4.1 HOMOGENOUS FLEETS

In the base parameterization where both fleets are identical, the Baranov-Nash (B-N), sole owner, and sequential models all make similar predictions to each other, exerting effort first to the areas with the highest rate of net return (the closest area to port), and switching to the other areas once stock levels became depleted enough to equalize rates of net return between areas (figure 3.1). The sequential model makes similar predictions to the sole owner and B-N models but effort is allocated coarsely- in whole day increments (a total of 10 fishing days allocated per model day due to a fleet size of 10 vessels). Most effort is exerted in area 1 at the beginning of the season, and as stocks are depleted, effort spreads out into areas where fishing costs are higher, but stocks are higher. Table 3.2 shows aggregate effort predictions by area throughout the season.

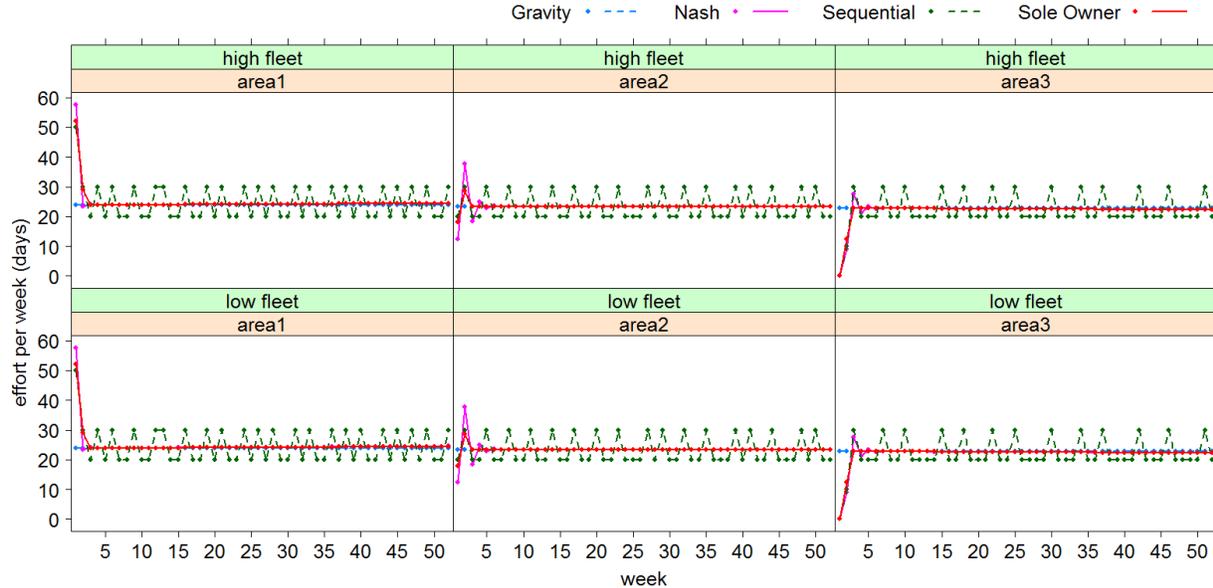


Figure 3.1: Predicted effort distributions under the base parameterization where fleets are identical in costs and catchability.

Table 3.2: Aggregate predictions of effort under the base parameterization

	Gravity		Sequential		Sole Owner		B-N	
	Low	High	Low	High	Low	High	Low	High
Area 1	1239.335	1239.335	1290	1290	1288.949	1288.906	1289.178	1288.841
Area 2	1213.315	1213.315	1210	1210	1212.373	1212.416	1212.385	1212.397
Area 3	1187.35	1187.35	1140	1140	1138.679	1138.679	1138.437	1138.762

After the initial distribution of effort into the higher cost areas (by week 3 in this parameterization), the predicted levels of effort in the low cost area increase gradually, while predicted effort in the far areas decrease. This gradual reallocation of effort to low cost areas is due to the fact that as stock size in the high cost area decreases, the impact of area-specific fishing costs has a stronger negative effect on the marginal net benefit of fishing in that area. This stock depletion effect reduces marginal net benefits of fishing in high cost (far away) areas at a faster rate than in the closer areas causing effort to concentrate in the area

that is closest to port. This can also be seen from equation 3.32- as stock size decreases in an area the attractiveness of that area decreases. However, for successively lower stock sizes, the (negative) slope of the first derivative of revenue decreases, and this is manifested in a gradual reallocation of effort towards low cost areas as the season progresses. To illustrate this effect, in the base case scenario the share of effort predicted by the gravity model in area 1 is 33.92% and 32.75% in area 3. By the end of the season the shares have changed to 34.07% and 32.6%, respectively. If the simulation is extended for a total of 10 seasons these shares change to 54.5% and 12.36%, respectively, and this occurs even though the stock size at the end of 10 seasons in area 3 is 15.94% bigger than that in area 1, compared to .004% bigger at the end of the first week of the first season.

When fleets are homogeneous the predictions of the B-N, sole owner, and sequential models are essentially the same and changes in price, initial biomass, catchability, and costs, affect each model's predictions in a similar fashion.

For higher levels of initial biomass, *ceteris paribus*, marginal revenue rates increase for all areas while marginal costs remain the same. The differences in marginal net revenue between areas therefore decrease and the overall predictions of the gravity model and the other three models become more similar. The effect of increases in price have the same effect on model predictions as that of an increase in initial biomass, and the mechanism is the same -- a higher price implies a higher marginal net revenue due to increases in marginal revenue while marginal costs remain the same. This implies that the differences in marginal net revenue between areas decreases at a faster rate as price increases, and overall model predictions become more similar. The effects of increases in the catchability coefficient are similar -- an increase in catchability increases the marginal revenue component of attractiveness for all areas, but does not affect the marginal cost component. Costs therefore become less important when determining *relative attractiveness* of each area, and effort distributions become more spread out and greater effort is exerted in the high cost areas. This implies that, in these models, fleets that have a higher catchability coefficient tend to spread their effort out more than fleets that have lower coefficients. As the level of catchability increases, marginal catch rates increase, *ceteris paribus*. This implies that stock levels in areas that are fished first are depleted faster, bringing marginal revenue rates in these areas down to the level of marginal revenue rates in high cost areas at a faster rate. Higher catchability coefficients imply that the differences in solutions between the gravity model, the Baranov-Nash, sole owner, and the sequential model will decrease as populations are fished down to levels that equate marginal net revenue between areas at a faster rate, decreasing differences between the gravity model predictions and the predictions of the other models.

Changes in the *level* of fishing costs, as long as the *differences* in costs between areas do not change, do not make any difference to the predicted distribution of fishing effort in the B-N, sequential, and sole owner models, as long as net benefits of fishing are still positive in all areas throughout the season. For the B-N, sequential, and sole owner models, when fishing cost differences between areas do not change *relative* marginal net benefits of fishing also do not change, and there is no change to predicted effort distributions. However, in the gravity model, as the level of costs increases, the denominator term in equation 3.32 decreases, causing the relative differences in net revenue rates between areas to increase. This makes the low cost areas relatively more attractive in this model, and relatively more effort is exerted in these areas. In other words a higher proportional level of fishing costs for all areas causes the gravity model predictions to be more concentrated in the low cost areas.

3.4.2 HETEROGENEOUS FLEETS

The B-N and sole owner models' predictions are highly affected by heterogeneity in catchability, and in ways that are non-intuitive. While changes in the costs of the other fleets do not appear explicitly in each fleet's net revenue function for each of these models other fleets' catchability coefficients do (equation 3.25). The B-N model takes other fleets' catchability coefficients into account through an *a priori* calculation of the other fleet's best response to arrive at their own best response, and eventually a Nash equilibrium. The sole owner model does not account for the fact that each fleet is a profit maximizer and the optimal effort schedule from a sole owner's perspective will therefore reflect the fact that overall fleet profit can be higher by distributing each fleet in ways that are sub-optimal from an individual perspective. The sequential model's predictions conform closely to those of the sole owner model when fleets are heterogeneous in catchability. Given that each fleet allocates each day's effort to the area that provides the highest expected net revenues one would expect a solution similar to the B-N model. However, the competitive interaction of exploitation competition, which acts as a dispersive force are not taken into account *a priori* in the sequential model and effort predictions align with those of the sole owner model. The gravity model evaluates the marginal net revenue rates at the beginning of the time period, at zero effort levels and the characteristics of other fleets are not taken into account when effort is distributed. Figure 3.2 shows model predictions for a low catchability fleet with the catchability coefficient fixed at the base level (.00025) and a high catchability fleet with a catchability coefficient of .0003. Table 3.3 shows the sum of effort for the season by fleet and area. The gravity model predicts effort that is spread out evenly across all of the areas.

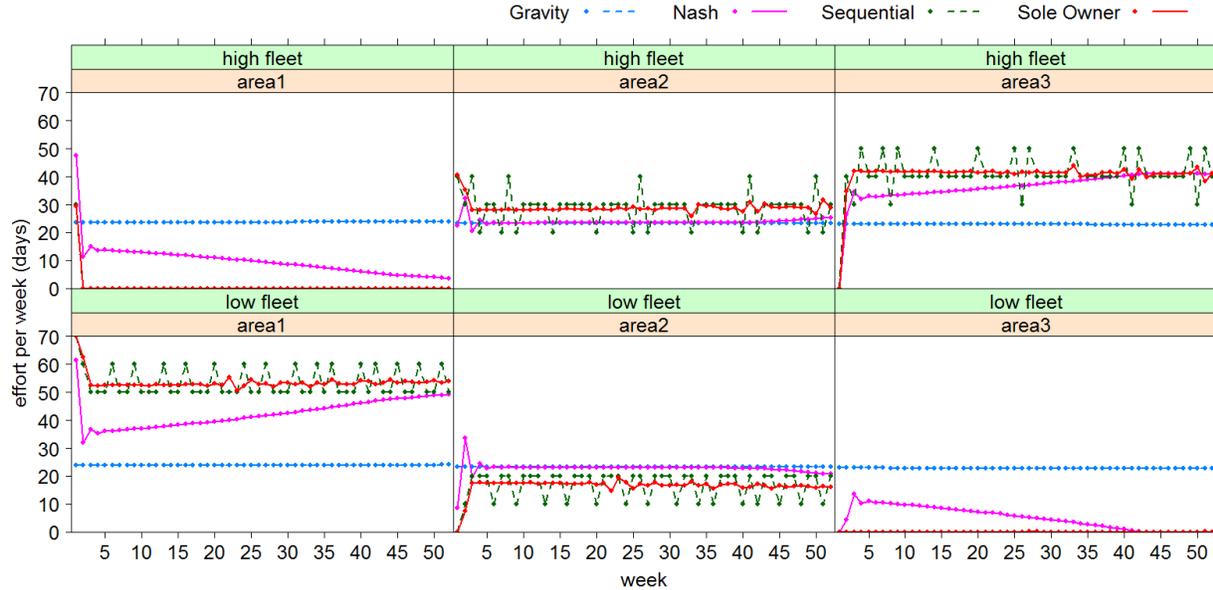


Figure 3.2: Predicted effort distributions with heterogeneous catchability. The catchability coefficient for the ‘high’ fleet is increased to .0003, all other parameters at base levels.

Table 3.3: Aggregate effort predictions for the scenario in figure 3.2

FLEET:	Gravity		Sequential		Sole Owner		B-N	
	Low	High	Low	High	Low	High	Low	High
Area 1	1240.581	1234.414	2780	30	2785.378	29.69756	2201.237	512.0598
Area 2	1213.315	1213.315	860	1500	853.7504	1503.876	1179.765	1239.001
Area 3	1186.105	1192.272	0	2110	0.871328	2106.426	258.9981	1888.939

Costs of fishing are affected by many things in practice, including fuel and lube prices, number of crew on board, vessel maintenance, and vessel depreciation. In our simple model we include costs as a constant amount per fishing day relating to each area with the implicit assumption that higher costs for the areas that are farther away from port arise from increased travel costs, including fuel and lube costs. We investigate how differences in both the level of costs between fleets, which could be attributed to differences in a fixed cost (such as license fees) between vessels, and the difference in costs between areas, which could represent

differences in fuel consumption between fleets, affect our model predictions. When fleets are homogeneous, as long as the differences in costs of fishing between areas remained the same, and if costs remained below the level that would drive net revenue rates to zero, a change in the overall level of costs had no impact on the effort distributions predicted by the B-N and sole-owner models, while the gravity model's predictions are affected by any kind of change in the costs of fishing. When fleets are heterogeneous in costs this result holds as long as the differences in costs between areas are the same for all fleets, i.e. there is no change in effort distributions with an increase in the level of costs. However, when the costs of fishing in a particular area changes in a way that preserves the ordering of costs, but causes a change in the difference between area-specific costs, model predictions are affected significantly. However, the sole owner, sequential, and B-N predictions are similar. Figure 3.3 shows model predictions for a low cost fleet with the base cost structure, and a high cost fleet with fishing costs of \$200, \$400, and \$600 per day for areas 1, 2, and 3, respectively. Table 3.4 shows the sum of effort over the season for each fleet in each area

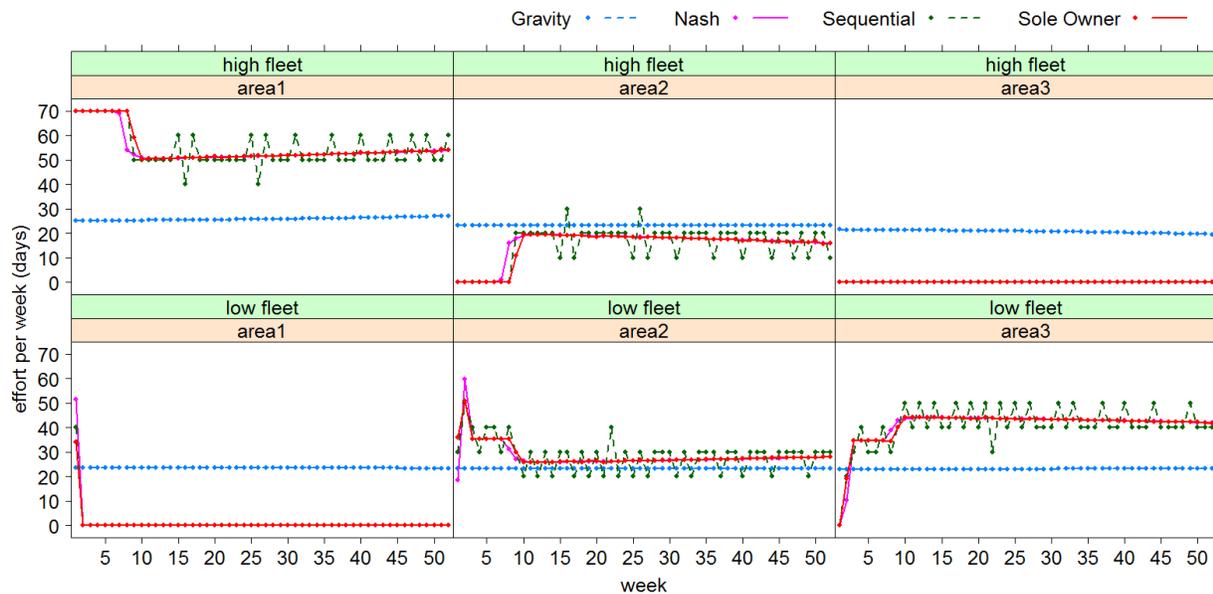


Figure 3.3: Predicted effort distributions with the heterogeneous costs. Fishing costs for the ‘high’ fleet increased to \$200, \$400, and \$600 per day in areas 1,2, and 3 respectively. All other parameters at base levels.

Table 3.4: Aggregate effort predictions for the scenario in figure 3.3

FLEET:	Gravity		Sequential		Sole Owner		B-N	
	Low	High	Low	High	Low	High	Low	High
Area 1	1225.705	1346.724	40	2850	34.01179	2855.571	51.46322	2830.797
Area 2	1213.192	1213.163	1480	790	1481.683	784.4293	1464.575	809.2031
Area 3	1201.103	1080.113	2120	0	2124.305	0	2123.962	0

When fleets are heterogeneous in costs the B-N, sequential, and sequential models predict that both fleets will operate in the low cost area at the beginning of the season. However, the low cost fleet's profit maximizing strategy is to stop fishing in area 1 after the first week. In the case of identical fleets one would expect this fleet to keep exerting some effort in area 1. However, the relatively high cost of fishing in area 2 means the high cost fleet exerts more effort in area 1. This added exploitation competition results in a lower rate of marginal net revenue for the low cost fleet in area 1 and causes it to exert more effort in area 2, and consequently in area 3 at a much earlier time. This illustrates a possible mechanism for the observation that vessels with high fishing efficiency spread their effort out more than other vessels (Abrahams and Healey 1990).

3.4.3 IFD PREDICTIONS

A corollary to our comparison is to examine the conditions under which the average net revenue rates in all areas are predicted to be equal, which represents the outcome that is described by the Ideal Free Distribution (IFD). When fleets are homogeneous, average net revenue rates are predicted to equalize for the sequential, Baranov-Nash, and sole owner models throughout the range of parameters tested. However, the gravity model does not make the IFD prediction under any set of parameters. Figure 3.4 shows average net revenue per unit effort for the base model setup. In these simulations effort is exerted in area 1 first, then into area 2 as the stock in area 1 is depleted to the point which equalizes marginal net revenue in area 2 with that of area 1. Eventually effort is exerted in area 3 and net revenue rates are equalized between areas.

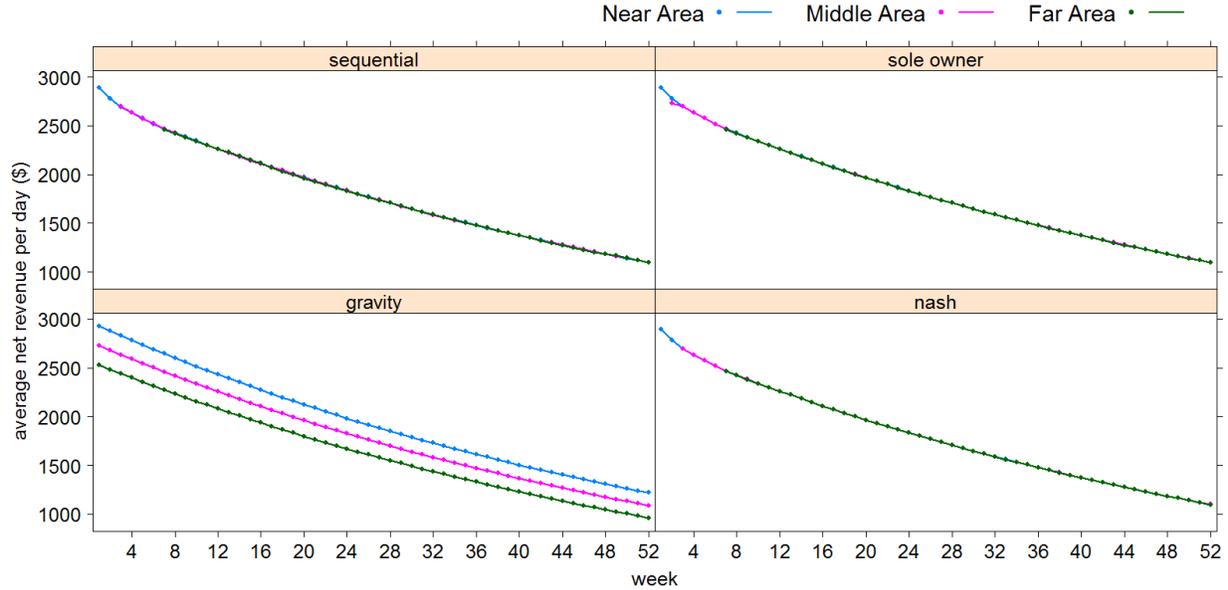


Figure 3.4: Ideal Free Distribution predictions for each model with parameters at base levels.

When fleets are heterogeneous, an IFD distribution is predicted by the Baranov-Nash, sequential, and sole owner models only when the heterogeneity is in fishing costs, and when the difference in costs between areas is the same for all fleets. This is an important result for future empirical analyses of IFD formation in fisheries. If the difference in costs is different for each fleet, the IFD prediction is not made. Similarly, when fleets are heterogeneous in catchability, none of the models we examine make an IFD prediction. Figure 3.5 shows the case for 2 fleets that are heterogeneous only in catchabilities.

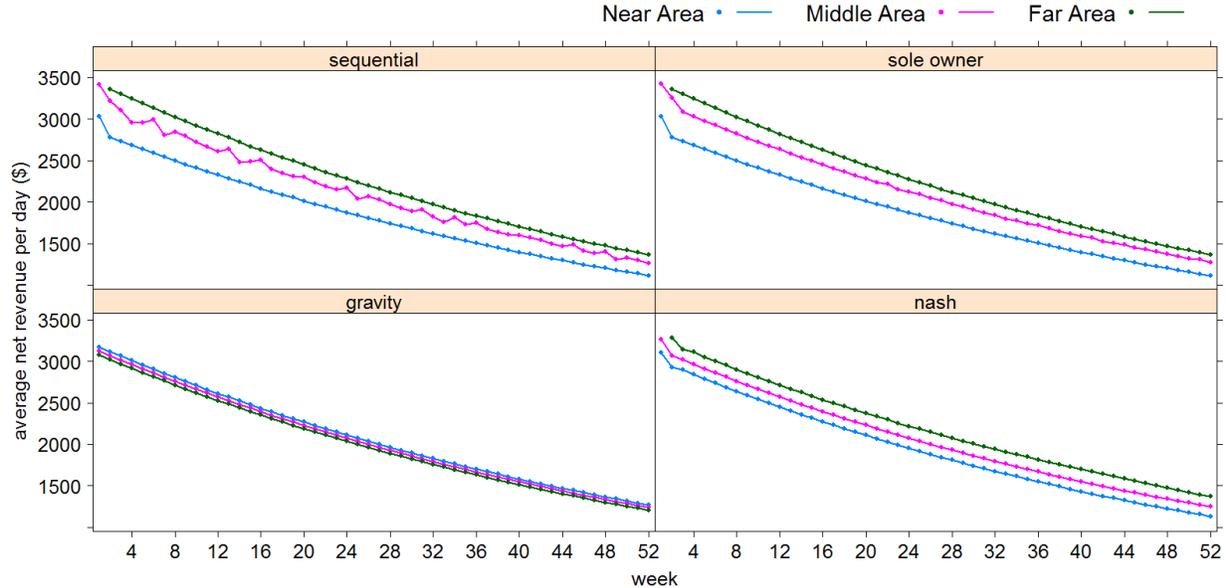


Figure 3.5: Ideal Free Distribution predictions with the catchability coefficient for the ‘high’ fleet increased to .0003 All other parameters at base levels.

3.5 Discussion

The results of our simple comparison illustrates the potential modeling implications of utilizing a method for spatially distributing fishing effort in bioeconomic simulation models that is not based on an explicit theory of how fishermen behave on the spatial dimension. In a simple comparison of the gravity model, which is not based on any explicit economic theory of behavior, to the Baranov-Nash (B-N) model, and two other methods for distributing fishing effort in simulation models, we show that the predictions of the gravity model differ in systematic ways to those of the other 3 models in the comparison. As indicated previously, the gravity model spreads effort out among areas in ways that do not make intuitive economic sense (Pelletier and Mahévas 2005). When fleets are homogeneous, the overall predictions made by the B-N, sole owner, and sequential models were very similar over a wide range of parameter values, with the caveat that the sequential model makes ‘coarse’ effort predictions compared to the continuous predictions of the other models. The degree to which these models’ predictions differed from those of the gravity model depended on the degree of heterogeneity between areas. In general, the more heterogeneous fishing areas were either in terms of stock size or distance from port, the more disparate the gravity predictions were from those of the other three models. In extreme cases area characteristics caused effort to distribute to all areas in the gravity model in relatively equal proportions while effort in the other models was predicted to

remain in only one area. This illustrates the potential erroneous predictions made by the gravity model if fleets do not distribute their effort in proportion to marginal profit in each area. The *levels* of the parameters in the model affect the similarity of the gravity predictions to the predictions of the other models. Keeping everything else constant, the higher the levels of catchability, stock size, and price, the more quickly differences in the marginal net revenues between areas decreased, and the faster effort spread to all areas in the model. While the gravity model is attractive partly due to its simplicity of use, in cases where areas and vessels are heterogeneous, theoretical justification for its use may be limited.

The predictions of the Baranov-Nash, sole owner, and sequential models were generally consistent with each other in that fishing effort was exerted in the highest valued patches first then move to the other patches. This behavior is consistent with predictions in the literature e.g. Gillis and Peterman (1998), and reinforces the idea that fleet movement acts as an averaging force, reducing economic differences between areas (Sanchirico and Wilen 2005; Smith, Sanchirico, and Wilen 2009). We show that when fleets are homogenous, predictions made by the three behavioral models are generally similar under a wide range of parameter values. This observation holds even when fishing vessels are heterogeneous in terms of their cost structure. When the costs of fishing differ between fleets, these differences lead to different predictions of effort distributions only when the fleets have heterogeneous *differences* in costs between areas. (see Fig. 3.3). When the difference in costs between areas is the same for two fleets, such as is the case with one vessel having a higher fixed cost (such as quota leasing cost) with variable costs of fishing (such as fuel costs) the same for the two fleets, all of the models predict that each fleet's effort distribution will be identical to the other. When the cost structure is such that the difference in costs of fishing between areas is different for the fleets, differences between the fleets' effort distributions predicted by each of the models occur. When one 'high cost' fleet has a relatively higher difference in fishing costs between areas than a 'low cost' fleet, we find that the behavioral models (B-N, sole owner, and sequential) predict that the low cost fleet will exert more effort in higher cost areas and the high cost fleet will exert more effort in the low cost areas. The mechanism is that the high cost fleet changes its behavior relative to the base case and maintains a high level of effort in the low cost area. This added exploitation competition causes marginal net revenues for the low cost fleet to drop much faster, with marginal net revenues in the other areas becoming more attractive at relatively earlier times. These dynamics are not captured by the gravity model.

When fleets are heterogeneous in terms of their relative fishing power (catchability coefficient in our models), their predictions diverge and model results differ in ways that are not intuitive. While the gravity model still predicts a relatively even distribution of fishing effort over all areas and throughout the season,

the behavioral models make different predictions to each other. If a 'high power' fleet has a higher catchability coefficient than a 'low power' fleet all of the behavioral models predict that the high power fleet will distribute their effort in higher cost areas, where reduced exploitation competition outweighs the extra costs involved in fishing in those areas. This observation provides a possible mechanism to explain the observations of Abrahams and Healey (1990), who observed that vessels with better fishing ability distributed effort over more areas than their less-able counterparts. In the case of heterogeneous catchabilities the sole owner model 'plays off' the fleets' exploitative abilities to arrive at a distribution of effort where total profits are maximized, while the B-N model arrives at a distribution of effort that is a Nash equilibrium -- one that neither fleet has an incentive to deviate from, and which is optimal from each individual fleet's perspective. In all of the simulations the sole owner model's predictions resulted in at least one of the fleet's profits in a time period being lower than in the Nash solution. This has important implications in models where distributional impacts among fishermen are calculated. The behavioral assumptions made in using the sole owner model and the B-N model differ. The sole owner model's assumptions do not necessarily abide by individual utility or profit maximizing axioms, in that each fleet does not maximize its own profits, while the B-N model does agree with individual profit maximizing behavior. The sole owner model may be useful as a benchmark in deriving the socially optimal solution (assuming no supply effecting consumer surplus) with which to compare other distributions. It may also provide a way of describing the gains of cooperation between fleets (Merino, Maynou, and García-Olivares 2007). The sequential model is also based on an explicit theory of individual fisherman behavior that explains why fleets will choose one area in which to fish for a given time period based on the characteristics of the area at the beginning of that time period and its own technical parameters. However, the sequential model has seen very little use in the published literature even though it has clear theoretical advantages compared to the gravity model. While intuitive, this method can only be resolved at as fine a temporal scale as is defined in the model- unlike the other models in the comparison, no fractions of weeks can be allocated between areas. We suggest that one of the main reasons that the sequential model has not been applied more widely in the literature is because of a perceived complexity of implementation compared to the gravity model. In our experience, however, the sequential model was relatively simple to incorporate into model code. Compared to the gravity model, we assert that the main drawback of its use lies in the granularity of its predictions, and in cases where the time it takes to reach a solution are important, provides a good alternative.

While the general pattern of the behavioral models predicting that the vessels with better fishing ability will distribute to more areas in the model agrees with observations in the literature (Abrahams and Healey 1990), the opposite prediction is made in the case of the theory of the Ideal Free Distribution (IFD). In IFD studies, vessels with a higher competitive ability are shown to generally be more prevalent in the better patches (in our case the low cost areas) (Sutherland and Parker 1985; Voges, Gordo, and Field 2005). While a mechanism for this observation has not been established, a conceptual difference is that our models rely on exploitation competition, i.e., the depletion effect on the resource as a measure of competitive ability, while the IFD relies solely on interference between vessels. A strong competitor in interference competition refers to the ability of that vessel to interfere with the effectiveness of other vessels' fishing activity with no exploitation effect. The mechanism that would result in these vessels being more prevalent in higher value patches is unclear. When an IFD occurs in fisheries, it represents a situation where average net revenues are equalized across the areas in the fishery. Gillis and Peterman (1998) showed that when fleets are homogenous and the main source of fish abundance decline is exploitation, the presence of even a small amount of interference competition is enough to equalize catch rate among grounds even when area characteristics are different. We have shown that when fleets are homogenous and areas are heterogeneous, a distribution of effort that is identical to that predicted by the IFD can occur when the sole source of competition is exploitation competition. Through our simulations, we have also shown that when fleets are heterogeneous, this distribution can occur, but only in cases where the *differences* between areas for each vessel in the fishery are similar. This has important implications for future research on IFD formation in fisheries.

In many models the question of *how much* effort to exert in a fishery is often decoupled from the question of *where* to exert it. The Baranov-Nash method can be used to calculate a *level* of effort in each area in the absence of a binding total effort limit. We did not demonstrate this in the simulations as the goal was to make the models as directly comparable as possible. However, this is an avenue for future work.

While models based on a statistical analysis of fishermen's behavior, such as a RUM, offer a defensible approach to distributing effort in a simulation model that is based on historical fishery conditions, these approaches are often time consuming, and theoretically difficult to grasp for non-economists. We argue that the B-N method is intuitively sensible, less time- and data-intensive than models based on the random utility framework, and, of the models in our comparison, is the most attractive from a theoretical economic standpoint. However, it is the most time intensive to incorporate into model code and computer resource intensive when solving. It should be noted that while time to compute solutions was relatively short for all

solutions (a few milliseconds for the gravity and sequential model, a few seconds for the sole owner and B-N models), when incorporated into models of greater complexity, which bioeconomic simulation models generally are, this difference in computation time is inevitably magnified, and can have serious implications for modeling projects. Computation time therefore becomes a non-trivial consideration when deciding on a choice of model, especially when results of two competing models are similar. We show the conditions under which the predictions made by the gravity model are likely to be similar to the three behavioral models in the comparison. When all vessels are treated as homogenous, and the differences in stock size or costs of fishing between areas is relatively small the gravity model is a simple method of distributing effort in a simulation model that may result in predictions that are similar to those made by behavioral models. However, when significant heterogeneity in the vessels exists, and areas characteristics are different, the gravity model may make effort predictions that diverge from predictions based on economic theory. The main assumptions underlying the B-N model are that all fishermen have complete knowledge regarding the other fleets' technological characteristics and the distribution of the resource stock. While clearly untenable, increased technology for imaging and finding fish stocks, as well as the use of satellite navigation and improved vessel communications may mean that these assumptions are no longer as strong. If one of the goals of bioeconomic simulation modeling is to realistically represent fishermen's decisions in time and space in order to examine the possible interactions between fishermen and resource dynamics, a model that is based on an individual profit maximizing theory arguably takes us further along the road to achieving that goal.

Simulation exercises such as the one we present are useful for exploring the behavior of models that are analytically intractable. Our simulation exercise is simple and abstracts from reality significantly, but its simplicity is also its strength. We abstracted away from stock dynamics and focused instead on the behavior of the fishermen explicitly and we generated results that are easier to interpret and to identify effects than if we had incorporated a higher degree of 'reality' into the model. To paraphrase Hilborn and Walters (1987), *even very simple simulations can help us to better understand the dynamics of fisheries.*

3.6 Conclusion

While the implications of including spatial fisherman behavior in fishery models for model predictions has been noted for many years, most bioeconomic simulation models of fisheries do not incorporate a method for spatially distributing fishing effort that is based on an explicit theory describing how fisherman behave in space. In this paper we introduce a novel method for spatially distributing fishing effort in bioeconomic

simulation models that is based on a theory of individual maximizing behavior. We show, through the lens of simulation, the possible implications of distributing effort using a model that is not based on a theory of individual behavior (the gravity model), and compare results to predictions made by our game theoretic method as well a sole owner model and the sequential model. The gravity model is attractive partly because of its simplicity, it is easy for non-economists to grasp, and is relatively easy to code into simulation models. However, the degree to which predictions made by the gravity model differ to predictions of the behavioral models depends on the degree of heterogeneity in the fishery. In general, as heterogeneity increases, the degree to which the gravity predictions conform to the other models' predictions diverges. We also show the general conditions under which the predictions of the three behavioral models diverge. If vessels are homogenous, these three models make very similar predictions. However, if vessels are heterogeneous in fishing ability, the choice of behavioral model has significant implications for effort predictions. Finally, we show that under exploitation competition only, a distribution of effort that mimics that of an Ideal Free Distribution is predicted by the behavioral models, and show that this prediction holds even if fleets are heterogeneous in cost structure, albeit only if cost differences between fishing areas for all vessels do not exist.

3.7 References

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4. THE BIOECONOMICS OF SOFT SHELL CRAB: EVALUATING THE IMPACTS OF CHANGING SEASON LENGTH IN OREGON'S DUNGENESS CRAB FISHERY.

4.1 INTRODUCTION

Fishery management measures that specify restrictions on the sex or size characteristics of retainable catch are generally designed to protect a stock's reproductive potential, a stock's growth potential, or both. The intuition is that undersize animals that grow at a high rate, or large animals and females that have a high reproductive value to the overall population, can be released back into the population and provide future economic benefits (Coggins et al. 2007). However, the extent to which this mechanism works depends on, among many other factors, the ability of the released animal to survive capture, handling, and post-discarding stress. Demersal fish caught in trawl nets, and those species of fish that are prone to barotrauma are thought to suffer relatively high levels of discard and handling mortality and mandates to discard these species are often designed under the assumption that none of these animals will survive discarding (Broadhurst, Suuronen, and Hulme 2006). However, other species such as crab and lobster caught using traps are thought to be fairly resilient to handling discarding stress, and regulations to discard certain components of the catch are designed under the assumption that many of these animals will survive and contribute to the future growth of the population and hence potential catch (Bunnell and Miller 2005).

In some crab fisheries a consideration that is not related to sex or size and that has the potential to determine both discard levels and the likelihood that an animal will survive handling is that of body condition due to stage of growth. While a crab's soft tissue grows continuously, its exoskeleton does not. Moulting is the process by which crab grow in shell size- shedding the old shell and revealing a new, larger, and (temporarily) 'soft' shell underneath. Soft shell crab are thought to suffer significantly higher rates of discard mortality than their hard shell counterparts (Kruse, Hicks, and Murphy 1994). In some cases, such as the blue crab fishery in Chesapeake bay, soft shell crab command a higher price and managers try to encourage fishermen's access to the resource at this stage, rendering increased handling mortality of soft shell legal sized animals largely irrelevant (Bunnell, Lipton, and Miller 2010; Huang et al. 2015). However, in other cases, such as the Dungeness crab fishery on the west coast of the U.S., soft shell crab are lower in meat quality and density and processors generally do not purchase these crab; management actions are designed to restrict fishermen's access to the resource at this stage of growth (Didier 2002). Increased handling mortality of soft shell crab is therefore an important consideration when designing management regulations in these fisheries, and given that handling mortality rates in any fishery are rarely estimated

(Benoît et al. 2012), represents a significant source of uncertainty to fishery managers, and one which has potentially important implications for the sustainability and profitability of fisheries (Davis 2002).

Management actions designed to address handling mortality concerns in crustacean fisheries are widespread and tend to focus on season length and timing restrictions which ostensibly reduce the probability that a soft shell animal will interact with the fishing gear in the first place. For example, the spiny lobster fisheries in New Zealand have relatively long restricted seasons in order to reduce pot related mortality (Breen and Kendrick 1997), and the Dungeness crab fisheries on the west coast of the U.S. have implemented seasonal closures since the mid-20th century to address soft shell mortality concerns (Didier 2002).

In Oregon, there has been renewed interest in examining the potential economic and biological impacts of further adjusting season length in the Dungeness crab fishery in order to protect soft shell crab which have little sale value (ODCC 2015). While some research has focused directly on the population effects of handling mortality (Coggins et al. 2007), and other research has indirectly examined the economic and biological impacts of discard mortality by comparing a range of alternative management strategies that have differential effects on mortality (Breen and Kendrick 1997; Bunnell, Lipton, and Miller 2010; Huang et al. 2015), we are aware of no research that has attempted to explicitly evaluate the economic *and* biological tradeoffs involved in implementing management measures designed to reduce discard mortality in a crab fishery.

The purpose of this paper is to develop a bioeconomic simulation model of the commercial Oregon Dungeness Crab (ODC) fishery to examine how changes in the season closure date may affect the level and distribution of profits in the fishery, and to determine how changes in the amount of soft shell crab mortality affect these profits. To the best of our knowledge, the ODC fishery has not been examined from a bioeconomic perspective. There is a reasonable level of knowledge regarding the biology of the Dungeness crab, including research on handling mortality rates (e.g. Yochum et al (in press)), that may be used to parameterize a representation of the biological dynamics of the stock. However, without a fishery independent estimate of the stock size or a rigorous examination and representation of the population dynamics of Dungeness crab, we are unable to make predictions of the *level* of economic impacts that may result from adjusting the season closure date. We focus our attention, therefore, on identifying a season closure date that maximizes economic performance in the fishery in a base representation of the model which is calibrated using the best available information from the literature, and then compare how this

closure date is affected by changes in fishery conditions such as recruitment size, timing of the moult, and handling mortality rates.

The overall simulation model combines a 3 cohort representation of the ODC stock where recruitment is determined by exogenous environmental forces, with a fleet dynamics model of the ODC fleet, where the amount of effort exerted in the fishery responds to changes in the abundance and cohort structure of the crab stock as well as economic conditions in the ODC fishery and other fisheries that ODC fishermen participate in. A realistic range of variability in recruitment is included in the model and the model is run over a range of model conditions in order to determine its sensitivity to model parameters. In the next section we give an overview of the economics and ecology of Oregon's Dungeness crab fishery and in sections 4.2 and 4.3 we present the biological and economic sub-models, respectively. In section 4.4 we present the combined bioeconomic simulation model and in section 4.5 we apply the model to hypothetical early season closure dates. We examine how changes in season closure dates affect both the level and distribution of economic impacts in the fishery, and how assumptions regarding the rate of handling mortality and the timing of the moulting process affect these impacts.

4.1.1 OREGON'S DUNGENESS CRAB FISHERY

Dungeness crab (*Cancer magister*) are a commercially important crustacean ranging from southern California to the Bering Sea, Alaska and are generally targeted by commercial fishermen using crab 'pots', which are baited metal traps. Since the first commercial landings were recorded in San Francisco bay in the 1840s the fishery has evolved to become the most valuable fishery, in ex-vessel value terms, in the California Current system (Rasmuson 2013; Dewees et al. 2004). The first commercial landings in the Oregon Dungeness Crab (ODC) fishery were recorded in 1889 (Demory 1990) and over the last several decades Oregon has contributed approximately 30% of the total coast-wide catch. Between December 2006 and August 2015, annual ex-vessel landing values of Dungeness crab in Oregon have ranged between \$29.43 million and \$50.15 million, making it consistently the most valuable fishery in the state of Oregon.

Hitherto unregulated, between 1948 and 1996 the management of the ODC fishery evolved to include seasonal closures to protect recently moulted crab, a moratorium on the retention of all female crab and under-size male crab (<159mm carapace width), and the inclusion of an escape hatch on all pots to allow crab in lost ('ghost') pots to escape (Didier 2002). While there was limited concern regarding the ability of the crab stock to replenish during this time, these management measures were intended to safeguard the reproductive and growth ability of the stock. As the fishery intensified towards the end of the 20th century,

the 'race for fish' that is characteristic of many open access fisheries led to significant overcapitalization in the fishery, high levels of occupational hazard from fishing in unsafe conditions, and conflict between different user groups, such as trawlers and crabbers (Demory 1990). This competitive behavior led to market gluts at the beginning of the season and poor product recovery rates which amplified inefficiencies in the fishery (Deweese et al. 2004). Another symptom of the race for crab was that while catch peaked in March and April prior to 1960, this peak gradually shifted towards the beginning of the season with the result that most of the season's catch is landed during the first 4-6 weeks of the season (Demory 1990; Deweese et al. 2004; Hackett et al. 2004).

As a response to these efficiency concerns, a limited entry program was established in 1996 which restricted the total amount of vessels that could operate in the fishery in a given season (Didier 2002). In 1998 a limit on the amount of crab that could be landed in a week period between June 15th and August 15th was implemented partly to protect soft shell crab from excessive handling mortality (Furman 2001). Finally, in 2006 a pot limit system was implemented which restricted the total amount of pots that vessels could use. The pot limit system was introduced as a tiered system where vessels were assigned a limit on the total number of pots they could use at a given time of either 200, 300, or 500 pots. The allocations for the limited entry and pot limitation programs were based on historical participation and fishing effort.

Since 2006 the management structure in the ODC fishery has been relatively stable. The fishery is managed cooperatively between the states of Washington, Oregon, and California with significant opportunities for input from stakeholders. The fishery is managed on a '3-S' (size, sex, season) system: only crab greater than 159mm carapace width are retainable, only male crab are retainable, and the season closes between August 14th and December 1st each year to protect moulting crab. In the last 8 years, the majority of the catch has been taken in the first 4 weeks of the season (figure 4.19), presumably when abundance of legal size males is high, which leads to high catch rates. In general, catch rates in the fishery are highest at the beginning of the season, and decrease towards the end of the season. While the traditional opening date of the ODC fishery is December 1st, the opening may be delayed if crab condition assessments made during pre-season tests indicate that the proportion of crab with meat recovery rates of less than 25% is higher than an acceptable level.

The ODC fishery has been certified as sustainable by the Marine Stewardship Council (Marine Stewardship Council 2010), and is commonly held up as an example of how to sustainably manage a crustacean fishery (Rasmuson 2013). The ODC fishery also allows significant input from stakeholders through the Oregon

Dungeness Crab Commission (ODCC). The ODCC was formed in 1977 as part of the Oregon Department of Agriculture's commodity commission program. This program allows 'growers' to tax themselves in order to increase their commodity's value, recognition and use, which in the case of the ODCC has resulted in a commitment to increase the profitability of the industry through "*promotion, education, and research*" (ODCC 2016a). The ODCC works closely with the Oregon Department of Fisheries and Wildlife (ODFW), the state agency responsible for ODC fishery management. The apparent sustainability of the ODC stock under the current '3-S' management paradigm, high ex-vessel revenues, and fishermen's participation in fishery management decisions through the ODCC have resulted in widespread faith in the current management structure and a reluctance to change among ODC fishermen. However, a very limited amount of research has been conducted on either the economics of the ODC fishery, or on the population size, structure, and dynamics of the crab stock. There is therefore a high level of interest among ODC fishermen, and the ODCC, in improving the state of knowledge regarding the fishery. While much of this desire for information discovery stems from feelings of resource stewardship among ODC fishermen, there is also interest in exploring ways that profitability in the fishery can be increased, particularly in ways that do not significantly change the existing management structure (ODCC 2015).

While there are few concerns regarding the sustainability of the ODC fishery, this is not driven by a rigorous assessment of their stock status and a formal assessment of the Dungeness crab stock in Oregon has not been undertaken to date. Rather, this optimism derives from the fact that while total fishery landings fluctuate from year to year, there has been no sustained downward trend in total fishery landings (Deweese et al. 2004). Landings of Dungeness crab in Oregon is often taken as a proxy of stock size and it is a common assertion that approximately 90% of the legal size male crab on the West coast of the U.S. are removed from the fishery each year (Deweese et al. 2004; Rasmuson 2013). Landings of Dungeness crab in Oregon and other west coast states fluctuate widely from year to year in a generally cyclical pattern that peaks approximately every 10 years (Hankin 1985; Demory and others 1990; Didier 2002; Dewees et al. 2004). While many explanations have been proposed for the cause of these fluctuations in abundance (see Hankin (1985) for a discussion), there is widespread consensus among fishery scientists that these fluctuations are due to changes in the abundance of crab that are recruited to the fishery and not changes in the dynamics of fishing effort (Hankin 1985; Heppell, Thompson and Price 2009).

In many fishery models a stock-recruitment relationship is specified which relates recruitment of new individuals in the population to the fishery as a function of the size and characteristics of the existing population. In the ODC fishery, however, it is thought that environmental influences during the larval stage

of a crab's life cycle may have the greatest influence in determining future crab abundance (Heppell, Thompson and Price 2009; Rasmuson 2013). In Oregon, Dungeness crab mate in the spring at the moment that mature female crab undergo moulting (ODFW 2016). Most male Dungeness crab then moult after the female moulting period in the late spring to summer although some moulting occurs throughout the year (Rasmuson 2013). After the initial moult the exoskeleton hardens over a period of two to three months, during which time they are in a soft shell state, and more susceptible to injury from handling (WDFW 2016). In Oregon, eggs hatch approximately 6 months after the female moult in January to March, and crab spend approximately 4 months as larvae before settling in the nearshore environment (Rasmuson 2013). During the larval phases survival rates and dispersion patterns are highly influenced by oceanographic conditions, including water temperature, current patterns, and availability of nutrients (Dunn and Shanks 2012). The current thinking is that the timing and pattern of currents in the California current system, which follow a cycle known as the Pacific Decadal Oscillation (PDO), is the main determinant of crab recruitment (Rasmuson 2013). The theory is that during a negative phase of the PDO, greater nutrient levels and cooler water temperatures result from stronger cool water currents flowing south as the California current (and weaker northward flows as the Alaska current). Both of these factors are thought to increase the survival of Dungeness crab larvae. Extremely high larval mortality rates coupled with extremely high numbers of crab larvae means that even a small improvement in larval stage survival rates can translate into a potentially huge increase in recruitment to the fishery (Hankin 1985). While there are likely to be many causes of the fluctuations in crab abundance between years, Shanks and Roegner (2007) showed that larval survival rates explained approximately 90% of the variability in the adult Dungeness crab population between San Francisco and Washington.

While much is known about the biology and life cycle of the Dungeness crab there is very limited information regarding its stock dynamics, partly because much of the information that is required to conduct a rigorous stock assessment has not been collected (Heppell, Thompson and Price 2009). For example, size and sex composition of the catch, and an accurate measure of the total number of pots used in the fishery were not collected until the recent change in management to reduce overcapitalization. (Didier 2002). However, starting in 2008 all ODC fishery participants are required to record fishing locations as well as other trip level information in vessel logbooks. While there has been no rigorous estimate of the size and age structure of the Oregon Dungeness crab stock, the fact that fishery catch has recovered to high levels within a few years of any drop in levels is indicative of a highly resilient population (Heppell, Thompson and Price 2009). In addition, there is no empirical evidence that suggests that the moratorium on retaining

females and small male crab has led to a sex and size distribution that significantly impacts female mating success (Hankin, Hackett, and Dewees 2005; Rasmuson 2013). In fact, some authors have suggested that the fishery is under-utilized and that the male size limit could be reduced and some females allowed to be retained without a significant effect on the reproductive potential of the population as a whole (Heppell, Thompson and Price 2009).

Currently, one of the main concerns in the fishery is the potential impact of fishing towards the end of the season on recently moulted (soft-shell) crab, which are generally not retained for sale (ODCC 2015). Most male crab in Oregon moult between April and September (Rasmuson 2013), and while they are in a soft shell state they are highly susceptible to handling mortality through being captured in pots, brought on deck, then released (ODCC 2015). The concern is that these removals from the population towards the end of a season are due to handling mortality and have a significant effect on the catch levels of saleable, hard-shell crab in subsequent seasons. While concern over handling mortality of soft shell crab is not new and regulations have been in place to reduce softshell harvests and mortality (e.g., the weekly catch limit of crab in the summer months and an August 14th season closure), no assessment of the potential impacts of ‘summer’ fishing has been conducted to date. Such an assessment is complicated by the fact that very little is known regarding either the timing of the moult, the distribution and behavior of soft shell crab, the ways these crab interact with fishing gear, or mortality rates from either handling or natural causes. In addition, the population levels of the stock, including the proportion of animals in a soft shell state, are not known for any particular time. While the biological impacts of summer fishing are important, the real issue is how these biological impacts translate into economic impacts i.e., the level, distribution, and sustainability of profits. Vessels in the ODC fishery are heterogeneous. These vessels hail from different ports, have different cost structures and physical characteristics, and catch different amounts of crab at different times throughout the season. The impact of summer fishing is therefore experienced asymmetrically on the fleet, and any management actions that are introduced to address such concerns are likely to result in both winners and losers.

A management measure that is commonly discussed to address concerns surrounding the handling mortality of soft shell crab is that of closing the season earlier than the traditional August 14th date (ODCC 2015; ODCC 2016b; Kelly Corbett 2016). This is a contentious issue- some fishermen traditionally fish into the summer months, although most do not (ODCC 2015). Closing the season earlier than the traditional date will likely have a negative impact on these fishermen, while potentially benefiting those who do not fish in the summer months. However, it is also possible that an early season closure will have such beneficial

effects on the crab population as a whole that catch amounts for all fishermen, including the group of summer fishermen, will increase to the point where everyone is better off from a profit perspective, even if profits are concentrated earlier season. Examining these tradeoffs necessitates the use of a bioeconomic modeling framework, which we now describe.

4.2 Biological Sub-Model

We focus the biological component of the model on the part of the Dungeness crab stock that is either recruited to the fishery, or will recruit to the fishery during the next moult (at least age 3). The effects of retaining only large males on the population of crab is not thought to result in a size or sex distribution that significantly affects female mating success (Hankin, Hackett, and Dewees 2005; Heppell, Thompson and Price 2009; Rasmuson 2013). In addition, adult recruitment into the fishery is not thought to depend heavily on the existing population of crab, but rather on oceanographic and other environmental conditions during the larval phase 4 years previous to recruitment (Rasmuson 2013). We argue that it is reasonable, therefore, not to explicitly include female crab and male crab that are younger than age 3 in the model, and to represent recruitment to the SL cohort as an exogenous process.

There are three cohorts in the biological sub-model:

- “*SL*” cohort: Male sub-legal hard shell crab (< 159mm carapace width) that will moult into legal crab (>159mm carapace width) during the next moult.
- “*LH*” cohort: Male legal size hard shell crab (> 159mm carapace width).
- “*LS*” cohort: Male legal size *soft shell* crab (> 159mm carapace width).

While there are varying degrees of hardness of crab carapaces, we define soft shell crab as those crab that are not normally retained due to the softness of their carapace, and hard shell crab as those crab with a shell condition that would not cause fishermen to discard them based on carapace hardness alone.

We specify a discrete time step with each interval, t , representing a 7 day period. Week 1 in the model starts on December 1st, and week 52 ends on November 30th, which reflects how a crab ‘season’ is normally prosecuted. We represent the recruitment process as an exogenous input of sub-legal (*SL*) crab (the ‘gift’) which occurs after the last week of the previous season and before the first week of the current season. Both the sub-legal hard shell (*SL*) and legal hard shell (*LH*) cohorts moult throughout the season into the legal

soft shell (*LS*) cohort. The moulting process is represented as a probability that an individual hard shell crab will ‘moult’ during a given time period. For each cohort, a , the probability of moulting during a week period, t , is m_{at} . As Dungeness crab are thought to remain in a soft shell state for approximately 3 months after the initial moult, after 12 model ‘weeks’, the crab that moulted 12 weeks previously are introduced into the *LH* cohort. Note that this later introduction into the *LH* cohort is composed of crab that originated both in the *SL* and *LH* cohort, after deaths due to natural causes or fishing are accounted for.

Two sources of crab mortality are represented in the model which, within a time period, are accounted for after the moulting processes occur: *natural mortality* and *fishing mortality*. Natural mortality, M_a , is time independent but cohort specific and represents the instantaneous rate of mortality for each cohort that arises from non-fishing factors. The instantaneous rate of fishing mortality, F_{at} , is time dependent and cohort specific and represents mortality arising from all fishing activity. There are several known sources of fishing mortality of Dungeness crab. Apart from retention for sale these include handling mortality, cannibalism in pots, ghost fishing, and mortality from other fisheries, such as the bottom trawl fishery (Rasmuson 2013). Handling mortality is the incidental mortality that occurs when a crab is captured in a pot, brought on deck, and released. Cannibalism in pots arises from crab being trapped in a pot with larger or more voracious crab, and is thought to be a significant source of crab mortality. Ghost fishing occurs when pots are lost at sea, and either not recovered, or recovered after the escape hatch has opened. Deaths from ghost fishing may be due to starvation, octopus predation, and/or cannibalism. The bottom trawl and recreational fisheries in Oregon are also thought to be a significant source of crab mortality (Didier 2002).

For the purposes of this paper, we combine all sources of fishing mortality, apart from mortality from other fisheries and ghost fishing, into a single percentage rate, h_a , which represents the probability that an individual crab will be killed by fishing activities, conditional on the crab being captured by the gear. The instantaneous rate of fishing *capture*, $C_{a,t}$, is the product of a catchability coefficient, q_a , and total fishing effort, f_t , in time period t :

$$C_{a,t} = q_a \cdot f_t \quad \text{Eq. 4.1}$$

The instantaneous rate of fishing *mortality*, F_{at} , is the product of the rate of fishing capture and the percentage mortality rate:

$$F_{a,t} = h_a \cdot C_{a,t} \quad \text{Eq. 4.2}$$

The instantaneous rate of total mortality, $Z_{a,t}$, is the sum of the rates of fishing mortality and natural mortality, $M_{a,t}$:

$$Z_{a,t} = F_{a,t} + M_{a,t} \quad \text{Eq. 4.3}$$

The biomass of each cohort, a , at time t , is $N_{a,t}$. Within a season, the initial biomass of soft-shell crab in time t , before deaths are accounted for, is the sum of the biomass of soft shell crab at the end of time $t-1$, plus the introduction of newly moulted crab (from the SL and LH cohorts), minus the outflow of hardened crab:

$$N_{a=LS,t} = N_{a=LS,t-1} + \sum_{a=SL,LH} N_{a,t-1} \cdot m_{a,t} - N_{a=LS,t-12} \cdot \exp\left(-\sum_{t-12}^{t-1} Z_{a=LS,t}\right) \quad \text{Eq. 4.4}$$

The biomass of the LH and SL cohorts after the moulting process has occurred but before mortality in each time period is:

$$N_{a,t} = N_{a,t-1} \cdot (1 - m_{a,t}) + N_{a,t-12} \cdot \exp\left(-\sum_{t-12}^{t-1} Z_{a,t}\right) \quad \text{for } a = LH, SL \quad \text{Eq. 4.5}$$

Total biomass killed due to fishing of cohort a , at the end of time period t is:

$$\frac{F_{a,t}}{F_{a,t} + M_a} N_{a,t} (1 - \exp(-(M_a + F_{a,t}))) \quad \text{Eq. 4.6}$$

Total biomass dying due to natural causes of cohort a , at the end of time period t is:

$$\frac{M_a}{F_{a,t} + M_a} N_{a,t} (1 - \exp(-(M_a + F_{a,t}))) \quad \text{Eq. 4.7}$$

Biomass of each cohort at the beginning of the subsequent period, $t+1$, and before moulting and hardening takes place is then:

$$N_{a,t+1} = N_{a,t} \cdot \exp(-(F_{a,t} + M_a)) \quad \text{Eq. 4.8}$$

4.3 Economic Sub-Model

The level and temporal distribution of fishing effort in the ODC fishery determines the amount of fishing mortality over time. Given population abundance, effort drives vessel profit through its determination of catch and the level of variable costs vessels incur. It is therefore the key variable in the bioeconomic simulation model and the focus of this section. We considered total fishing effort to be determined by two separate decisions made by ODC fishermen:

- 1) whether or not to participate in the fishery in a given time period (*vessel participation*), and
- 2) how much *effective effort* a vessel should exert in a given time period, conditional on participating in that time period

These two considerations formed both the basis of our estimation strategy, and the structure for the economic fleet component of the bioeconomic model.

4.3.1 VESSEL PARTICIPATION

Vessels in the ODC fishery exhibit remarkably stable temporal patterns of fishery participation. In general, vessels enter the fishery on the day the season opens to take advantage of extremely high catch rates in the first weeks of the season, and then exit the fishery at some point before the season closes on August 14th of the subsequent year. Figure 4.1 shows the week of entry to the ODC fishery and the week of exit to the ODC fishery aggregated over the 2007-2014 seasons. Week 1 corresponds to the opening week of the season- generally Dec 1st- and week 37 corresponds to August 14th in each year- the traditional closure date.

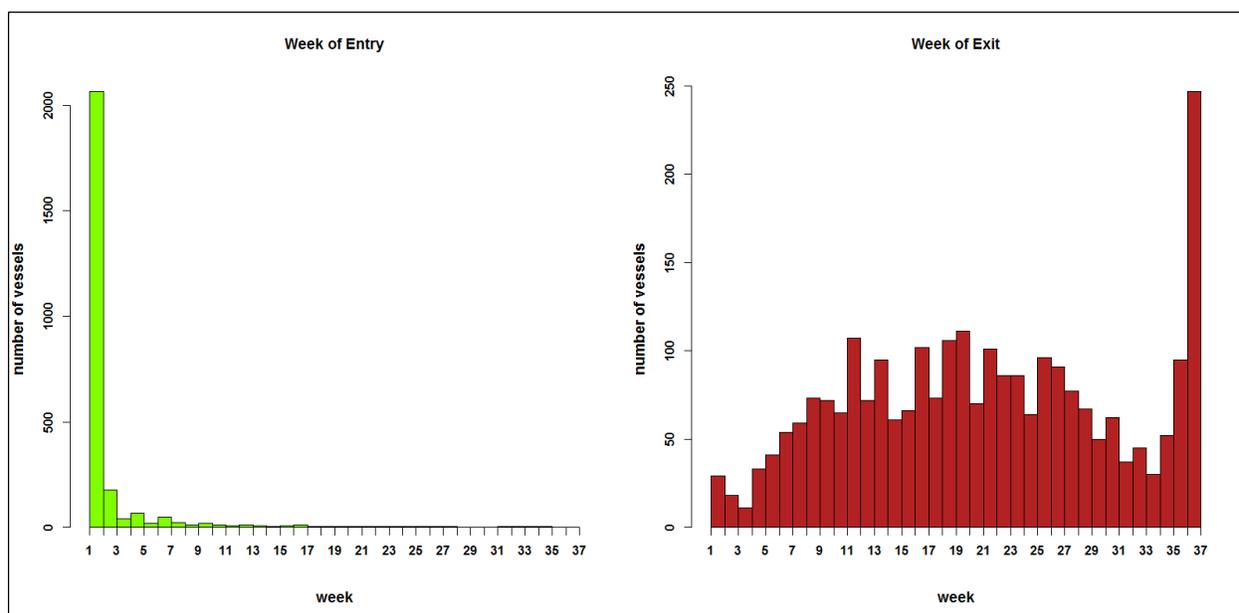


Figure 4.1: Entry and Exit weeks of ODC vessels aggregated over the 2007-2014 seasons.

Due to the high costs of both moving gear from the fishing grounds to a storage facility and moving pots back to the fishing grounds from the storage facility, once a vessel ‘exits’ the ODC fishery, re-entry generally does not occur until the next season (ODCC 2015). The main exception to this pattern occurs with vessels concurrently holding either a Washington (WA) state Dungeness crab permit or California (CA) state Dungeness crab permit. These vessels will generally fish in each state at least once per year to keep the permits active (Kelly Corbett 2016). In these cases vessels will either start the season in another fishery then enter the ODC fishery after the season has opened, or will exit the ODC fishery earlier than they would have if they did not possess multiple permits. While the data on ODC vessels’ participation in the WA/CA Dungeness crab fisheries were not available to us, the numbers of ODC vessels that participate in these fisheries is thought to have been relatively small, especially in recent years. In addition, the ODC fleet has remained remarkably stable over the last 8 years, with minimal variation in total vessel numbers or composition of the fleet by tier permit. The tier permit level specifies the maximum number of pots that a vessel can deploy at one time and is positively correlated with vessel length. Table 4.1 shows the total number of vessels participating in the ODC fishery by season, as well as the total number of active vessels (vessels that actually participated in the fishery) by permitted pot tier.

Table 4.1: Number of vessels by pot tier license by season.

season	total vessels	200 tier	300 tier	500 tier
2007	335	53	145	137
2008	312	51	134	127
2009	307	53	128	126
2010	325	58	137	130
2011	341	62	142	137
2012	319	60	139	120
2013	318	56	139	123
2014	315	50	137	128

The particular characteristics of the ODC fishery including the fact that the season structure has been relatively consistent over the last decade and that individuals generally exit the fishery only once in each season, provides a rare opportunity to apply a duration model to the *in-season exit* behavior of fishermen. Duration analysis, also known as survival analysis in the health sciences, or failure time analysis in engineering fields, is a method for analyzing ‘time to event’ data (Singer and Willett 2003), where an ‘event’ is a measurable, discrete, outcome. In economics and the social sciences, duration modeling is commonly used to model spells of unemployment, with the first known application in the early 1970s (Lancaster 1972). Since then duration models have been applied widely in such diverse applications as timing of hurricane evacuation by individual households (Hasan, Mesa-Arango, and Ukkusuri 2013), the adoption of conservation practices by farmers (D’Emden, Llewellyn, and Burton 2006), the effects of social context on the initiation of cigarette use (Reardon, Brennan, and Buka 2002), and the investigation of factors affecting highway project time delays (Anastasopoulos et al. 2012). See Hosmer Jr and Lemeshow (1999) and Klein and Moeschberger (2005) for good overviews of the models and techniques used in regression modeling of time to event data.

Two fundamental concepts in duration analysis are the *survival probability* and the *hazard probability*. The survival probability at a particular time, t , refers to the proportion of an initial group or population that has not experienced the ‘event’ up until that time interval, with a *survival function* the set of these probabilities. The *hazard probability* in time interval t refers to the probability that individuals in a population will experience the event in that time interval *conditional on those individuals not having experienced the event up to that time*. The *hazard function* refers to the pattern of these hazard probabilities over time (Singer and Willett 2003; Singer and Willett 1993), and is the main focus of regression modeling (Greene 2000). Duration models are generally characterized as non-, semi-, or fully-parametric, depending on the assumptions made regarding the distribution of duration times. Non-parametric models, the most common

of which is the Kaplan-Meier estimator (Kaplan and Meier 1958), are commonly used for exploring suitable forms of the hazard function before covariates are added to the model, or when no covariates are specified. In these models survival and hazard are calculated empirically. Semi-parametric hazard models generally assume that hazard is composed of two parts: a part that depends on individual characteristics, and a part that does not depend on individual characteristics. In these models no functional form for a baseline hazard is assumed- baseline hazard is fully general- and the effects of covariates are then seen as proportional shifts away from this baseline hazard. The most famous of these, the Cox Proportional Hazards (PH) model (Cox 1972) has seen rich use in the economic literature (Ran, Keithly, and Yue 2014). Parametric models of hazard, also known as Accelerated Failure Time (AFT) models, allow covariates to accelerate (or decelerate) the survival function, for which a distributional assumption is made. Fully parametric models make more efficient use of the data than semi-parametric methods as they do not ignore the effects of covariates in time periods where no events are observed (D'Emden, Llewellyn, and Burton 2006), but also constrain the form of the baseline hazard function to fit the distributional assumption. Common distributional assumptions for the distribution of duration times are the Gompertz, exponential, and Weibull distributions, depending on the shape of the observed hazard probability profile over time (Greene 2000).

While a rich and varied literature exists on the application of duration models to economic issues, they have rarely been applied to fisheries, and never (to the best of our knowledge) to model the in-season exit behavior of fishermen. Smith (2004) contributed the first application of duration modeling to fishermen behavior to analyze the factors influencing fleet attrition in the California red sea urchin fishery. Attrition was modeled as a long-term decision to permanently leave the fishery, and the time to event was the length of time that passed between fishery entry and exit. The author found that both individual characteristics of the fisherman and policy variables such as season length were significant determinants of fishermen's decisions on whether to exit the fishery or not, thereby illustrating the model's policy relevance. Holloway and Tomberlin (2006) conducted a duration analysis on the California commercial salmon fishery in order to demonstrate its use in fisheries analysis. They found that physical vessel characteristics as well as the length of time vessels had operated in the fishery were significant factors explaining the probability of vessels leaving the fishery. More recently, Ran, Keithly, and Yue (2014) estimated a duration model combined with a model of reference dependent preferences to investigate the factors affecting the length of single fishing trip in the Gulf of Mexico shrimp fishery. The most recent application of a duration model to commercial fisheries analyzed the effects of fishery subsidies on the decision to exit the Spanish purse seine fleet (Cordón Lagares and García Ordaz 2015).

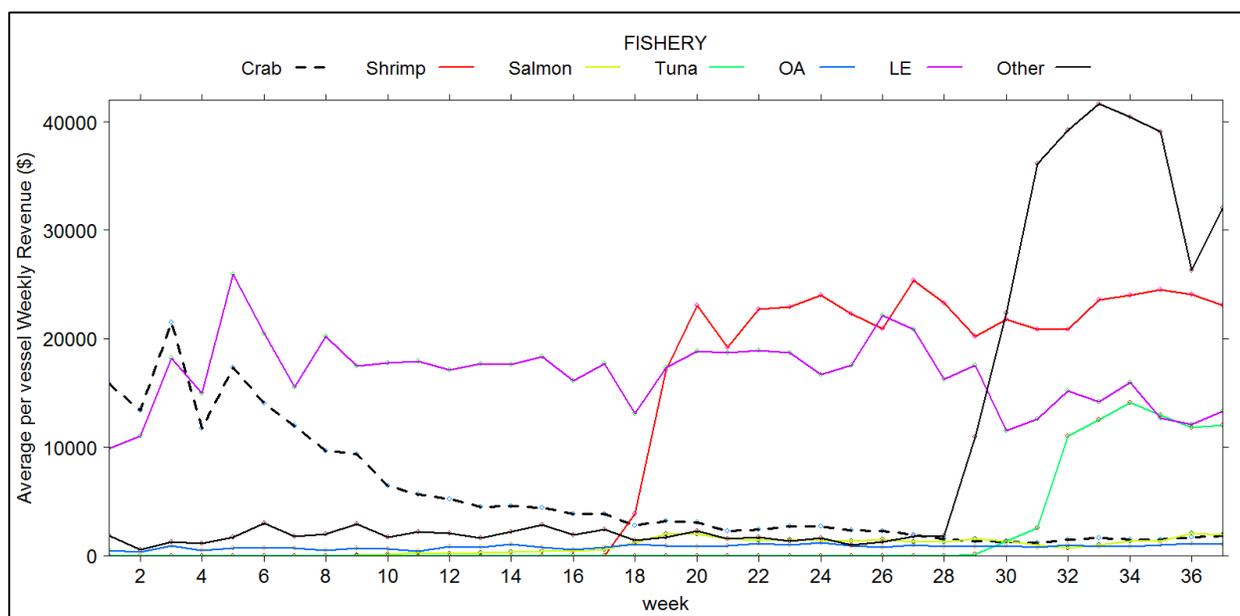
None of these studies examined the in-season exit behavior of fishermen, focusing instead on either long-term exit (the decision to leave the fishery for good), or micro-term exit (the decision to end a fishing trip). This is perhaps due to the fact that the nature of most fisheries precludes the use of duration analysis for determining in-season exit. For example, many fisheries are characterized by seasons that are so short that all vessels exit the fishery at the same time e.g. the Pacific Halibut fishery in Oregon. In other cases seasons are long but barriers to re-entry (such as gear re-deployment costs) are minimal resulting in fishermen entering and exiting the fishery several times throughout the season. Many fisheries are characterized by some form of property rights regime where vessels are free to fish at any time during the year and exit, in most cases, when their quota portfolio becomes constraining. In all of these cases the application of duration analysis is complicated by structural characteristics of the fishery and multiple entry/exit decisions. In these cases multinomial choice models based on the random utility framework (after McFadden and others 1973) are perhaps better suited to the analysis. In contrast, in the ODC fishery vessels generally enter the fishery at the same time and make an exit decision which is not reversed (due primarily to significant costs of gear redeployment and decreasing catch per unit effort as the season progresses (ODCC 2015)), and provides a unique opportunity for applying seasonal duration type models.

4.3.1.1 Empirical Duration Exploration

While all vessels enter the fishery at roughly the same time, the shape of their empirical survival functions differs according to the portfolio of alternative fisheries that a vessel participates in. For example, ODC vessels that also participate in the shrimp fishery have a much higher hazard rate at the beginning of the season, and do not generally participate in the ODC fishery after April in each year. As part of the initial duration exploration we divided vessels into initial groups based on participation in alternative fisheries in order to determine if the behavior of these groups differed in a systematic fashion, and if so, could they be modeled as separate ‘sub-fleets’. In order to accomplish this we categorized all possible alternate fisheries that ODC vessels participated in into several groups and identified groups of vessels that shared similar alternate fishery participation portfolios. Table 4.2 shows the alternative fisheries identified and figure 4.2 shows the average revenues throughout each season of all of the fisheries that were included in the analysis.

Table 4.2: List and description of the alternative fisheries that ODC fishermen participate in.

<i>Alternative Fishery</i>	<i>Description</i>	<i>Season Dates</i>
Shrimp	trawl gear targeting shrimp	(March- December)
Limited Entry (LE) groundfish	LE permitted vessels targeting the groundfish complex	(year-round)
Open Access (OA) groundfish	OA permitted vessels targeting the groundfish complex	(year-round)
Salmon	salmon trolling	(March- October)
Tuna	albacore tuna trolling	(June-September)
Other	all other fisheries (e.g. whiting, halibut, sardine)	(various times)

**Figure 4.2:** Average weekly revenue per vessel in the alternative fisheries for the 2008-2014 seasons.

Using all fish tickets for those vessels that participated in the ODC fishery between the 2007 season (Dec 2006-Aug 2007) and the 2014 season (Dec 2013-Aug 2014), vessels were characterized into ‘groups’ based on the portfolio of alternative fisheries each vessel participated in. A hierarchical methodology was followed based on both the season timing and value of the alternative fishery. We posited that, most of the time, vessels would exit the ODC fishery for their next best economic opportunity. The Limited Entry groundfish (LE) fishery and the shrimp fishery are the next most valuable fisheries (in revenue terms) on average after the ODC fishery so after placing all vessels that did not participate in an alternative fishery in a ‘crab’ group, groups were defined for vessels that participated in the shrimp fishery (‘shrimp’), and those that participated in the LE fishery (‘le’). A ‘shrimple’ group was defined for those vessels that participated in both the shrimp and LE fisheries. The Open Access groundfish (OA) fishery is open year round but has

a relatively low value. Those vessels that participated in just the OA fishery were placed into an ‘*oa*’ groups, and two more groups, ‘*oasalmon*’ and ‘*oatuna*’ were created for vessels that participated in the OA and salmon fisheries and OA and tuna fisheries, respectively. Finally, groups of vessels that participated in the salmon (‘*salmon*’) and tuna (‘*tuna*’) fisheries were defined. These groups are mutually exclusive: vessels in a given season may not belong to more than one sub-fleet, and all vessels are represented by a sub-fleet. Table 4.3 shows the initial groupings by alternative fishery participation and all possible fisheries that vessels participated in:

Table 4.3: Initial groups for the empirical survival estimation.

<i>Main Vessel Grouping</i>	<i>Group Code</i>	<i>All vessels in group also participate in these fisheries:</i>	<i>Vessels may participate in these fisheries:</i>
crab only	<i>crab</i>	none	none
LE groundfish	<i>le</i>	LE groundfish	OA groundfish, salmon, tuna, other
OA groundfish	<i>oa</i>	OA groundfish	OA groundfish
OA groundfish/salmon	<i>oasalmon</i>	OA groundfish + salmon	OA groundfish, salmon, tuna, other
OA groundfish/tuna	<i>oatuna</i>	OA groundfish + tuna	OA groundfish, tuna, other
salmon	<i>salmon</i>	salmon	salmon, tuna, other
tuna	<i>tuna</i>	tuna	Other
shrimp	<i>shrimp</i>	shrimp	tuna, other
shrimp/LE groundfish	<i>shrimple</i>	shrimp + LE groundfish	tuna, other

Empirical survival functions were estimated using the Kaplan-Meier method (Kaplan and Meier 1958) for each of the main fleet groupings as:

$$\hat{S}(t) = \frac{\text{Number of vessels remaining in the fishery at time } t}{\text{Number of vessels in the fishery at the start of the season}} \quad \text{Eq. 4.9}$$

While the simplicity of the Kaplan Meier method is one of its strongest qualities it cannot be effectively used to determine the quantitative effects of covariates on survival time. It is useful in this case for both determining the average duration behavior of the initial groupings in order to identify ‘aggregated groups’, that is those groups that behave relatively similarly and can be represented by statistical models of hazard determination. Subfleets were defined for each season and these subfleets were aggregated before the empirical survival functions were estimated. The estimated survival functions are plotted in figure 4.3.

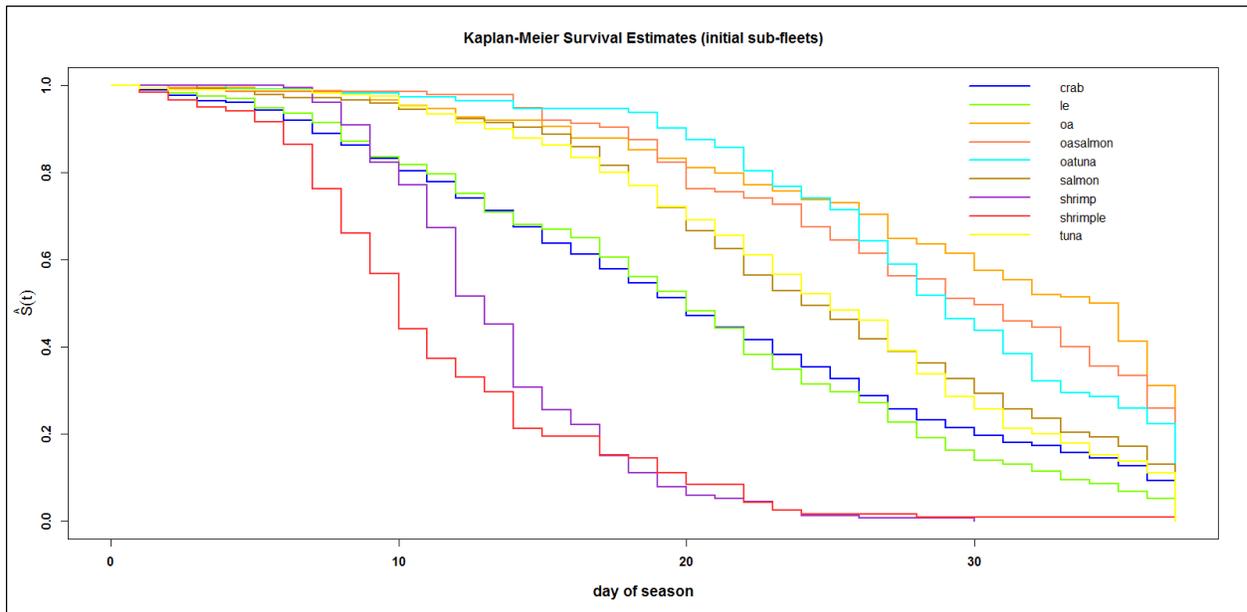


Figure 4.3: Kaplan-Meier survival functions for the initial sub-fleet groups. Data were aggregated over the 2007-2014 seasons.

It is immediately apparent that there appear to be 4 aggregated groups that behave fairly similarly, which we now define as ‘sub-fleets’ for modeling purposes. Wilcoxon tests for differences between the 9 survival curves imply that there is no statistical difference between the curves for three sets of groups: 1) ‘*crab*’, ‘*le*’, 2) ‘*oa*’, ‘*oasalmon*’, ‘*oatuna*’, and 3) ‘*salmon*’, ‘*tuna*’. These sets formed 3 separate sub-fleets- ‘*crable*’, ‘*oa*’, and ‘*saltun*’ respectively. A Wilcoxon test for differences between the ‘*shrimp*’ and ‘*shrimple*’ survival curves rejects the null hypothesis that there is no significant difference between the curves. However, given that these curves follow the same general pattern and because of a limited number of observations for these two groups, they were combined to form a separate ‘shrimp’ sub-fleet. Results of Wilcoxon tests for differences between initial sub-fleets are presented in table 4.4.

Table 4.4: Results of the Wilcoxon tests for differences in the Kaplan-Meier survival functions. The comparisons are between the initial sub-fleet groupings aggregated into 4 groups.

Test for Difference between:	χ^2 statistic (df)	p-value
oa, oasalmon, oatuna	3 (2)	.223
salmon, tuna	0 (1)	.917
crab, le	.2 (1)	.659
shrimp, shrimple	20.8(1)	5.16e-06

Table 4.5: Final sub-fleets combined from the initial sub-fleet groups.

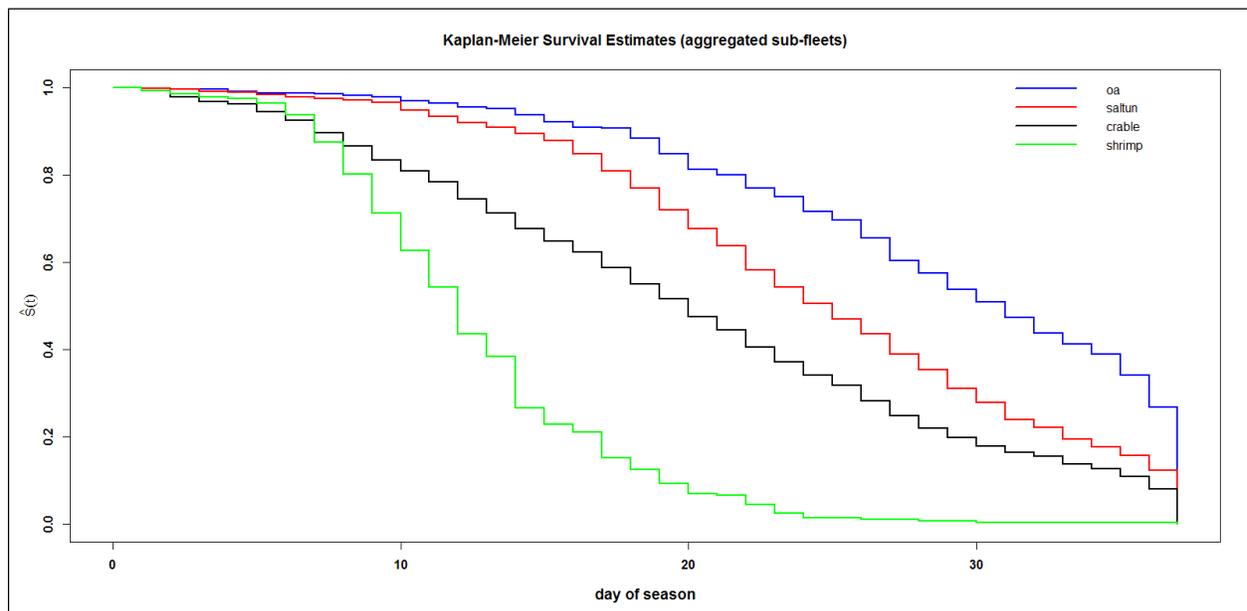
Original Groups Combined:	Sub-fleet names
'crab' + 'le'	'crable'
'shrimp' + 'shrimple'	'shrimp'
'oa' + 'oasalmon' + 'oatuna'	'oa'
'salmon' + 'tuna'	'saltun'

The null hypotheses that there is no difference between the Kaplan Meier survival curves of the aggregated sub-fleets are rejected by Wilcoxon tests at the $p=0.001$ level (Table 4.6)

Table 4.6: Wilcoxon tests for differences between the final sub-fleet's Kaplan-Meier survival functions.

χ^2 statistic	oa	saltun	crable	shrimple
oa				
saltun	62.5 (2.66e-15)***			
crable	193 (0)***	92.5 (0)***		
shrimp	511 (0)***	555 (0)***	191 (0)***	

Kaplan-Meier estimates of the survival functions for the aggregated sub-fleets are presented in figure 4.4.

**Figure 4.4:** Kaplan-Meier survival functions for the final sub-fleet groupings.

These 4 sub-fleets, characterized by historical behavior of alternative fishery participation in each season, form the main fleet structure in the bioeconomic simulation model. Predicting exit times on a sub-fleet basis incorporates a level of realism that would be difficult to represent if all vessels were modeled as a single fleet. In addition predicted economic impacts on a sub-fleet basis arguably enables us to represent a measure of distributional impacts in the fishery. For example, the ‘oa’ fleet was composed mainly of smaller vessels with a 200 pot limit while the ‘shrimp’ fleet was composed of large trawl-capable vessels, most with 500 pot limits. While sub-fleet composition changes from year to year, this change is relatively modest.

4.3.1.2 Discrete Time Hazard Model

We implemented a Discrete Time Hazard (DTH) duration model (Singer and Willett 1993) where the *event* we modeled is an individual vessel exiting the ODC fishery (when a vessel makes its last delivery for the season), and the *time to event* is the length of time that passes from the date the season opens until an individual vessel exits. We did not assume a distributional form for the baseline hazard, instead allowing it to be estimated fully generally. This was partly due to the issue of ‘ties’, which arises through the coarseness of the data. A tie occurs when two individuals experience the event at the same time, and a large number of ties can lead to bias in parameter estimates when using continuous time methods (Hertz-Picciotto and Rockhill 1997). Ties are pervasive in discrete time specifications, and raise no significant issues in the estimation procedure (Singer and Willett 2003). Another reason for choosing a discrete time specification was that there are many discrete events throughout the course of a season which potentially have a significant effect on hazard such as the timing of alternative fishery openings. Capturing these effects using a functional specification for time (as is the case with fully parametric models), is problematic given the number of potential events. However, including a set of discrete time dummy variables in a fully general specification of time is relatively straightforward and as holidays fall in the same time period in each year, and other annual events (such as timing of alternative fishery openings) are generally consistent, the average of these effects is captured conveniently in the parameter on the time dummy. Finally, specifying discrete time for the duration model estimation meant that the results could be easily synchronized with the biological sub-model in the simulation framework, which simplified the overall modeling task.

Hazard, the focus of the regression model, can be thought of as a function relating covariates that represent fishery conditions to the probability that a vessel will exit in a given time period. The value of hazard in any time period must therefore lie in the open interval (0, 1). Performing an odds transformation on the hazard probabilities ensures that hazard is bounded in this interval. However, as odds are bounded below

by 0, linear predictions of odds hazard could theoretically lead to negative predictions. Logit transforming (also known as log-odds) hazard ensures that that all possible predictions from a linear regression model leads to values of hazard that lie on the unit interval (Singer and Willett 2003, Jaeger 2008).

The logit transformation of raw hazard for individual i in time t is the log of the odds ratio (inside parentheses):

$$\text{logit} (h(t)_{it}) = \ln \left(\frac{h(t)_{it}}{(1 - h(t)_{it})} \right) \quad \text{Eq. 4.10}$$

Transforming logit hazard into raw hazard is accomplished using the inverse logit (logit^{-1}) transformation:

$$h(t)_{it} = \frac{1}{1 + \exp^{-\text{logit} (h(t)_{it})}} \quad \text{Eq. 4.11}$$

The general specification of the model is to specify logit hazard for each vessel in each time period as a function of 1) a set of time dummies for each week period, d_1 - d_{37} , 2) a set of k time invariant covariates, X_{ik} , and 3) a set of m time varying covariates Z_{imt} (Equation 4.11).

$$\text{logit} h(t_{it}) = [\alpha_1 D_1 + \alpha_2 D_2 + \dots + \alpha_{37} D_{37}] + \beta_{1j} X_{i1} + \dots + \beta_{kj} X_{i2} + \delta_{1j} Z_{i1t} \dots + \delta_{mj} Z_{imt} \quad \text{Eq. 4.12}$$

The set of dummies and their respective parameters define the ‘base’ logit hazard function for each fleet, which is the logit hazard function for a theoretical vessel that has zero values for all time invariant and time varying variables. The theoretical effect of the time invariant variables is therefore to shift the base logit hazard function in each time period proportionally according to the value of the parameter- the ‘proportional logit hazard’ assumption (Singer and Willett 1993). The interpretation of the effects of the time varying variables on logit hazard is more complicated -- while the value of time varying variables changes over time, the effect of the *parameter* on logit hazard is assumed to be constant over time, but the overall effect on hazard is time-varying (Singer and Willett 2003). While the proportional logit hazards assumption may seem overly restrictive, given that each vessel has unique values of time-varying covariates, each vessel theoretically has a unique logit hazard function. In addition, while the effect of parameters is linear (proportional) on the logit scale, this translates into non-linear proportionality on the probability scale.

An important implication for our estimation strategy was that while some vessels only participated in the ODC fishery for one season the majority of vessels participated in several seasons. Observations on the same vessel between seasons are therefore likely to be non-independent as unobserved heterogeneity on the individual vessel level and may affect the timing of vessel exit. The implications of this unobserved heterogeneity to our model (if untreated) is to possibly introduce bias into the estimates of the standard errors of the parameter estimates, and the parameter estimates themselves. In both standard linear regressions with a continuous and unbounded dependent variable, and regressions with a binary dependent variable, the presence of unobserved heterogeneity leads to incorrect statistical inferences as the standard errors of the estimates are biased (Agresti and Kateri 2011; Beck, Katz, and Tucker 1998). In general, standard errors are underestimated, leading to overly optimistic statistical inferences. To see why, note that the denominator in the formula for calculating the standard error of a parameter estimate in a standard regression model is the square root of n , the number of observations. Implicit in this formula is the assumption that each individual observation contributes an equal amount of information to the model. However, if observations for the same vessel are correlated, each observation does not contribute the same amount of information as outcomes for the same vessel are likely to be relatively similar over the years (Miles 2016). In this case, the standard error estimate is inflated, leading to overly optimistic statistical inferences. The standard treatment is to correct the estimates of the standard errors for clustering (on individual vessels in our case) by dividing the number of observations in the standard error calculation by a variance inflation factor, which corrects for intra-group correlation (Hanley et al. 2003; Hosmer Jr, Lemeshow, and Sturdivant 2013). Another option is to use a robust estimator of the covariance matrix such as Huber-White's sandwich estimator, which is currently implemented in most statistical programs. For an overview of this estimator, see Freedman (2012) and STATA corp. (2016).

While in a standard linear regression the parameter estimates remain consistent when observations are non-independent, and standard errors can then just be corrected for clustering, the consequences of unobserved (and untreated) heterogeneity in a logistic regression are to introduce duration bias into the parameter estimates (Barber et al. 2000; Hausman and Woutersen 2014; Rodriguez 2016). In our model, there is potential for bias in both our estimates of baseline hazard and the estimates of the time invariant and time varying parameters. The same vessels are likely to display similar exit behavior across seasons but the estimator of baseline hazard reflects the average hazard over all vessels in the fleet. The base hazard parameters will therefore reflect the behavior of only a subset of vessels later in the season. This issue is also reflected in the estimates of the coefficients on the other variables in the model. For example, vessels

that stay in the fishery later due to unobserved characteristics (such as a deep love for crab fishing), may bias the population estimates of the effects of observed variables (such as crab revenue) on the probability of fishery exit in a given time period. It is important to account for unobserved heterogeneity in duration models for these reasons (Hausman and Woutersen 2014; Barber et al. 2000). Two major model specifications that account for unobserved heterogeneity in duration models are the fixed effects model and the random effects model.

Fixed effects models effectively include a separate intercept for each group, where a group is defined such that observations are correlated within a group but uncorrelated between groups. They are popular for analyzing panel data as they make it possible to control for group characteristics, and the reason why one may assume conditional independence of the observations (Allison and Christakis 2006; Rodriguez 2016). Implementing the fixed effects model in a logistic regression, however, is complicated by the fact that consistency of the Maximum Likelihood (ML) estimators requires that the number of parameters be fixed as n increases (Agresti and Kateri 2011). This implies that simply adding a dummy variable to the model for every vessel might cause inconsistency of the parameter estimates. Instead, using the conditional logit fixed effects estimator allows consistent estimation of the model with the drawback that time invariant and group-specific effects can't be estimated as group effects are 'differenced' out of the model (Agresti and Kateri 2011). Another drawback of the conditional fixed effects estimator is that, when working with discrete time data, these models fail when covariates are a monotonic function of time so no control for time itself can be introduced (Allison and Christakis 2006).

An alternative specification is a random effects model where the unobserved heterogeneity is treated as a random variable and can be thought of as allowing the intercept for each group to vary randomly. Instead of a parameter for each group, a parametric assumption for the distribution of the unobserved heterogeneity over all groups is made and the parameters of the distribution are estimated. Population average probabilities from the random effects model can then be obtained by averaging the group-specific probabilities over the random intercept distribution. Random effects models also have the benefit that time invariant effects can be estimated. However, random effects models assume that the random effects are independent across vessels, or in other words uncorrelated with observed vessel specific covariates. Essentially this means that if there are unobserved vessel specific factors that affect covariates such as a vessel's revenue in a given week *and* the decision of whether or not to exit (which seems highly likely), the parameters of a random effects logit model are likely biased.

Given these issues, we estimated the pooled logistic regression model for each sub-fleet separately and corrected the estimated standard errors for non-independence by clustering on individual vessels using White's sandwich estimator (Freedman 2012). Kasperski (2015) took a similar approach, conducting separate estimations for effort level predictions for different classes of vessels in their bioeconomic simulation of a multi-species fishery. The fact that sub-fleets were defined based partly on historical exit behavior implies that they are natural 'groups' for a fixed effects model. By performing the estimation on each sub-fleet separately, however, we account for the effects of at least some of the unobserved heterogeneity by allowing the baseline hazard function and other parameters to be calculated separately for each group of vessels. We introduce additional fixed effects into each model by including dummy variables to indicate the class of pot tier that a vessel was licensed for and the season that each observation is from. Pot tier is highly correlated with vessel length, which is commonly used as a proxy for fishing power or capacity and the assumption is therefore that observations are independent between groups. Another benefit of specifying the estimation in this way is to partially relax the proportional logit hazards assumption (Singer and Willett 2003), which would have constrained the logit hazard curves for two vessels differing in only a single characteristic, such as their participation in the shrimp fishery, to be proportional in each time period. A more reasonable assumption would be that vessels that share the same set of behavioral characteristics (such as their portfolio of other fisheries participation) share a common 'base' logit hazard function, and the proportional logit hazards assumption operates on vessel characteristics such as pot limit (which is a rough proxy for vessel size), and vessel revenues and costs (Reardon, Brennan, and Buka 2002).

The explanatory variables that would theoretically affect the probability of a vessel exiting the ODC fishery during a given week included variables that measured economic and biological conditions in the ODC fishery as well as vessel specific variables. While weather conditions theoretically affect the probability of a vessel exiting the fishery in a given time period, the inclusion of the time dummies effectively includes average weather effects. Fixed effects for season were included as a dummy variable corresponding to the season the observation was from. The pot tier license that vessels held in a given year was included as a set of dummy variables. Vessel specific weekly revenue in the ODC fishery, as reported on fish tickets was included. To include the effects of opportunity costs of participating in the ODC fishery on the probability of vessel exit the ratios of average weekly revenue in all of the alternative fisheries to vessel specific weekly revenue in the ODC fishery were included. A dummy variable for participation in these alternative fisheries was included and multiplied by the revenue ratio measure- as a result, the revenue ratios only appeared in the dataset for those vessels that historically participated in the alternate fisheries. Historically vessels that

make up the shrimp fleet have not participated in the ODC fishery after week 20 so time dummies after that week were omitted. There were also very few observations for the shrimp fleet after week 13 of each year so the predictive power of the model for this fleet is limited after this time. Table 4.7 describes all variables included in the estimation procedure.

Table 4.7: Description of the variables used in the discrete time hazard model

<i>Variable</i>	<i>Description</i>
$d_i, i=1,\dots,37$	$d_i = 1$ if observation is in week i , where i the number of weeks from December 1 st .
tier200	dummy=1 if vessel held a 200 tier license
tier300	dummy=1 if vessel held a 300 tier license
tier500	dummy=1 if vessel held a 500 tier license
season _s	dummy if observation was in season s
revenue	sum of a vessel's weekly ODC revenue (\$)
rev SH	weekly ratio of average shrimp revenue to a vessel's ODC revenue
rev LE	weekly ratio of average LE revenue to a vessel's ODC revenue
rev OA	weekly ratio of average OA revenue to a vessel's ODC revenue
rev SA	weekly ratio of average salmon revenue to a vessel's ODC revenue
rev TU	weekly ratio of average tuna revenue to a vessel's ODC revenue
rev OT	weekly ratio of average other fishery revenue to a vessel's ODC revenue
fuel price	weekly average price of #2 diesel for Oregon ports (PacFIN extraction) (\$)

The log-likelihood equations for the pooled logistic regression are:

$$\ln(\text{Likelihood})_j = \sum_{i=1}^{n_j} \sum_{t=1}^{T_i} EXIT_{it} \cdot \ln h(t_{it}) + (1 - EXIT_{it}) \cdot \ln(1 - h(t_{it})) \quad \text{Eq. 4.13}$$

where i is an individual vessel, $h(t_{it})$ is logit hazard (given in Eq. 4.11), n_j is the number of vessels in each fleet j , T_i is the total number of time periods that each vessel participates in, and $EXIT_{it}$ is an indicator that takes the value 1 if a vessel exits during time period t , and 0 otherwise.

This function expresses the log probability that we would actually observe the exact pattern of events, given the values of our covariates. In effect our model specifies a logistic regression procedure, the only difference being the presence of a dummy variable for each time period. Each individual, i , therefore contributes T_i terms to the log likelihood function. The regressions were conducted omitting the model intercept in order to include all 37 time dummies. Fleet effects are relative to the 200 tier class of vessel for each fleet, apart from the shrimp fleet (which had no 200 tier vessels) where the base group was the 300 tier vessel class. All estimations were conducted in Stata 14 (StataCorp and others 2007).

The parameters on the week dummies were significant for all fleets and negative until the last week. A predicted base hazard of 0 on the logit scale implies an exit probability of 50% in that time period, and this generally was not the case until the last week of the season. If there were no exit events in a particular week for a fleet the effect of the parameter could not be estimated, which was the case for some weeks early in the season for the open access (OA) and salmon/tuna (saltun) fleets, and late in the season for the shrimp fleet. The parameter on ODC revenue was significant and negative for all fleets except for the crab fleet. A negative sign on the parameter of a time-varying variable such as ODC revenue implies a negative marginal effect of that variable on the probability that a vessel exits. To calculate the effect of that variable in a given time period on logit hazard the level of the variable is multiplied by the parameter to give the full effect on logit hazard. The parameters on the ratio of other fisheries revenue to ODC revenue were mostly insignificant at the 5% level, suggesting that vessels may not take revenue in other fisheries into account when exiting the ODC fishery, and rather respond to revenues in the ODC fishery. The two exceptions were the ratio of OA revenue to crab revenue for the crab fleet, and the ratio of 'other' revenues to crab revenue for the saltun fleet. The parameter on fuel price was significant and positive for the oa and saltun fleets, implying that vessels in these fleets, which were on average smaller boats, responded to changes in the price of fuel when making exit decisions. There was no difference in base logit hazard between the 200 tier and 300 tier fleets for the crab and oa fleets based on asymptotic standard errors. However, the Akaike Information Criterion (AIC; Akaike 1998) decreased when this distinction was removed from the saltun fleet estimation so it was retained in the specification for input into the simulation model. The shrimp fleet, which has no 200 tier vessels, is composed mainly of 500 tier vessels. There was no significant difference in exit behavior, holding revenue differences constant, between the 300 and 500 tier vessels of the shrimp fleet. Parameters that were significant at the 5% level, or caused a decrease in model fit as measured by the AIC were included in the final specification. These parameters, as well as their estimates and asymptotic standard errors are presented in table 4.8.

Table 4.8: DTH results. Parameter estimates, asymptotic standard errors and p-values for the final model specifications.

Parameter	CRABLE FLEET			OA FLEET			SALTUN FLEET			SHRIMP FLEET		
	Est.	ASE	P-value	Est.	ASE	P-value	Est.	ASE	P-value	Est.	ASE	P-value
d1	-3.6750	0.4375	0.0000	(omitted)			(omitted)			-3.3805	1.1349	0.0030
d2	-3.2589	0.2635	0.0000	-3.7469	1.1105	0.0010	-4.9739	1.0250	0.0000	-3.0857	0.8561	0.0000
d3	-3.9087	0.3576	0.0000	(omitted)			-4.5829	0.8530	0.0000	-3.5849	0.8270	0.0000
d4	-4.6943	0.5010	0.0000	-3.7589	0.8226	0.0000	-5.3846	0.7727	0.0000	-4.3907	1.0169	0.0000
d5	-3.4327	0.2194	0.0000	-4.5553	1.0421	0.0000	-4.7113	0.5948	0.0000	-3.4806	0.6242	0.0000
d6	-3.3705	0.2401	0.0000	(omitted)			-5.2489	0.8556	0.0000	-2.6959	0.4828	0.0000
d7	-3.0693	0.2285	0.0000	-4.8533	1.0821	0.0000	-5.6153	0.7547	0.0000	-1.7476	0.3369	0.0000
d8	-2.9181	0.2022	0.0000	-4.9076	1.0715	0.0000	-5.3681	0.6714	0.0000	-1.5617	0.3440	0.0000
d9	-2.9237	0.1944	0.0000	-4.4274	0.7796	0.0000	-5.2471	0.6007	0.0000	-1.3490	0.3006	0.0000
d10	-3.1089	0.2109	0.0000	-4.2554	0.7265	0.0000	-4.2279	0.4469	0.0000	-1.2403	0.3108	0.0000
d11	-3.0812	0.2423	0.0000	-4.5269	0.8246	0.0000	-4.4260	0.4290	0.0000	-1.2075	0.2923	0.0000
d12	-2.5431	0.1694	0.0000	-3.9159	0.6415	0.0000	-4.4447	0.4837	0.0000	-0.6531	0.2848	0.0220
d13	-2.5985	0.1970	0.0000	-5.3658	1.1145	0.0000	-4.4535	0.4620	0.0000	-1.0682	0.3042	0.0000
d14	-2.6878	0.1996	0.0000	-3.5669	0.5405	0.0000	-4.4428	0.4371	0.0000	-0.3245	0.3151	0.3030
d15	-2.5321	0.2013	0.0000	-3.3944	0.5370	0.0000	-4.1531	0.4381	0.0000	-0.3849	0.4457	0.3880
d16	-2.7741	0.2193	0.0000	-3.7862	0.5509	0.0000	-3.5368	0.3873	0.0000	-1.4082	0.6178	0.0230
d17	-2.4321	0.1807	0.0000	-5.4632	1.0842	0.0000	-3.4811	0.3701	0.0000	-0.3019	0.3569	0.3980
d18	-2.1793	0.1972	0.0000	-3.0906	0.5238	0.0000	-3.1607	0.3865	0.0000	-0.7834	0.4764	0.1000
d19	-2.3806	0.1775	0.0000	-2.7952	0.4924	0.0000	-3.1341	0.3668	0.0000	-0.4066	0.3893	0.2960
d20	-2.0604	0.1740	0.0000	-2.8386	0.5226	0.0000	-3.1169	0.3822	0.0000	-0.3044	0.5173	0.5560
d21	-2.1987	0.2049	0.0000	-3.8555	0.6091	0.0000	-3.1340	0.3721	0.0000	-	-	-
d22	-2.0585	0.1864	0.0000	-2.9596	0.5020	0.0000	-2.7606	0.3706	0.0000	-	-	-
d23	-1.9137	0.1951	0.0000	-3.1550	0.5055	0.0000	-2.9344	0.3551	0.0000	-	-	-
d24	-2.2134	0.2108	0.0000	-2.6479	0.5274	0.0000	-3.0257	0.3816	0.0000	-	-	-
d25	-2.0485	0.2217	0.0000	-3.1126	0.5467	0.0000	-2.9077	0.3800	0.0000	-	-	-
d26	-1.6750	0.2000	0.0000	-2.4067	0.4745	0.0000	-2.9526	0.3939	0.0000	-	-	-
d27	-1.5154	0.2038	0.0000	-2.1317	0.4572	0.0000	-2.4759	0.4070	0.0000	-	-	-
d28	-1.4792	0.2241	0.0000	-2.7153	0.4872	0.0000	-2.6695	0.3834	0.0000	-	-	-
d29	-1.6395	0.2685	0.0000	-2.3763	0.4968	0.0000	-2.5582	0.3841	0.0000	-	-	-
d30	-1.7682	0.2507	0.0000	-2.6421	0.5276	0.0000	-2.6362	0.4077	0.0000	-	-	-
d31	-1.9750	0.2851	0.0000	-2.3454	0.4755	0.0000	-2.5446	0.4260	0.0000	-	-	-
d32	-2.0989	0.3413	0.0000	-2.2716	0.4995	0.0000	-2.8661	0.4557	0.0000	-	-	-
d33	-1.4739	0.2346	0.0000	-2.4134	0.5361	0.0000	-2.4835	0.4387	0.0000	-	-	-
d34	-1.8616	0.3459	0.0000	-2.3184	0.5442	0.0000	-2.6919	0.4739	0.0000	-	-	-
d35	-1.3692	0.2544	0.0000	-1.6780	0.4362	0.0000	-2.8785	0.4815	0.0000	-	-	-
d36	-0.8236	0.2217	0.0000	-1.0640	0.4196	0.0110	-1.8514	0.4264	0.0000	-	-	-
d37	4.4122	0.9809	0.0000	5.2851	1.1159	0.0000	(omitted)			-	-	-
revenue	-9.990E-06	0.0000	0.1770	-5.088E-04	0.0001	0.0000	-1.985E-04	0.0000	0.0000	-2.450E-05	0.0000	0.0330
fuel price	-	-	-	0.1891	0.0827	0.0220	0.2247	0.0726	0.0020	-	-	-
tier300	-	-	-	0.3800	0.3025	0.2090	0.6255	0.2410	0.0090	-	-	-
tier500	0.3152	0.1281	0.0140	0.9156	0.3599	0.0110	0.7517	0.2880	0.0090	-	-	-
rev OA	0.1085	0.0275	0.0000	-	-	-	-	-	-	-	-	-
rev OT	-	-	-	-	-	-	0.0047	0.0018	0.0100	-	-	-

4.3.2 EFFECTIVE EFFORT

The duration model predicts how endogenous and exogenous changes in fishery conditions (catch rates, input/output prices, and opportunity costs) affect the number of vessels participating in the fishery during a given time period. In order to estimate total effective fishing effort, which is the main input into the biological module, it was necessary to combine our duration model estimates of fleet participation in each time period with an estimate of effective effort per vessel in each time period.

Two characteristics of the ODC fishery aided us in defining effective effort. First, vessels generally utilize the maximum number of pots they are permitted to use over the entire course of the season i.e., their pot ‘tier’ (ODCC 2015). For example, this implies that a vessel with a 300 pot limit will generally have 300 pots deployed on the fishing grounds throughout the course of the season. While this is not strictly true, especially for vessels in the 200 tier class, information on the total number of pots used is not collected (Didier 2002; Kelly Corbett 2016). This characteristic also implies that the soak time of each pot per week is a week! Secondly, pots are generally rebaited every time they are ‘pulled’ and re-deployed, and pots are most effective in the first 12-24 hours after rebaiting, and relatively ineffective after that time frame (ODCC 2015). We therefore defined effective effort (EE_{it}) for each vessel i in each week period, t , as the number of pots deployed (NP_{it}) per vessel multiplied by the proportion of those pots that were tended (pots pulled (PP_{it}) divided by NP_{it}), or just number of pots pulled:

$$EE_{it} = NP_{it} * \frac{PP_{it}}{NP_{it}} = PP_{it} \quad Eq. 4.14$$

In modeling effective effort, one consideration was that it should include a measure of number of trips made per vessel where a trip is defined as a vessel leaving port, exerting fishing effort, and returning to port. Defining trips is important as many variable vessel costs are incurred on a trip level. For example, significant fuel costs are incurred steaming between port and the fishing grounds at the beginning and end of trips and taking this granularity into account is important for simulating vessel profits. An issue that presented itself when trying to measure the number of trips in the fishery was that our two main data sources -- vessel logbooks and fish tickets -- did not provide an accurate measure of number of trips made. Logbook data were provided as ‘records’, which were effectively one page of a logbook (pertaining to a ‘string’ of pots), and it is unclear how the number of strings pulled pertain to trips. The number of fish tickets is a more accurate measure of trips made than individual logbook records as a fish ticket is generated each time a vessel delivers to a first receiver. It is rare for vessels to make more than one trip per day (ODCC 2016b),

but in some cases multiple fish tickets will be generated for a single trip, such as in the case where a vessel delivers to more than one first receiver or uses two different gear types in the same trip. We decided that aggregating fish tickets on a vessel/day basis was the most accurate method for defining trips. Even if multiple fish tickets were generated for the same trip, they were likely generated on the same day, and that, except in extremely rare circumstances, vessels did not make more than one trip per day (ODCC 2016b).

A priori, our expectation was to perform an estimation procedure on the number of trips a vessel takes in a given week of the season conditional on having not exited the fishery, and then to estimate how the number of pots pulled per trip is affected by changes in fishery conditions, conditional on taking a trip. However, while a reliable estimate of the number of trips could be made using fish ticket data, defining the number of pots pulled per trip was hampered by the characteristics of the logbook data, which contained the information on pots pulled. Logbook data were problematic for a number of reasons. First, logbooks were only required to be filled out starting from the 2008 season, and compliance was relatively low for the first several years of this requirement. Compliance, as measured by the percentage of total fish tickets (which we assume to have a 100% reporting rate) captured by the logbook data, was approximately 68%, 78% and 90% for the 2008, 2009, and 2010 seasons, and averaged 93.5% between the 2011 and 2014 seasons (Kelly Corbett 2016). It is unknown if logbook data were incomplete in a systematic or random fashion, but it is reasonable to assume that whether or not a vessel captain completed their logbooks, logbooks was correlated with factors that may also affect fishing behavior and which may cause sampling bias. In addition there is a relatively low level of trust in the accuracy of the reported data, particularly for the first few years of the new logbook reporting requirements (ODCC 2016b). Secondly, due to resource limitations, starting from the 2012 season, only 30% of the total logbook 'records' were transcribed into an accessible database on a stratified sampling basis. Each month 30% of all records for each port in Oregon were randomly selected to be transcribed and it is unknown whether each vessel's records in these years reflected all of their weekly effort. This meant that later in each season, when the number of vessels participating decreased significantly, data coverage on a sub-fleet basis was relatively poor. Taking these data limitations into account we decided that it was impractical to estimate how the number of pots per trip changed in response to fishery conditions. Rather, in order to examine how weekly effort responds to fishery conditions we calculated the average number of pots pulled per trip for each vessel on a sub-fleet basis and averaged over the 2008-2014 seasons, and then combined this metric with a statistical model of number of trips made per week to arrive at the total number of pots pulled per week.

4.3.2.1 Weekly Number of Trips Estimation

We estimated how the number of trips a vessel takes per week varied throughout each season, and in response to fishery conditions such as catch rates, crab prices, fuel costs, and opportunity costs. While log transformed linear regression models have been used in the past to model count data there are various drawbacks to doing so, including biased and inefficient parameter estimates and a limited ability to handle zero counts (Pradhan and Leung 2006; Rijnsdorp, Daan, and Dekker 2006). Count models are generally estimated using either a Poisson model, negative binomial model, or one of many derivatives (see Hilbe (2014) for a good overview; Long and Freese 2006).

Before we could proceed in specifying a suitable count model the dataset was amended in a number of ways. First, the fish ticket data only contained records for those vessels that actually made a delivery in a given week. It was relatively common for a vessel to fail to deliver Dungeness crab during one or more of the weeks before its week of exit. Reasons for this could include severe weather, a vessel participating in other fisheries in between tending its crab gear, or simply because of a fisherman's normal fishing behavior. Including these 'zero' records is an important step as these records contribute valuable information to the model, and preclude the use of a truncated distribution for the counts when one is not needed. Following Smith (2002), additional data records were created specifying a zero trip count and maintaining all pertinent information for all missing weeks including any weeks prior to a vessel's week of first delivery. Note that while the vast majority of vessels entered the fishery in week 1 of each season (figure 4.1), this procedure meant that we created records pertaining to weeks prior to a vessel's entry into the fishery in some cases. As discussed previously, vessels that participated in Washington or California Dungeness crab fisheries made up the vast majority of late entrants, of which there are relatively few (0-10% per season). In addition, severe weather, mechanical breakdowns, or crew issues are other causes of late entry (ODCC 2015). Variables that were not vessel-specific (such as fuel prices) and vessel specific but non time-varying (such as the pot tier license held) were easily carried over into the new 'zero' records. The time varying and vessel-specific variables were all based on weekly revenue of each vessel. For missing values of revenue we imputed the average of revenue in that week and season of all other vessels holding the same pot tier license. For missing values of the revenue ratio variables (ratios of other fisheries' revenues to ODC revenue), the average value of that variable was also imputed on a pot tier basis, but the variables were multiplied by an indicator of whether or not a vessel participated in the alternative fisheries in that season. Finally, these revenue based variables were lagged by one week to avoid simultaneity -- the value in week 1 became the lagged value for week 2, and so on.

Perhaps the most well-known count model specifies the count as a Poisson distributed random variable. Following (Hilbe 2014) the Poisson distribution can be expressed as:

$$f(y_i|\lambda) = \frac{\exp^{-\lambda_i} \lambda_i^{y_i}}{y_i!} \quad \text{Eq. 4.15}$$

Where y is the count variable which can take on any positive integer value in the interval $[0, \infty)$, and λ is the expected mean of the distribution of y . When incorporating covariates into a Poisson regression a common formulation is:

$$\lambda_i = \exp(X_i' \beta) \quad \text{Eq. 4.16}$$

Where λ_i is the expected number of occurrences of the count variable for that individual, X_i is a matrix of covariates, and β is a vector of parameters, the focus of our estimation. The exponential form guarantees a non-negative value for the predicted mean of the distribution.

It is important to introduce a scale variable to recognize either the possible range of values that a count may take, the length of time, or the area of space that a count is measured over. In our case the scale variable refers to the maximum number of trips that a vessel can make. Given our definition of a trip using fish ticket data, the minimum number of trips a vessel could take in a week period was 0, and the maximum number 7. We effectively reformulated the count equation taking into account the scale variable t_i , which in our case is just the scalar 7. If the expected value of the rate is λ_i the expected value of the count is λ_i multiplied by t_i . In this case the count equation becomes (Pradhan and Leung 2006):

$$\lambda_i t_i = \exp(X_i \beta + \ln(t_i)) \quad \text{Eq. 4.17}$$

The Poisson distribution exhibits equi-dispersion i.e. the mean of the distribution is equal to its variance. If this assumption is violated the result is consistent but inefficient parameter estimates and is considered the main issue in count models when fitting models (Long and Freese 2006; Hilbe 2014). This assumption of equi-dispersion can be violated in several ways, including measurement error and the presence of excess zero observations on the dependent variable (Greene 1994). Overdispersion occurs when the variance of the data is greater than the mean, and underdispersion occurs when the opposite is true. The most common remedy for overdispersion is to estimate a negative binomial model, which includes an extra dispersion parameter, although this model is inappropriate when underdispersion exists (Hilbe 2014). Again following Hilbe (2014), the negative binomial probability distribution can be expressed as:

$$f(y_i|\lambda, \alpha) = \binom{y_i + \frac{1}{\alpha} - 1}{\frac{1}{\alpha} - 1} \left(\frac{1}{1 + \alpha\lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha\lambda_i}{1 + \alpha\lambda_i}\right)^{y_i} \quad \text{Eq. 4.18}$$

Where y is the count variable which can take on any positive integer value in the interval $[0, \infty)$, α is the dispersion parameter, and λ is the expected mean of y . In this case the variance of the distribution is equal to: $\lambda + \alpha\lambda^2$. A common test for overdispersion in a Poisson model is conducted by estimating a negative binomial model and evaluating the dispersion parameter. If the dispersion parameter is not significantly different to zero then a Poisson model is preferred as it is more efficient (Hilbe 2014; Pradhan and Leung 2006).

When count data contain a substantial number of zero observations, conventional Poisson and negative binomial models fail to describe the data well, often under-predicting the zero observations (MacNeil, Carlson, and Beerkircher 2009; Poston Jr and McKibben 2003). For example, Minami et al. (2007) suggest that the negative binomial model may overestimate parameters when fitted to data with many zero values. In addition, overdispersion can be indicated if the number of zeros in the data are greater than what a regular count model would predict (Greene 1994). In these cases using a model that explicitly accounts for a high number of zeros in the dataset is called for. Hurdle models, such as the two part delta lognormal model (Maunder and Punt 2004) split the dataset into two parts- one part containing only the zero observations, and another part containing the records with all of the positive counts. The two subsets of the data are estimated using different models. Mixture models, such as the Zero-Inflated Poisson (ZIP) model (after Lambert (1992)), assume that observations are governed by two different processes -- a Bernoulli process that generates just zero values, and a Poisson or negative binomial process that generates a regular distribution of counts, which includes zeros (Hilbe 2014). In this case the zeros are the product of two random terms, only the product of which are manifested in the data and are estimated concurrently (Greene 1994). The choice of using a hurdle or mixture model to account for excess (or structural) zeros should be based on theory. If the zero observations are generated by a separate mechanism to the positive counts then it may be appropriate to use a hurdle model. If the process generating structural zeros is intertwined with the process generating the 'regular' zeros and positive counts then a mixture model is more appropriate (Hilbe 2014).

For reasons discussed below we included the ZIP model specification in our analysis but did not include the Zero Inflated Negative Binomial (ZINB) specification. We therefore do not present the ZINB model's

theoretical specification, but for a good overview, see Hilbe (2014). The Zero-Inflated Poisson model has two separate components. First, a binary component estimates the probability that a count is a structural zero, commonly using logistic regression (Lambert 1992; Greene 1994; Hilbe 2014). The count component of the model then models all of the counts, including the zeros, as the manifestation of a Poisson process.

Using a logit specification, the probability of observing a structural zero, denoted by θ , is then:

$$\theta = \frac{1}{1 + \exp(Z'\gamma)} \quad \text{Eq. 4.19}$$

Where Z is a matrix of explanatory variables for the generation of zero counts, and γ is the vector of parameters to be estimated.

The probability of observing a count of zero, is therefore:

$$\text{Prob}(y = 0) = \theta + (1 - \theta)\exp^{-\lambda} \quad \text{Eq. 4.20}$$

The probability of observing a non-zero count is:

$$\text{Prob}(y = d_i) = (1 - \theta) \frac{\lambda^{d_i} e^{-\lambda}}{d_i!} \quad \text{Eq. 4.21}$$

Count models have seen widespread use in the fisheries economics literature. For example, (McConnell, Strand, and Blake-Hedges 1995) combine a random utility model of site choice with a Poisson model of anglers' expected catch at each of these sites. Gillig, Ozuna Jr, and Griffin (2000) combine a Poisson model for estimating the number of trips that fishermen take with a demand model to estimate the value of the red snapper fishery in the Gulf of Mexico. Scrogin et al. (2004) use a ZIP model to examine anglers' expectations of catch in a combined random utility model of fishing location choice. Kasperski (2015) conducts a Poisson regression for vessel decisions on the number of trips to take and combined the results with a bioeconomic model of inter-dependent fish stocks. Smith (2002) modeled fishermen's participation decision, and given participation their fishing location choice by combining a negative binomial model of number of trips taken with a Seemingly Unrelated Regression model of location choice. Pradhan and Leung (2006) used both a Poisson model and a negative binomial specification to explore the factors affecting sea turtle interactions in the Hawaiian pelagic longline fishery and applied each model to different target species types based on whether the data exhibited overdispersion or not.

Recently there has been much interest in comparing the performance of different modeling specifications, generally evaluated in terms of a model fit statistic such as the Akaike Information Criterion (AIC) (Akaike 1998). For example, MacNeil, Carlson, and Beerkircher (2009) compare a range of Generalized Linear Models (GLMs), hurdle models, and mixture models in the analysis of shark depredation rates in the Atlantic pelagic longline fishery. There was a high preponderance of zeros in the data and the authors found that the hurdle and mixed models outperformed the GLMs. Vaudor, Lamouroux, and Olivier (2011) compare the performance of the Poisson, NB, ZIP, and ZINB when estimating the abundance of 12 freshwater fish species. They found that the negative binomial model worked well for a wide range of sample characteristics, the ZIP and Poisson models worked best when mean and variance were relatively low, and ZINB worked best when the mean was very high. Lewin et al. (2010) compare regular count models, hurdle models, and mixture models in their ability to deal with zero inflated datasets and found that when the dataset included a large number of zero counts only hurdle and mixture models could be reliably applied.

Given the dataset we used for the count data model was based on the same dataset used for the duration model estimation, our data potentially exhibited non-independence between observations on the same vessels. When dealing with longitudinal data the same suite of models that are used in logistic regression can be used in Poisson regression analysis including fixed effects and random effects (and many more) models (Cameron and Trivedi 2013). However, including a dummy variable for each vessel/year combination would have resulted in several thousand extra parameters so the fixed effects estimator was unfeasible. Using a conditional fixed effects specification is again an option but estimating the effect of time invariant variables using this model is not possible. Specifying a random effects model would be to assume that the random effects are independent across vessels, or in other words uncorrelated with observed vessel specific covariates. Essentially this means that if there are unobserved vessel specific factors that affect covariates such as a vessel's revenue in a given week and the decision of how many trips to take in that week (which seems probable), then the parameters of a random effects logit model are likely biased. In addition to the theoretical limitations of the use of these panel models, a practical consideration was that the results were destined to be incorporated into a forward-looking bioeconomic simulation model. A mechanism for incorporating results of, for example, a random effects panel model into the simulation would have been considerably more complicated to incorporate in the model than the pooled model specification.

We therefore take a similar approach to Kasperski (2015), and to the estimation of the duration model in section 4.3.1, by conducting separate regressions for each sub-fleet separately and including fixed effects for the different pot tier levels. This approach is also somewhat similar to Pradhan and Leung (2006), who presume that there may be vessel specific effects that affect the probability of sea turtle interaction. They incorporate this effect using a dummy variable for a vessel’s previous history of sea turtle interactions, but not for each vessel per se. To account for the potentially correlated error structure we estimate the models using robust standard errors clustered on individual vessels using Huber-White’s robust variance estimator (Freedman 2012; STATA corp. 2016).

In deciding on the exact model specification we examined the mean and variance of the counts of number of trips per week for each of the 4 sub-fleets. It appears that overdispersion was limited in all 4 datasets, with significant underdispersion in the shrimp dataset. Table 4.9 shows the mean and variance of the counts of number of trips per week for each of the 4 sub-fleets.

Table 4.9: Characteristics of the amended dataset used in the effective effort estimation.

Sub-Fleet	Number of Observations	Mean	Variance
crable	23723	.934915	1.189339
OA	11123	1.060865	1.277629
saltun	16180	1.003337	1.066062
shrimp	3094	.840659	.518088

Given the way we amended the fish ticket data set we decided that the most suitable model *a priori* to model the number of trips fishermen take in a week was a mixture model- either a ZIP model or a Zero-Inflated Negative Binomial (ZINB). The reason for this was that the zeros in the dataset were generated by a mixture of processes including one process where fishermen don’t take a trip in a given week period, and another one where the fisherman has not entered yet and zero records were created by a separate data generating process. While negative binomial and ZINB models are suitable when the dataset exhibits overdispersion due to the presence of some high counts (Lewin et al. 2010), our data did not exhibit high counts and an examination of the mean and variance statistics indicate that overdispersion was limited. Vaudor, Lamouroux, and Olivier (2011) showed that the ZINB model works best when the means of the count variable are very high. Given this, and the fact that the ZINB failed to converge for several of the alternative specifications tested we did not use the ZINB model in our analysis. We estimated the regular Poisson, negative binomial, and the zero-inflated Poisson model and compared model fit using the AIC. As negative binomial models are unsuitable when underdispersion is present (Hilbe 2014), we did not estimate these

models for the shrimp sub-fleet. A commonly used test for whether a zero-inflated model is appropriate was proposed by (Vuong 1989). However, the statistic relies on the true likelihood function and as our use of a robust covariance matrix means we are estimating quasi-likelihoods, tests that rely on the true likelihood, such as the likelihood ratio test or Vuong test, are not valid (Hilbe 2014).

In our model specification we included fixed effects for the particular week of the season and the pot tier license that each vessel held. Lagged weekly revenue, the average price of fuel, and the opportunity costs of making a trip, represented by the ratio of other fisheries' weekly revenues to ODC weekly revenues were included. The inflation portion of the ZIP model was conditioned on dummy variables representing the first 6 weeks of the season. Covariates are described in table 4.10:

Table 4.10: Description of the variables used in the ZIP model.

<i>Variable</i>	<i>Description</i>	<i>Inflation?</i>	<i>Poisson?</i>
$d_i, i=1, \dots, 37$	$d_i = 1$ if observation is in week i	$d(\text{inf})1-d(\text{inf})6$	x
tier200	dummy=1 if vessel held a 200 tier license		x
tier300	dummy=1 if vessel held a 300 tier license		x
tier500	dummy=1 if vessel held a 500 tier license		x
season _s	dummy if observation was in season s		x
lagrev	sum of a vessel's weekly ODC revenue (\$) in the previous week.		x
SH	ratio of average weekly revenue in the shrimp fishery to a vessel's ODC weekly revenue.		x
LE	ratio of average weekly revenue in the LE fishery to a vessel's ODC weekly revenue.		x
OA	ratio of average weekly revenue in the OA fishery to a vessel's ODC weekly revenue.		x
SAL	ratio of average weekly revenue in the salmon fishery to a vessel's ODC weekly revenue.		x
TUN	ratio of average weekly revenue in the tuna fishery to a vessel's ODC weekly revenue.		x
OTH	ratio of average weekly revenue in all other fisheries to a vessel's ODC weekly revenue.		x
offset	a column of 7s was included as the offset variable to reflect the maximum value of the count		x

The estimation was conducted for the 4 sub-fleets separately using the Poisson, negative binomial, and ZIP model specifications. In all cases the AIC indicated that ZIP was the preferred model. Parameters that were not significant at the 5% level using a Wald test, and did not cause a decrease in the AIC when removed, were removed from the model and the model re-estimated.

The parameter estimates on the week dummies were all significant, picking up a time trend showing the average number of trips per week decreasing slightly throughout the season. For each sub-fleet, a parameter estimate on at least one of the revenue ratio variables were significant and negative, indicating a negative marginal effect of that variable on the number of trips a vessel takes. For the crable fleet, the parameter on the ratio of LE groundfish revenue to ODC revenue was significant, for the OA fleet the parameter on the ratio of OA revenue to ODC revenue was significant, for the saltun fleet the parameter on salmon revenue was significant, and for the shrimp fleet the parameter on shrimp revenue was significant. This suggests that the average number of trips each sub-fleet makes in a week period decreases when opportunity cost of participating increases. Lagged revenue was a significant positive predictor for the number of trips taken per week for the OA and saltun fleets although this effect was not significant for the crable and shrimp fleets. This indicates that the higher a vessel's revenue in the previous time period, the more likely the vessel's captain was to increase the number of trips he/she took in the next time period. The fixed effects on pot tier were mostly insignificant predictors of number of trips taken. The exception was the shrimp fleet where vessels who had a 500 pot tier license took less trips on average than 300 tier vessels (there were no 200 tier vessels in the shrimp fleet). This suggests that pot tier does not have a significant effect on the number of trips that vessels take in a week period. Although vessels with higher pot tiers exert more effort, this higher effort is reflected in the number of pots each vessel pulls *per trip* (see figure 4.6). The interpretation of the parameters is in the opposite direction for the inflation part of the model. A positive parameter indicates a positive effect of that variable on the probability that an observation was a zero count. The dummy variables for the first 6 weeks of the season were significant and indicated that, on average, zero observations were more likely to occur in week 1 of the season, then week 2, and so on. Final model specifications and parameter estimates are shown in table 4.11.

Table 4.11: Zero-Inflated Poisson model results. Parameter estimates, asymptotic standard errors, and associated p-values for the final model specifications.

	<i>CRABLE FLEET</i>			<i>OA FLEET</i>			<i>SALTUN FLEET</i>			<i>SHRIMP FLEET</i>		
<i>PAR.</i>	<i>Est.</i>	<i>A.S.E.</i>	<i>p-value</i>	<i>Est.</i>	<i>A.S.E.</i>	<i>p-value</i>	<i>Est.</i>	<i>A.S.E.</i>	<i>p-value</i>	<i>Est.</i>	<i>A.S.E.</i>	<i>p-value</i>
d1	-6.0538	0.0464	0.0000	-6.2392	0.1070	0.0000	-6.1202	0.0765	0.0000	-6.3927	0.2128	0.0000
d2	-6.4991	0.0538	0.0000	-6.6061	0.1121	0.0000	-6.5692	0.0789	0.0000	-6.2123	0.1944	0.0000
d3	-6.6857	0.0607	0.0000	-6.6781	0.0855	0.0000	-6.5878	0.0665	0.0000	-6.2883	0.1968	0.0000
d4	-7.2185	0.0905	0.0000	-7.1232	0.1362	0.0000	-7.0500	0.0683	0.0000	-6.4603	0.2077	0.0000
d5	-6.7875	0.0617	0.0000	-6.6735	0.0879	0.0000	-6.6142	0.0618	0.0000	-6.1681	0.2189	0.0000
d6	-7.1658	0.0800	0.0000	-6.8598	0.1060	0.0000	-7.0776	0.0670	0.0000	-6.4933	0.2096	0.0000
d7	-6.8552	0.0473	0.0000	-6.6271	0.0690	0.0000	-6.7242	0.0684	0.0000	-6.2098	0.2336	0.0000
d8	-6.7931	0.0459	0.0000	-6.5931	0.0743	0.0000	-6.7213	0.0633	0.0000	-5.9586	0.2447	0.0000
d9	-7.0690	0.0477	0.0000	-6.9141	0.0777	0.0000	-6.9319	0.0670	0.0000	-6.2225	0.2532	0.0000
d10	-7.1497	0.0458	0.0000	-6.9683	0.0755	0.0000	-6.9685	0.0691	0.0000	-6.1113	0.2604	0.0000
d11	-7.1606	0.0378	0.0000	-7.0281	0.0689	0.0000	-6.9498	0.0639	0.0000	-5.9179	0.2895	0.0000
d12	-7.0803	0.0434	0.0000	-6.8540	0.0802	0.0000	-6.9835	0.0664	0.0000	-5.9294	0.3029	0.0000
d13	-7.2674	0.0450	0.0000	-7.0718	0.0682	0.0000	-7.0468	0.0706	0.0000	-6.1628	0.3274	0.0000
d14	-7.1663	0.0384	0.0000	-6.9738	0.0732	0.0000	-7.0467	0.0716	0.0000	-5.8956	0.3002	0.0000
d15	-7.4807	0.0481	0.0000	-7.2759	0.0854	0.0000	-7.2887	0.0796	0.0000	-6.4872	0.3828	0.0000
d16	-7.3765	0.0473	0.0000	-7.1744	0.0884	0.0000	-7.2380	0.0761	0.0000	-6.2115	0.3417	0.0000
d17	-7.2386	0.0444	0.0000	-7.0290	0.0873	0.0000	-6.8723	0.0704	0.0000	-5.8081	0.3479	0.0000
d18	-7.2470	0.0479	0.0000	-6.9487	0.0781	0.0000	-6.9845	0.0721	0.0000	-5.7064	0.3866	0.0000
d19	-7.2324	0.0498	0.0000	-6.9662	0.0822	0.0000	-6.9298	0.0768	0.0000	-4.3463	0.3554	0.0000
d20	-7.2569	0.0499	0.0000	-6.9780	0.0727	0.0000	-6.8638	0.0783	0.0000	-2.7544	0.5167	0.0000
d21	-7.3747	0.0594	0.0000	-7.0605	0.0928	0.0000	-7.0769	0.0818	0.0000			
d22	-7.1252	0.0483	0.0000	-6.8591	0.0834	0.0000	-6.8400	0.0738	0.0000			
d23	-7.4691	0.0639	0.0000	-7.0536	0.0846	0.0000	-7.0187	0.0835	0.0000			
d24	-7.1030	0.0532	0.0000	-6.8845	0.0896	0.0000	-6.8816	0.0769	0.0000			
d25	-7.3977	0.0778	0.0000	-7.2014	0.0832	0.0000	-7.1475	0.0862	0.0000			
d26	-7.2982	0.0617	0.0000	-7.0326	0.0969	0.0000	-6.8799	0.0977	0.0000			
d27	-7.2634	0.0682	0.0000	-6.9766	0.0862	0.0000	-6.8369	0.0831	0.0000			
d28	-7.3511	0.0783	0.0000	-7.1182	0.1078	0.0000	-6.9179	0.1089	0.0000			
d29	-7.3718	0.0779	0.0000	-7.0310	0.0903	0.0000	-6.7889	0.0882	0.0000			
d30	-7.3260	0.0894	0.0000	-7.1915	0.0921	0.0000	-6.8440	0.1106	0.0000			
d31	-7.1557	0.1002	0.0000	-7.1168	0.0986	0.0000	-6.7527	0.1204	0.0000			
d32	-7.1957	0.1350	0.0000	-7.0017	0.1294	0.0000	-6.7531	0.1671	0.0000			
d33	-6.7351	0.1258	0.0000	-6.9426	0.1173	0.0000	-6.5140	0.1446	0.0000			
d34	-6.9439	0.1188	0.0000	-7.0493	0.1209	0.0000	-6.6329	0.1452	0.0000			
d35	-6.7748	0.1077	0.0000	-6.7070	0.0797	0.0000	-6.4951	0.1371	0.0000			
d36	-6.7559	0.1007	0.0000	-6.4669	0.1038	0.0000	-6.3504	0.1140	0.0000			
d37	-6.3323	0.0774	0.0000	-6.3249	0.0558	0.0000	-6.2092	0.0991	0.0000			
tier300							-0.0910	0.0738	0.2170			
tier500							-0.1275	0.0930	0.1700	-0.7275	0.1890	0.0000
lagrev				1.01E-05	0.0000	0.0000	4.86E-06	0.0000	0.0000			
LE										-0.1442	0.0474	0.0020
OA				-0.1184	0.0521	0.0230						
SAL							-0.1410	0.0262	0.0000			
TUNA	-0.0158	0.0040	0.0000				-0.0053	0.0024	0.0240			
OTHER							-0.0073	0.0022	0.0010			
SHRIMP										-0.7573	0.1492	0.0000
INFLATION MODEL PARAMETERS												
d1	18.1414	0.2802	0.0000	18.9874	0.2849	0.0000	19.7809	0.2636	0.0000	-15.6169	0.5625	0.0000
d2	17.1696	0.2661	0.0000	18.1667	0.3767	0.0000	18.2174	0.4941	0.0000	-16.1999	0.5107	0.0000
d3	16.3413	0.3166	0.0000	17.5692	0.4761	0.0000	2.1133	1.6825	0.2090	-16.1519	0.4650	0.0000
d4	13.5798	8.7330	0.1200	16.8718	1.5778	0.0000	0.3841	0.3248	0.2370	-16.0290	0.4688	0.0000
d5	16.1558	0.3711	0.0000	16.9430	0.7408	0.0000	0.3211	0.3492	0.3580	-16.2036	0.5027	0.0000
d6	15.9104	0.7565	0.0000	18.6531	0.3279	0.0000	0.8075	0.8649	0.3510	-15.7098	0.5625	0.0000
constant	-18.5135	0.3058	0.0000	-19.7328	0.2810	0.0000	-20.7711	0.2667	0.0000	-3.1879	0.4837	0.0000

For input into the bioeconomic simulation framework the predictions of the number of trips in each week period, t , for each sub-fleet, j , are calculated as follows:

$$trips_{jt} = \left[1 - \left(\frac{\exp(constant + d_{(INF)t})}{1 + \exp(constant + d_{(INF)t})} \right) \right] \left[\exp(d_{jt} + tier500_j + lagrev_j \cdot LAGREV_{jt} + \sum_{k=1}^K ratrev_{kj} \cdot RATREV_{jt}) \right] \quad Eq. 4.22$$

Where $trips_{jt}$ is the predicted number of trips for sub-fleet j in time t , $LAGREV_{jt}$ is the value of lagged revenue for sub-fleet j in time t , $ratrev_{kj}$ is the parameter on ratio of the k th alternative fishery revenue to ODC revenue in time t ($k = OA, LE, \text{salmon}, \text{shrimp}$), and $RATREV_{jt}$ is the value of the ratio of the k th alternative fishery to ODC fishery for fleet j in time t .

4.3.3 SUB-FLEET REFINEMENT

For input into the simulation model it was necessary to refine our definition of sub-fleets so calculations of participation and effort, using our statistical results, could be made in a way that simplified the modeling task. We subsequently defined a total of 10 sub-fleets based on original sub-fleet specifications (see table 4.9), and the pot tier composition of each sub-fleet. For example, the crable fleet was split into 2 sub-fleets: a 200/300 tier vessel sub-fleet, and a 500 tier vessels, one of which participated in the WA/CA fisheries. Refined sub-fleets are defined in table 4.12.

Table 4.12: Definitions of the 10 refined sub-fleets that are used in the bioeconomic simulation model.

Sub-fleet code	Description
cr23	200 and 300 tier crable fleet vessels
cr5	500 tier crable fleet vessels
oa2	200 tier oa fleet vessels
oa3	300 tier oa fleet vessels
oa5	500 tier oa fleet vessels
st2	200 tier saltun fleet vessels
st3	300 tier saltun fleet vessels
st5	500 tier saltun fleet vessels
sh3	300 tier shrimp fleet vessels
sh5	500 tier shrimp fleet vessels

Figure 4.5 shows average weekly revenue per vessel by sub-fleet over the 2008-2014 seasons. Revenue starts off at a high level and attenuates very rapidly. The initial trough and peak is due to the 2012-2014 seasons opening 2, 4, and 2 weeks later than usual, respectively.

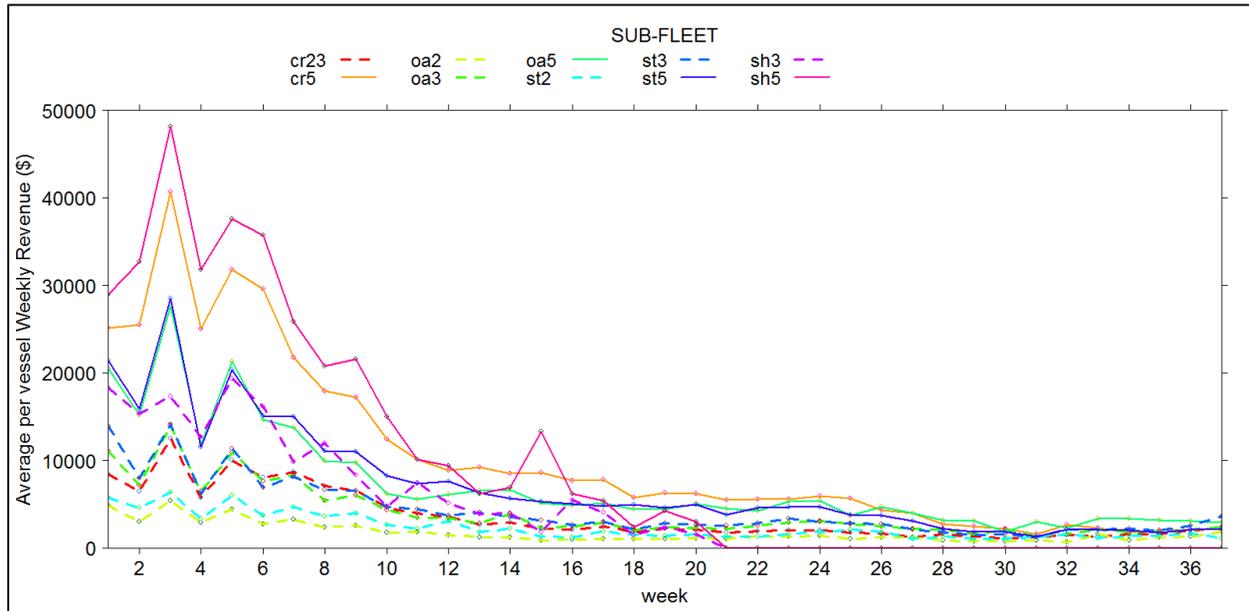


Figure 4.5: Average weekly ODC revenues per vessel 2008-2014.

4.3.4 TOTAL EFFORT PER WEEK

The input into the biological sub-model is the total number of pots pulled per week. This is calculated as the product of 1) the number of vessels participating in the fishery (using the duration model results), 2) the number of trips made per vessel given participation (using the ZIP model results), and 3) the number of pots per trip made per week.

To calculate a metric for the number of pots pulled per trip we first converted the number of pots pulled per day into a per trip measure. Table 4.13 shows the comparison between total number of trips using the fish ticket data, and using the logbook data detailed in section 4.3.2.

Table 4.13: Comparison of metrics for estimating the number of ODC fishing trips.

season	trips (fish ticket method)	trips (logbook method)	corrected logbook 'trips'	% higher
2008	6330	5405	7948	25.6%
2009	6414	5555	7121	11.0%
2010	7209	6583	7315	1.5%
2011	7323	7897	8584	17.2%
2012	6328	2189	7762	22.7%
2013	6181	2170	7778	25.8%
2014	5950	2125	7456	25.3%

After correcting for compliance rates the logbook defined trip totals were on average 13.83% higher in each season than the fish ticket defined totals. We also calculated this difference on a tier, and combined tier-subfleet basis. However, some of the corrections were lower than 1 and some were higher than 6. We therefore decided to use the average correction of 13.83% to arrive at the number of pots pulled per trip by subfleet and week. Using our refined sub-fleets (table 4.12) we estimated the average number of pots pulled per vessel per trip by sub-fleet between 2008 and 2014 and corrected them by the correction factor (figure 4.6). The potential for inaccurate reporting, the limited number of vessels in the oa5 and st2 fleets in all years, and the fact that the number of vessels used to calculate the average pots per trip in the later part of the season is relatively small, contribute to some curves displaying significant variation between weeks especially during the latter part of the season. However, disregarding this variation the pattern of pots pulled per trip appears to remain remarkably constant across seasons, with no particular season standing out from the average.

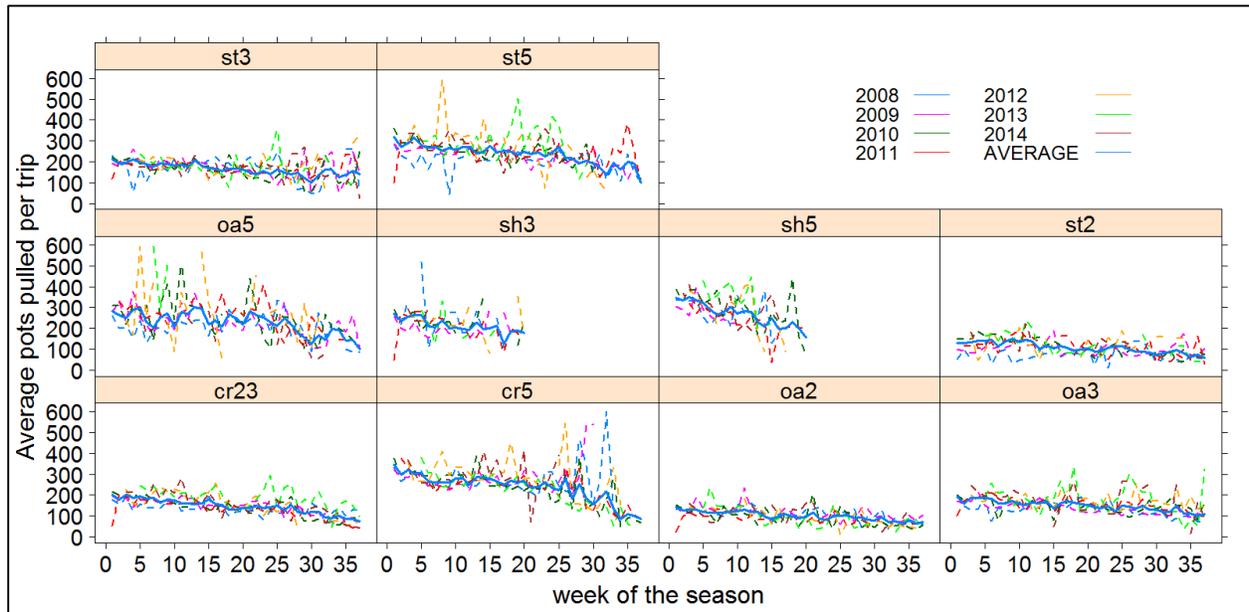


Figure 4.6: Historical number of pots pulled per fish ticket-defined trip. The blue line indicates the average number of pots pulled per week by sub-fleet and was the metric used as input into the bioeconomic simulation model.

4.4 Historical Comparison

In order to examine the performance of these models in predicting weekly effort in the ODC fishery we used the historical average data for model inputs including weekly revenues by subfleet, fuel prices, and starting numbers of vessels in each subfleet. We then estimated exit behavior and number of trips per week for each season from 2008-2014. We used the average number of pots per subfleet per week (figure 4.6) to estimate the total number of pots pulled in the fishery and compared these predictions to what was observed historically. We compare the predicted levels of vessel participation, the number of trips per week, and the total number of pots in the fishery both by subfleet, and aggregated over subfleets.

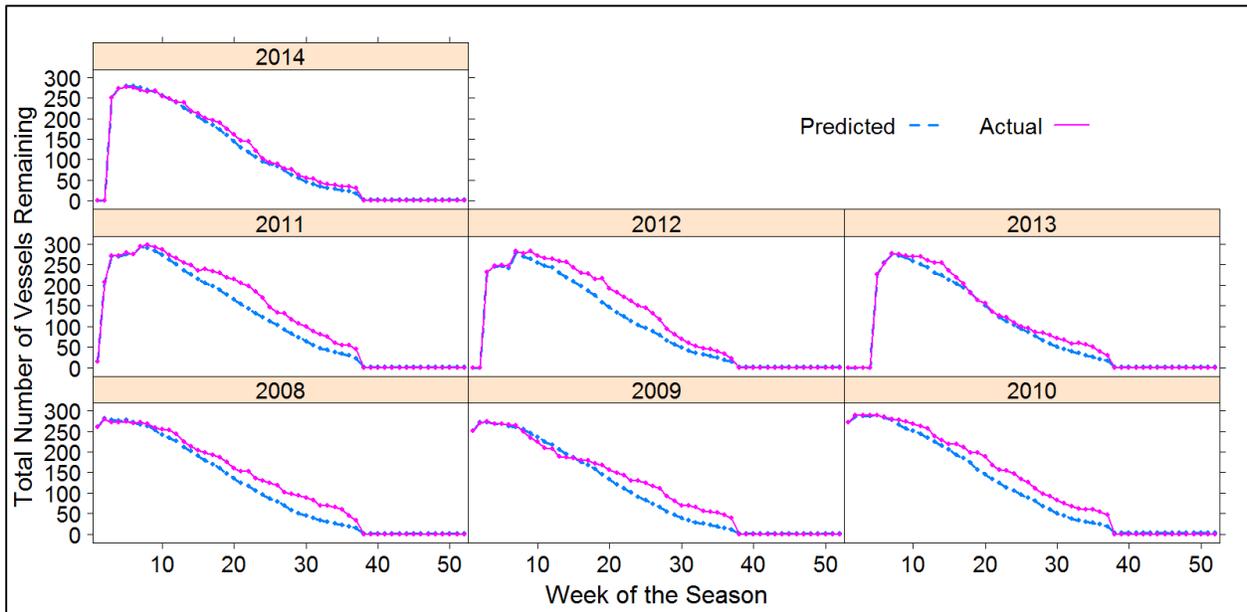


Figure 4.7: Predicted and observed total number of vessels in the fishery for each season 2008-2014.

Overall, the total number of vessels predicted using historical data conforms reasonably well to what was observed. The duration model underpredicts the number of vessels remaining in the fishery consistently and this under-prediction is most noticeable at the end of the season. Figure 4.8 shows the comparison on a subfleet basis by comparing residuals (observed – predicted) by week averaged over the 7 seasons. Inspecting these plots it is apparent that the ‘crable’ fleet predictions are biased downwards. The average differences between the observed and predicted values are distributed relatively evenly for all other fleets. Note that due to the structure of the duration model when an under-prediction is made early on in the season in one period, even if the predictions for the rest of the season are unbiased the under-prediction is observed for the rest of the season.

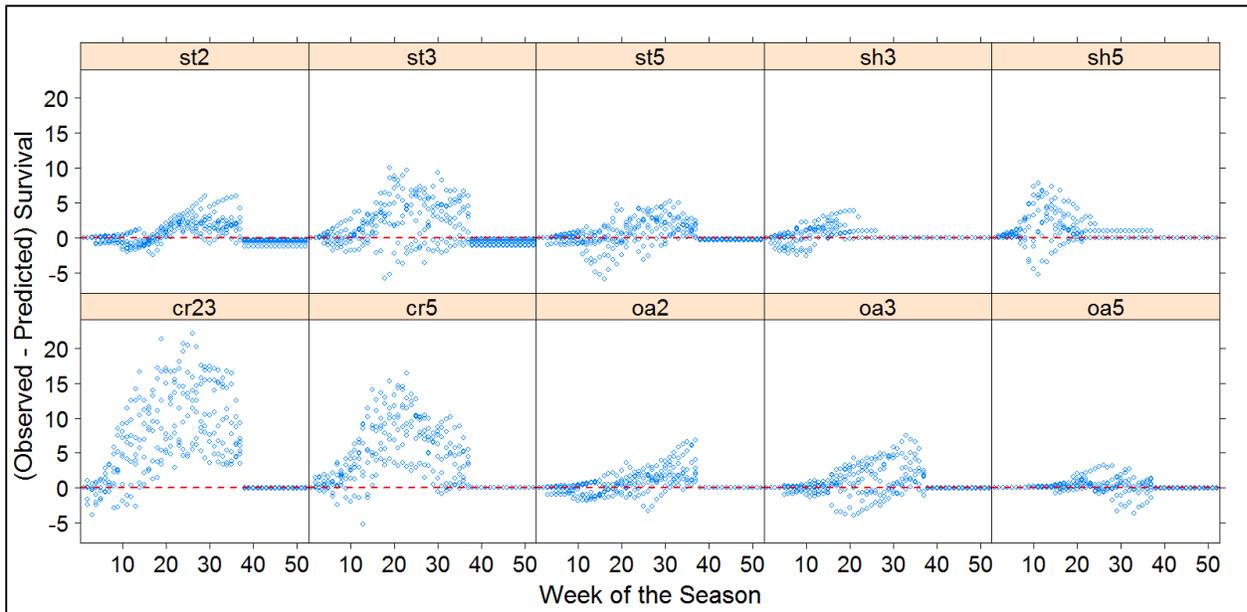


Figure 4.8: Average residuals on number of vessels remaining in the fishery. Average observed number of vessels minus predicted number of vessels by subfleet and week of season.

Figure 4.9 shows the comparison for predicted versus observed total number of trips per week predicted by the ZIP model. The predicted number of trips per week was calculated using the ZIP model predictions for number of trips per week per vessel and multiplying this number by the historical number of vessels in the fishery. Overall, the ZIP model makes predictions that are reasonable, and conform to an ‘average’ trend line.

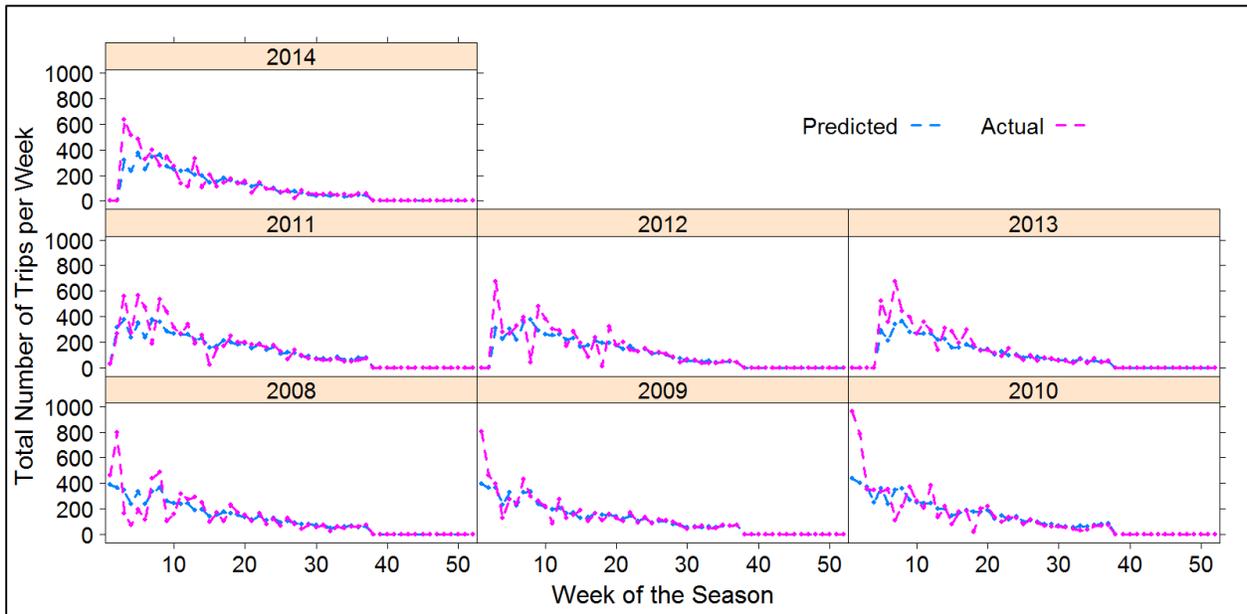


Figure 4.9: Predicted and observed total number of trips by week and season. The predictions were generated using the ZIP model results in table 4.11 and multiplying the prediction of number of trips per vessel per week by this historical number of vessels in the fishery.

Inspecting the average residual graphs on a sub-fleet basis, predictions appear to be centered around zero (figure 4.10).

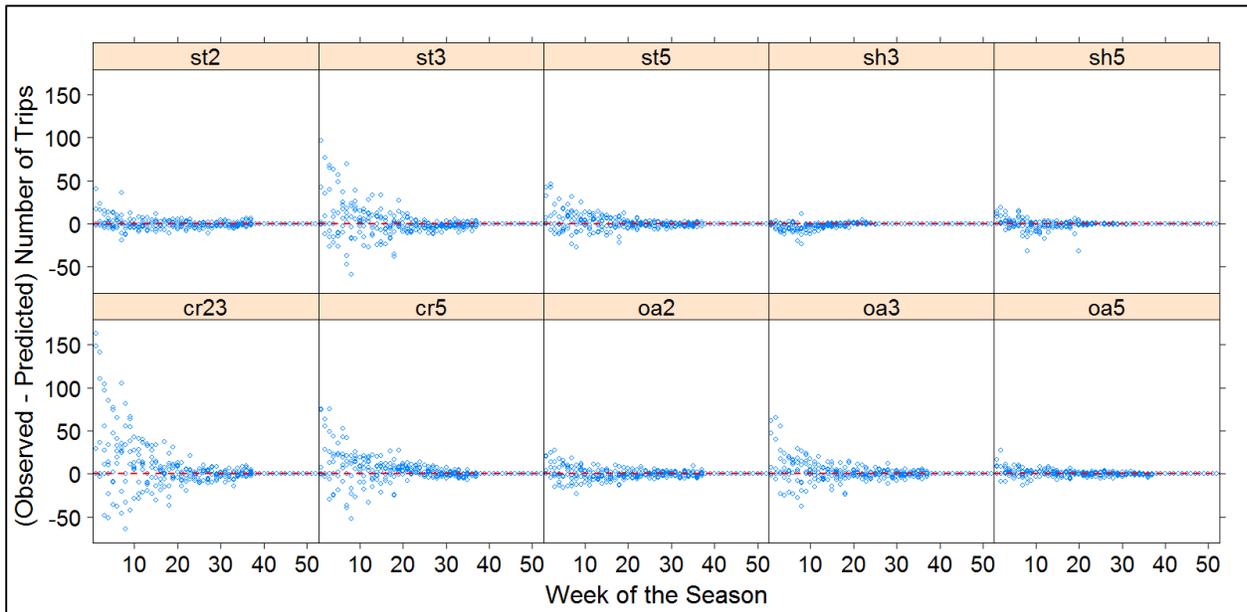


Figure 4.10: Average residuals on number of trips made by subfleet. Observed total number of trips minus predicted total number of trips averaged over the 2008-2014 seasons

Figure 4.11 shows the product of the two model's predictions versus what was historically observed in terms of number of pots pulled per week. The predicted number of pots pulled was calculated as the number of vessels predicted by the duration model multiplied by the number of trips per vessel predicted by the ZIP model, multiplied by the average number of pots pulled per trip (figure 4.12).

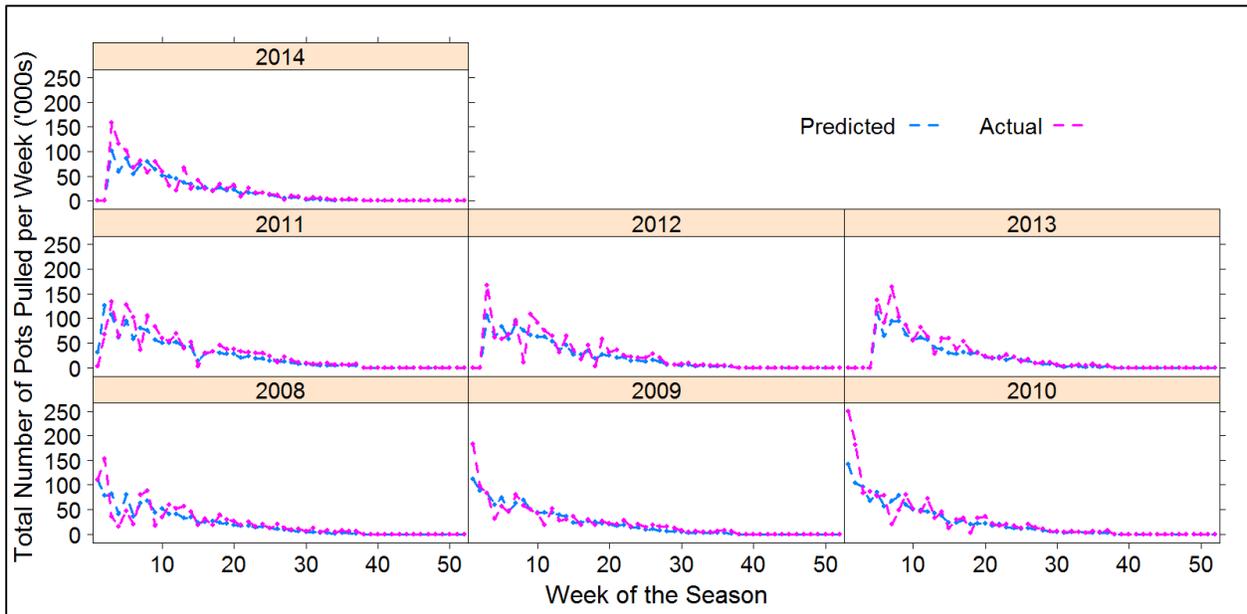


Figure 4.11: Aggregate effort predictions measured as the number of pots pulled per week. The duration model predictions were combined with the ZIP model predictions to generate the aggregate predictions.

Figure 4.12 shows the aggregate predictions by sub-fleet. The underprediction of the duration model is apparent in the residuals for the crable fleet.

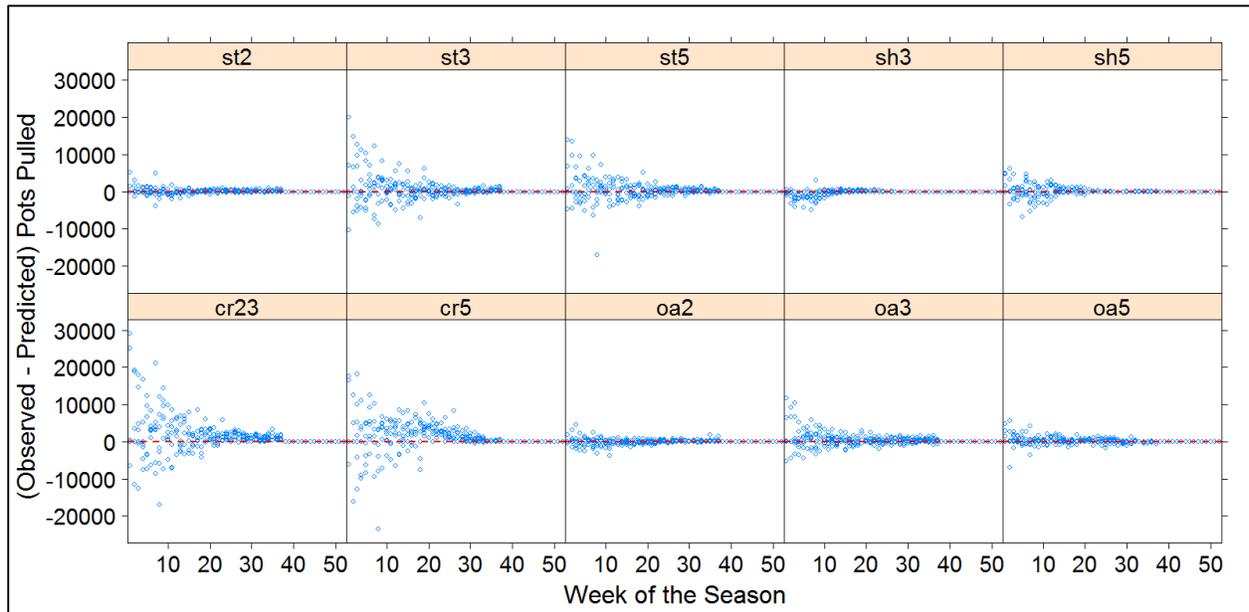


Figure 4.12: Average residuals on total effort made by subfleet. Observed total effort minus predicted total effort averaged over the 2008-2014 seasons

The duration and ZIP models predictions, while imperfect, demonstrate that combining these two statistical models with an average number of pots per trip metric provides a reasonable and intuitive mechanism for predicting how effort in the ODC fishery changes in response to conditions in both the ODC fishery, and other commercial fisheries in Oregon. We now combine these models with the biological submodel to form the overall simulation model.

4.5 SIMULATION MODEL

The purpose of the simulation model is to identify the season closure date that results in maximum annual ODC fishery profits and to examine how this closure date is affected by our assumptions on the rate of handling mortality of soft shell crab, the timing of the moult, and the level of recruitment in the ODC fishery. We use a Monte-Carlo framework where the level of recruitment (the ‘gift’) is determined randomly at the beginning of each season (iteration), and the season is closed in week increments starting at week 21 (which roughly corresponds to April 15th) up to the traditional closure date of week 38 (~August 14th). For each season closure date a separate population of Dungeness crab is maintained which allows us to compare the effects of alternate closure dates with the exogenous inputs the same for each scenario.

4.5.1 SIMULATION CALIBRATION

The biological component of the model relies on an effort input from the economic fleet component. Given this effort input and hypothesized values of the ‘gift’, natural mortality, handling mortality, and moulting parameters, the latter three which were based on best estimates from the literature (see table 4.14), the biomass of each cohort varies throughout each season. However, in order for model output to reasonably mimic historical values of catch it was necessary to calibrate the model for values of catchability, q , and the annual exogenous input of sub-legal Dungeness crab (the ‘gift’). We accomplished this calibration by calculating average historical values of effort (total number of pots pulled per week) and varying both the level of the ‘gift’, and the catchability coefficient until the model predictions of average weekly catch mimicked historical values of average weekly catch. Holding the catchability coefficient constant, the higher the ‘gift’, the more catch increased at the beginning of the season relative to the rest of the season. Holding the ‘gift’ constant, the lower the catchability coefficient the lower was catch at the beginning of the season, but the more catch spread out throughout the season. There are infinitely many combinations of the gift and q in our model that will yield annual model catch that equals historical annual catch. However, at very low catchability levels and keeping the difference in total annual model and historical catch below 10,000lbs, model catch in the first 4 weeks of the season was extremely low, and model catch during the rest of the season (weeks 5-37) was extremely high. As the level of the catchability coefficient increased these difference decreased until catchability was equal to approximately .000000918. As catchability increased past this point model catch at the beginning of the season increased, with catch during the rest of the season decreasing. We therefore fixed catchability at the point where the difference between catch at the beginning and for the rest of the season was minimized, which varied depending on the level of the gift. At this catchability value, the value of the gift that resulted in model predicted catch that was equal to historical catch was 73.74 million lbs. Figure 4.13 illustrates the catchability calibration.

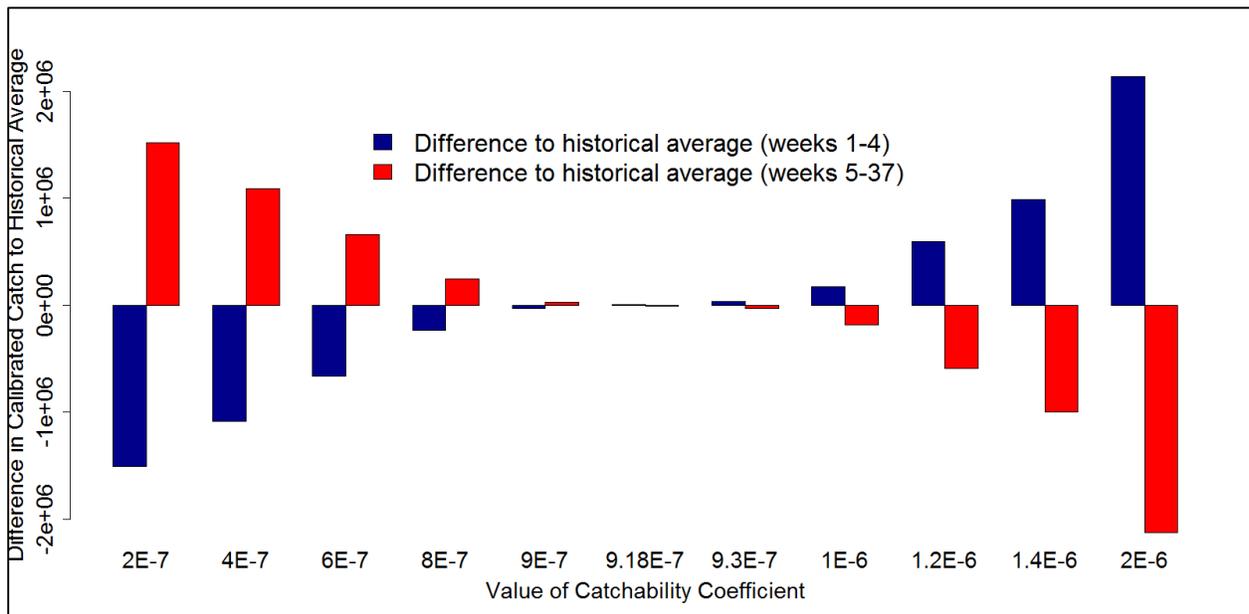


Figure 4.13: Illustration of the calibration procedure. A value of catchability of $9.18 \text{ E-}7$ equated model predicted catch with historical catch, and also equated both early and late season predictions to the observed values.

After the catchability coefficient was calibrated we ran the simulation on each season separately in order to determine an appropriate range for the gift. This entailed using the estimated catchability coefficient and varying the level of the 'gift' in each season until model predicted catch was within 10,000 lbs of historical catch. Figure 4.14 shows the seasonal calibration using the calibrated catchability coefficient and historical levels of effort. The values of the 'gift' that fit the historical catch profiles were 56.9 million lbs, 92.63 million lbs, 91.5 million lbs, 62.9 million lbs, 83.4 million lbs, and 67.2 million lbs in the 2008 to 2013 seasons, respectively. Note that the 'gift' affects harvest levels in the *next and subsequent* seasons, not the season that it occurs at the beginning of. The cohort of sub-legal crab must undergo moulting and suffer a year of natural and handling mortality before reaching harvestable age.

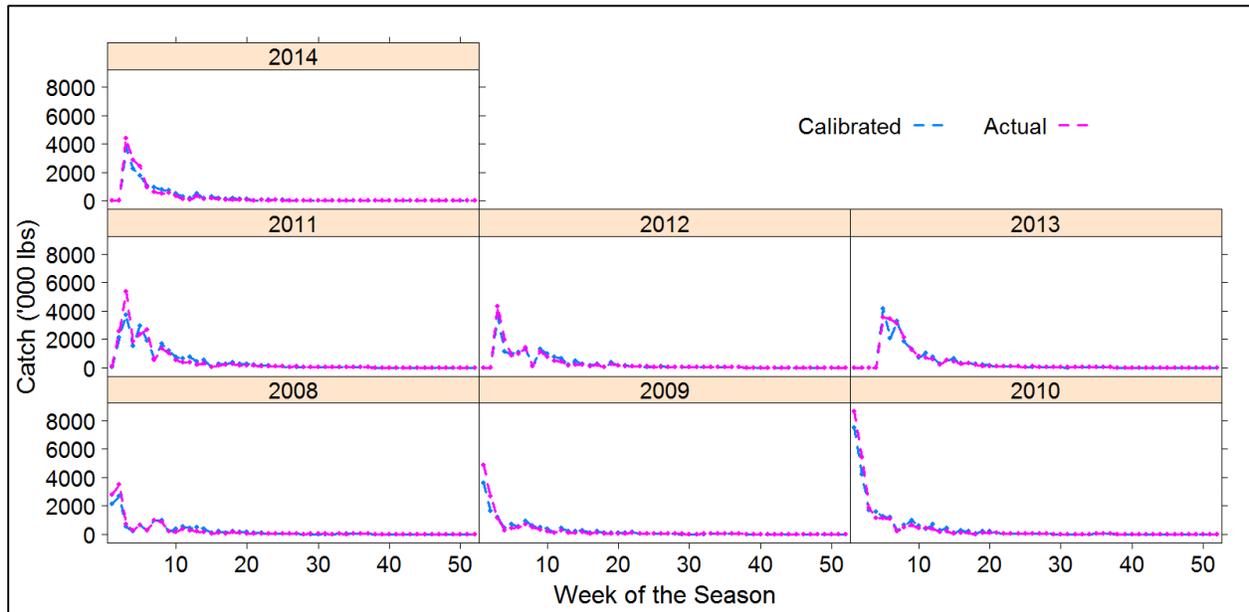


Figure 4.14: Calibrated model predictions and observed catches by season. The calibrated value of catchability was used and the level of the gift was adjusted so that annual predicted catch equaled observed catch.

Using our calibrated value for the catchability coefficient and having ascertained a reasonable range for the level of the gift we conduct a series of Monte-Carlo simulations to analyze the potential impacts of closing the ODC season at a range of different dates towards the end of the traditional season. The simulation procedure is represented in figure 4.15. We make 1000 iterations for each season closure date and allow the gift to vary over a uniform distribution with a minimum and maximum that reflects our calibration levels. The levels of all other model parameters are fixed for the base case scenario, and are shown in table 4.14.

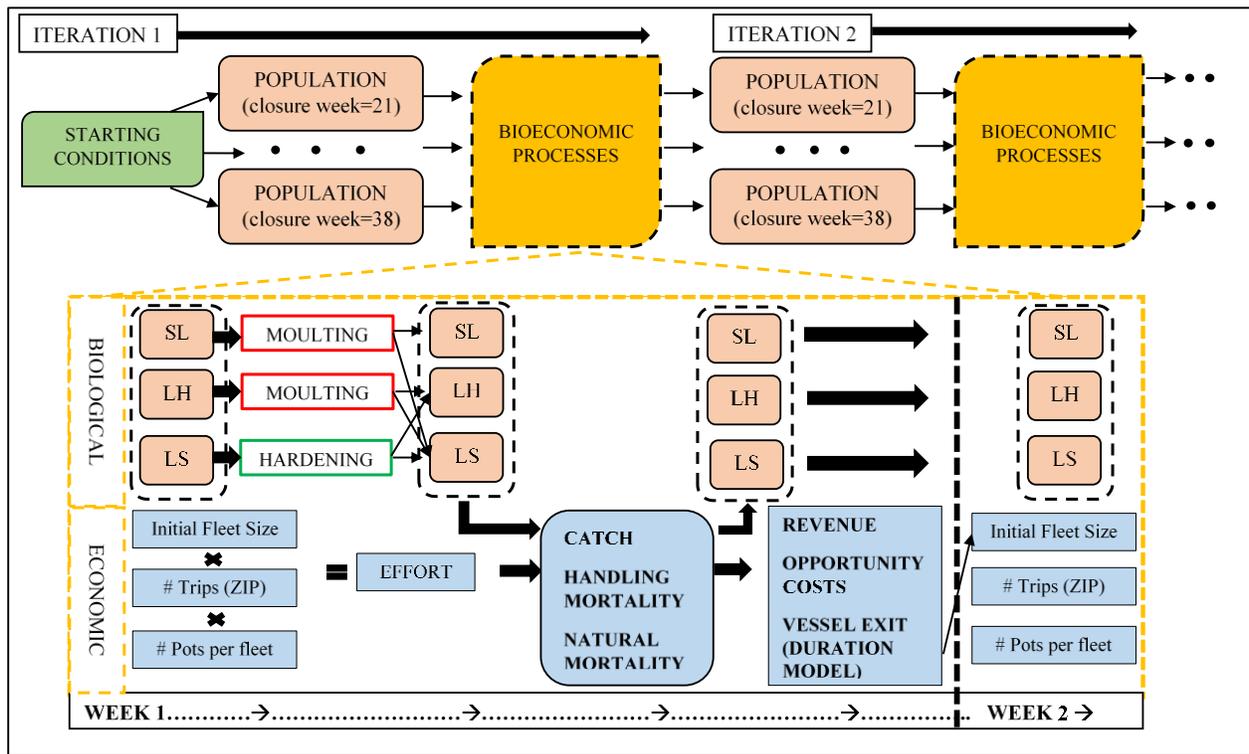


Figure 4.15: Illustration of the branched simulation structure. Starting in iteration 1 with an initial biomass of LH cohort crab 18 different populations were created pertaining to a closure week in each of weeks 21-38. Bioeconomic processes, illustrated in the yellow dotted box, operate on a weekly scale during each ‘iteration’, which corresponds to an annual period. Within each week moulting and hardening occur followed by the mortality processes. Fishing mortality depends on the initial fleet size calculated by the duration model and the number of trips per vessel made calculated using the ZIP model. These statistics depend on the weekly revenue generated in each time period, which is a function of the biological processes. The starting biomass of the LH cohort in the first iteration was the average ending value of the LH biomass in the calibrated model. In subsequent iterations the starting biomass of the LH cohort was the value carried over from the previous iteration. Starting values of the SL and LS cohorts were the value of the gift, and zero, respectively.

While the economic parameters were available from fish ticket data, the biological parameters that were used in the simulation were based on best estimates from the literature. The timing of the moult is thought to vary randomly from year to year and according to geographic region (Robinson et al. 1977; Demory 1985; Dunham et al. 2011). We generated an approximate pattern of moulting from hard shell cohorts to the soft shell cohort for the ODC fishery based on a study by Yochum et al (in press). Instantaneous natural mortality rates for Dungeness crab have been estimated previously (Smith and Jamieson 1989; Hankin et al. 1989), although differential rates based on stage of moulting were not estimated until Zhang et al. (2004a). These authors estimated a non-moulting instantaneous annual rate of 0.97 year^{-1} with a standard

error of 0.39 year⁻¹ for hard shell crab and a rate of 4.27 year⁻¹ during the moulting period. The authors suggest a rate of 1.25 year⁻¹ as a representation of all animals in the population. Based on these rates we utilize an instantaneous weekly rate of .02, which corresponds to an annual rate of 1.04 year⁻¹. For handling mortality we base our percentage rate on Yochum et al. (in press), who calculate a 5 day mortality rate (the percentage of crab caught that die within 5 days of release) of 9% (95% Confidence Interval 3% -16%) for soft shell male crab, and 1% (95% Confidence Interval 0-2%) for hard shell male crab. Table 4.14 shows the biological and economic parameters used in the simulation.

Table 4.14: Base parameters used in the simulation model.

Parameter/ Variable	Description	Time Period	Cohort	Value
$m_{a,t}$	% of crab in cohort a that moult in time t	t=1:17	$a=LH, SL$.001%
“	“	t=18:20	“	2%
“	“	t=21:25	“	5%
“	“	t=26:27	“	10%
“	“	t=28:29	“	25%
“	“	t=30:31	“	60%
“	“	t=32:35	“	80%
“	“	t=36:38	“	90%
$h_{a,t}$	% mortality rate of cohort a if captured	t=1:28	SL, LH, LS	2%, 99%, 9%
$h_{a,t}$	% mortality rate of cohort a if captured	t=29:37	SL, LH, LS	2%, 95%, 9%
$M_{a,t}$	instantaneous rate of natural mortality	all	all	.02 per week
$q_{a,t}$	catchability coefficient	all	all	.000000918
$gift$	exogenous recruitment of SL cohort (uniformly distributed)	t=1	SL	50-100 million
Price	Dungeness crab Price (see figure 4.21)			
Trip Cost	Variable Cost per trip (see figure 4.22)			
Fuel Price	Average Price of #2 diesel fuel December 2006-December 2014			
SH	Average weekly revenue in shrimp fishery 2007-2014			
LE	Average weekly revenue in Limited Entry groundfish fishery 2007-2014			
OA	Average weekly revenue in Open Access groundfish fishery 2007-2014			
SA	Average weekly revenue in salmon fishery 2007-2014			
TU	Average weekly revenue in tuna fishery 2007-2014			
OT	Average weekly revenue in ‘other’ fishery 2007-2014			

4.5.2 BASE CASE SIMULATIONS

Under the base set of parameter values, the sub-legal (SL) cohort starts off each season at the level of the exogenous input of crab (the ‘gift’). Throughout the season this cohort decreases due to handling mortality, natural mortality, and through the moulting process (which moves crab from the SL to the soft shell (LS))

cohort). There are no SL crab left by the end of the season. The harvestable cohort (LH) also suffers fishing and natural mortality as well as moulting throughout the season and this cohort decreases in size until week 30 after which it increases due to hardening crab from the LS cohort. The LS cohort increases due to influxes from the SL and LH cohorts due to moulting (natural and handling mortality also occur) until approximately week 34 (~August 1st), and then decreases through natural mortality, handling mortality, and hardening of crab into the LH cohort. There are no LS crab left at the end of the season and the amount of crab left in the LH cohort at the end of week 52 form the starting biomass in the LH cohort in the next year. Figure 4.16 illustrates cohort dynamics throughout each season.

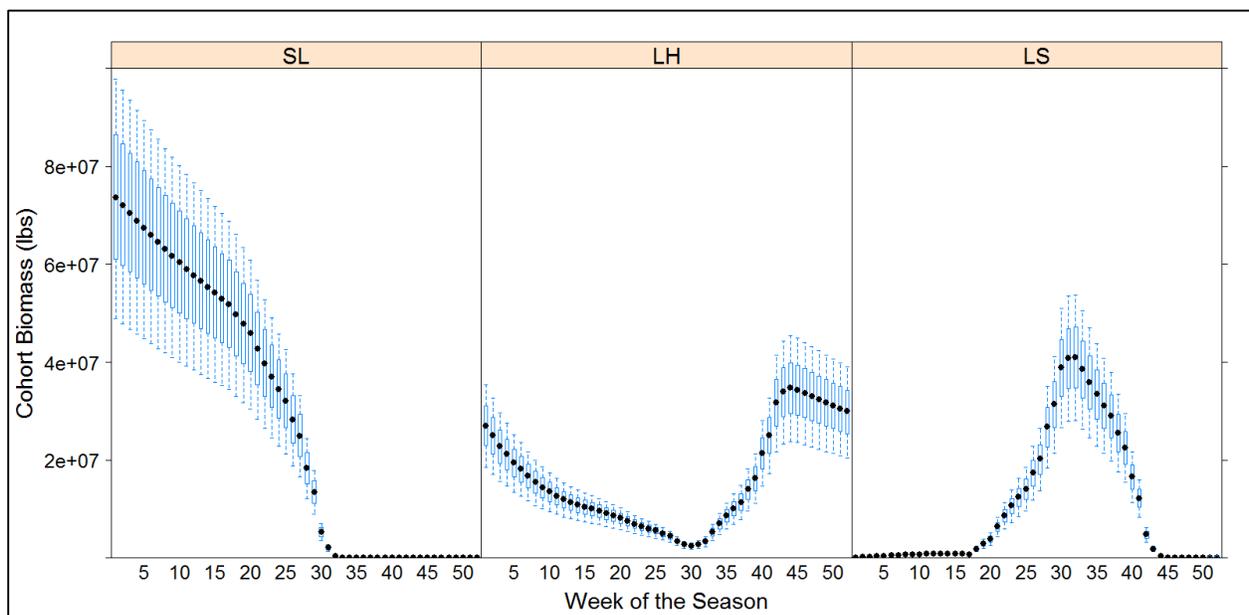


Figure 4.16: Changes in cohort biomass throughout the season for the base parameterization. The dot represents the median of the data, the box limits the 25th and 75th percentiles, and the ends of the whisker the range.

Figure 4.17 shows the total number of trips taken throughout the season. Effort per week starts off extremely high, decreases steadily throughout the season, and shows a slight increase toward the end of the season due to increases in catch rates as a result of hardening crab. The only source of variation in effort per week in the base scenario is variation in revenue, which is derived indirectly through the random variation in the gift at the beginning of each year which affects catch levels. The higher the biomass of harvestable crab, the higher effort levels, and vice-versa.

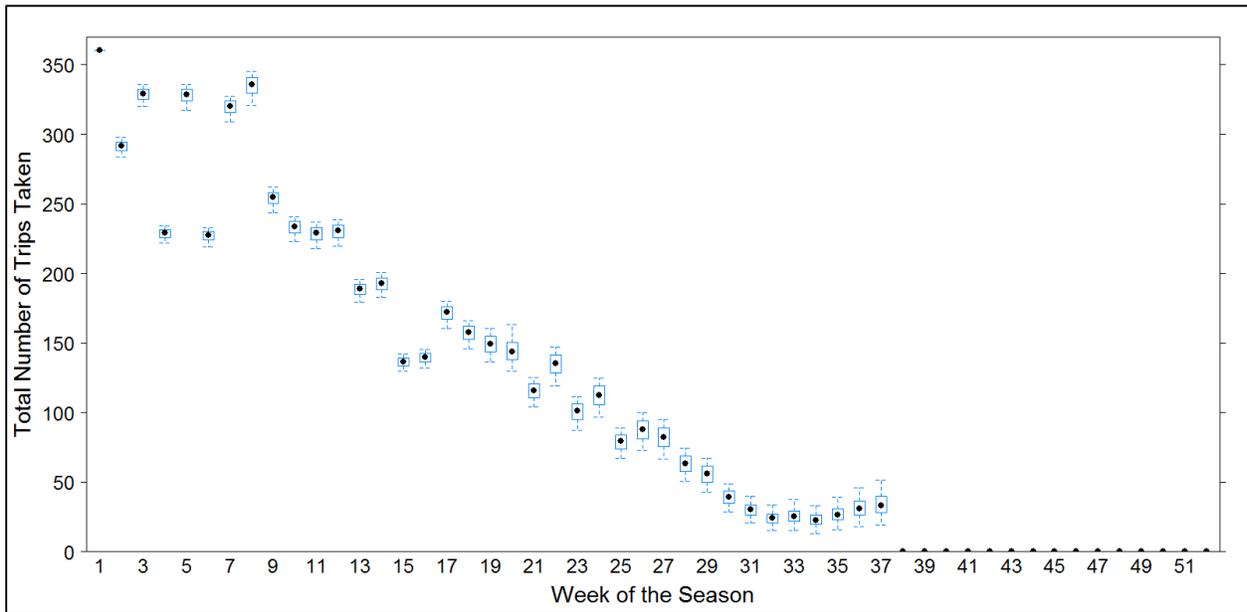


Figure 4.17: Total number of trips taken in the base simulation with a traditional August 14th closure date.

Figure 4.18 shows the number of trips taken on a subfleet basis. The largest amount of effort is exerted by the saltun (st2, st3, st5) and crable (cr23, cr5) fleets. The open-access (oa2, oa3, oa5) and saltun fleets show relatively high effort at the end of the season while the shrimp and crable fleets exit relatively earlier.

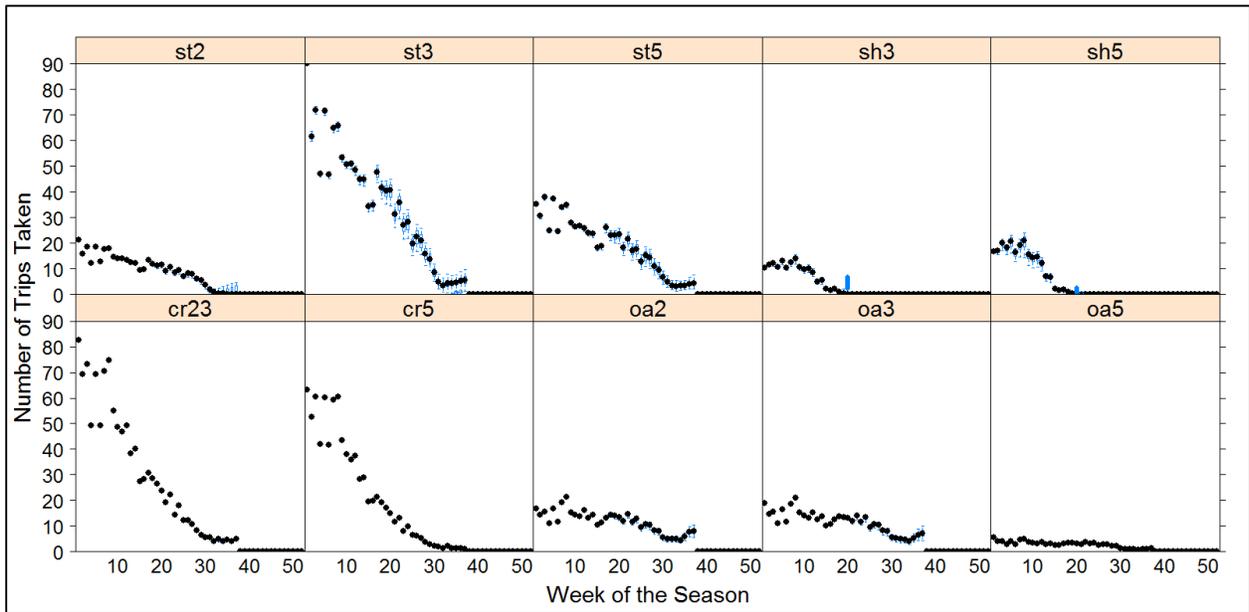


Figure 4.18: Number of trips taken by sub-fleet (base parameters).

Figure 4.19 shows total fishery catch per week. Catch starts off at extremely high levels of between 1.5-3.0 million lbs per week and attenuates very quickly, which is a key characteristic of the ODC fishery. Total catch is reduced to a weekly average of .5 million lbs by week 12 of the season.

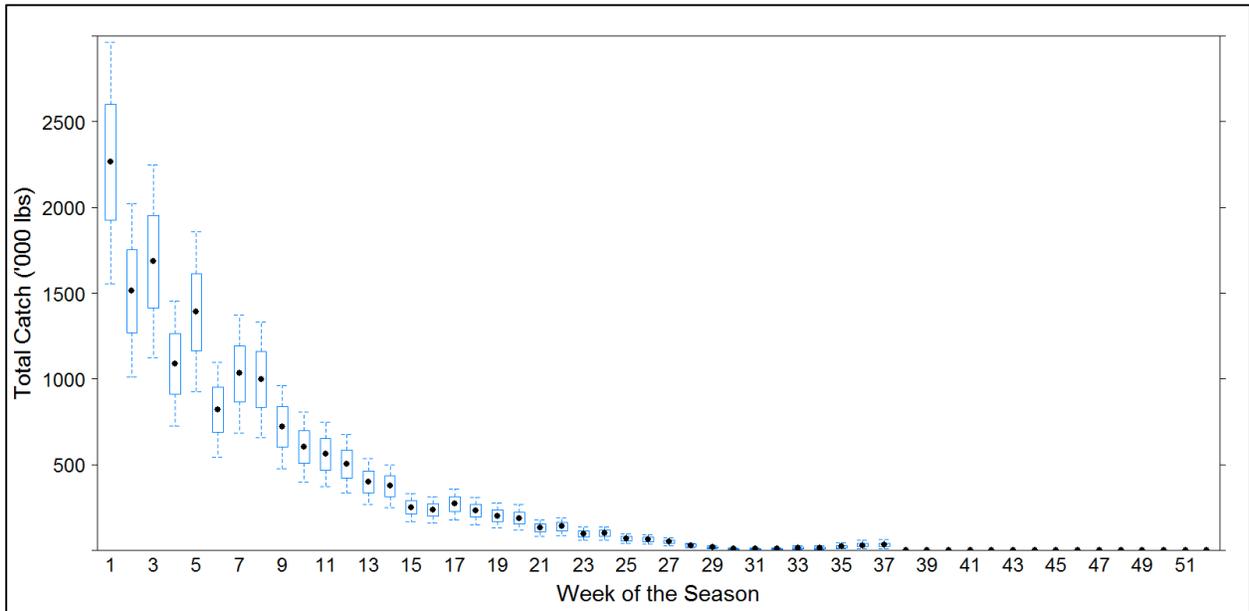


Figure 4.19: Total catch in the base simulation with a traditional August 14th closure date.

Figure 4.20 shows catch dynamics by subfleet. Subfleets that exert the most effort catch the most crab. The open-access and saltun fleets catch relatively more at the end of the season than the other subfleets. The shrimp fleets catch nothing after week 20, and the crable fleets catch very little after week 30.

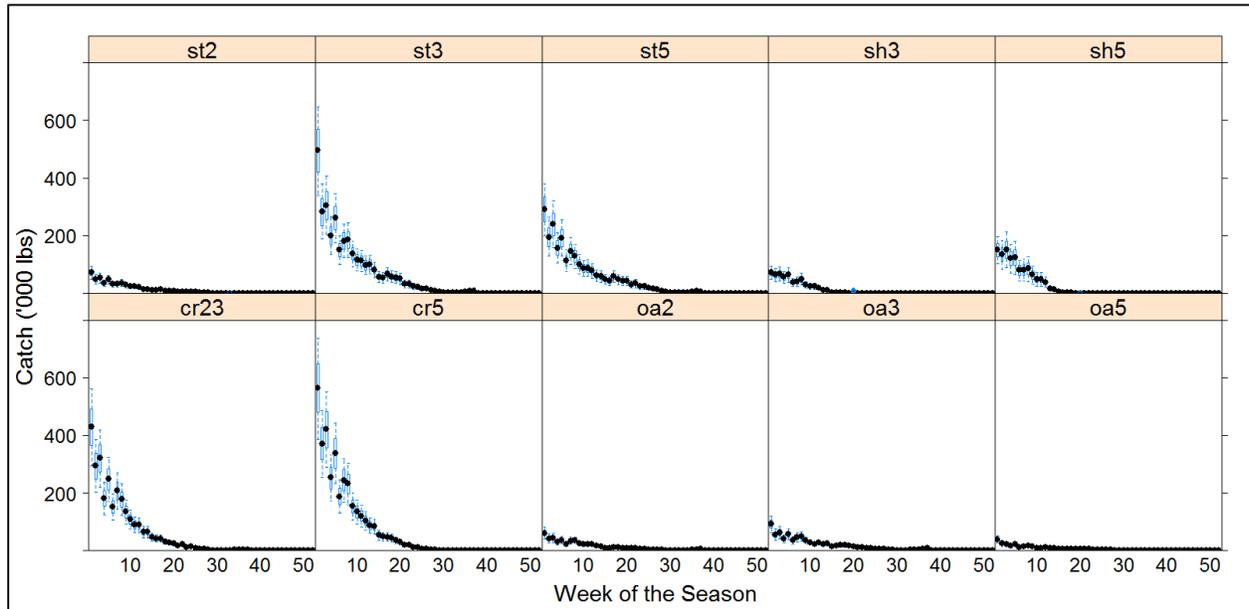


Figure 4.20: Catch by sub-fleet in the base simulation with a traditional August 14th closure date.

Figure 4.21 shows the price trend that was used in the simulations. This price trend was calculated as the average landed price of crab for a given season week in the 2007-2014 seasons. Price starts off at a relatively low level, increases until week 25, and then decreases after this date. This pattern is thought to be due to a decreasing quantity of landed crab for the first 25 weeks of the season, which causes price to increase steadily, and then lower crab quality after this date which causes price to respond downwards (Didier 2002).

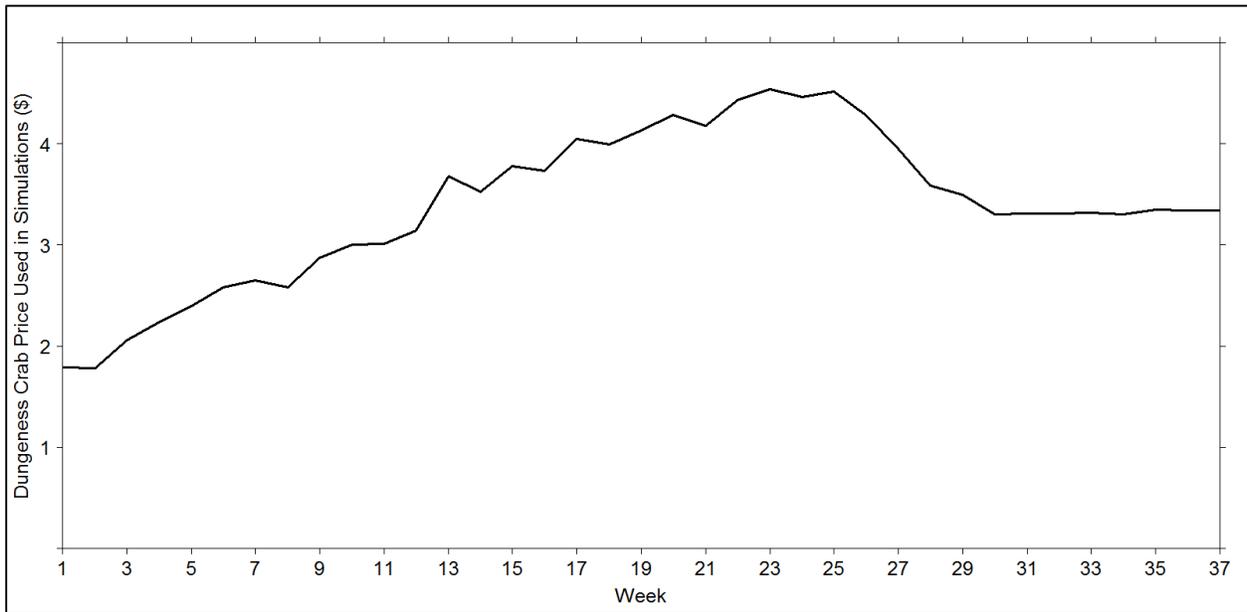


Figure 4.21: Price of Dungeness crab used in the simulations.

Figure 4.22 shows the cost of fishing used in the simulations. Costs are week and subfleet specific and have a general downward trend for all subfleets. Trip costs were calculated as the per trip fuel and ‘other’ daily costs plus the number of pots per trip per subfleet multiplied by a per pot measure of bait costs from Dewees et al. (2004; table 3).

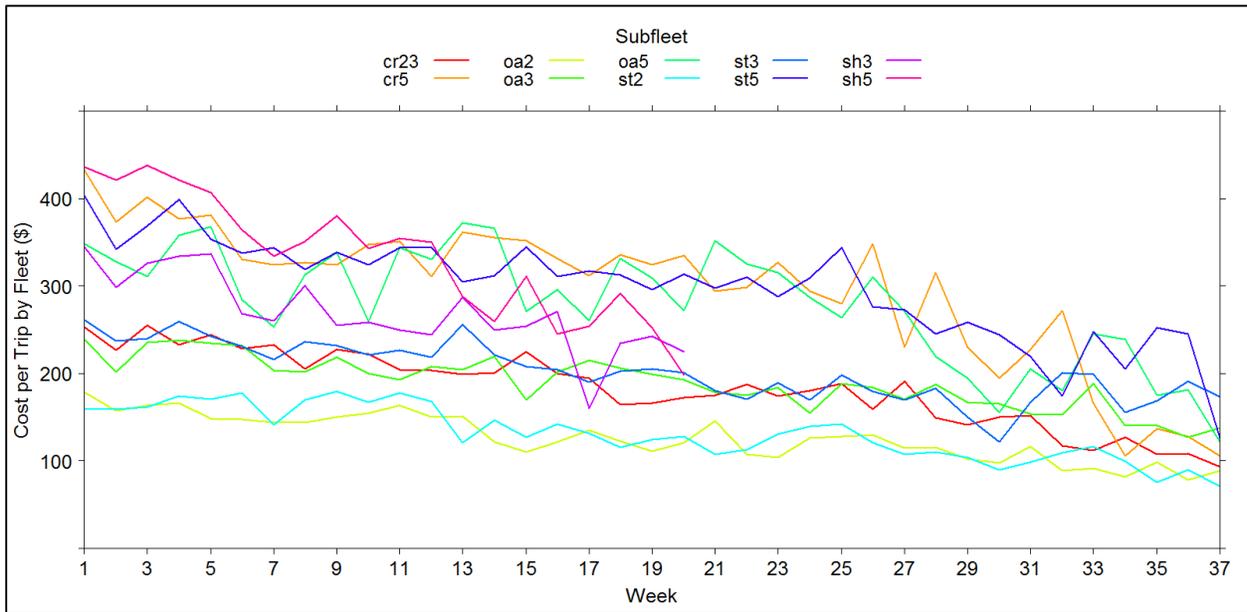


Figure 4.22: Cost per trip used in the simulations. Costs were calculated as a length adjusted cost per pot from Dewees et al. (2004) multiplied by the number of pots per trip (figure 4.6).

Figure 4.23 show the pattern of total profit in the fishery throughout the season, which is calculated as total revenue minus total costs. Profit is extremely high at the beginning of the season and attenuates until week 30, after which it starts to increase. The late season increase is due to significant amounts of hardening crab re-entering the harvestable (LH) cohort after week 33 which increases catch rates.

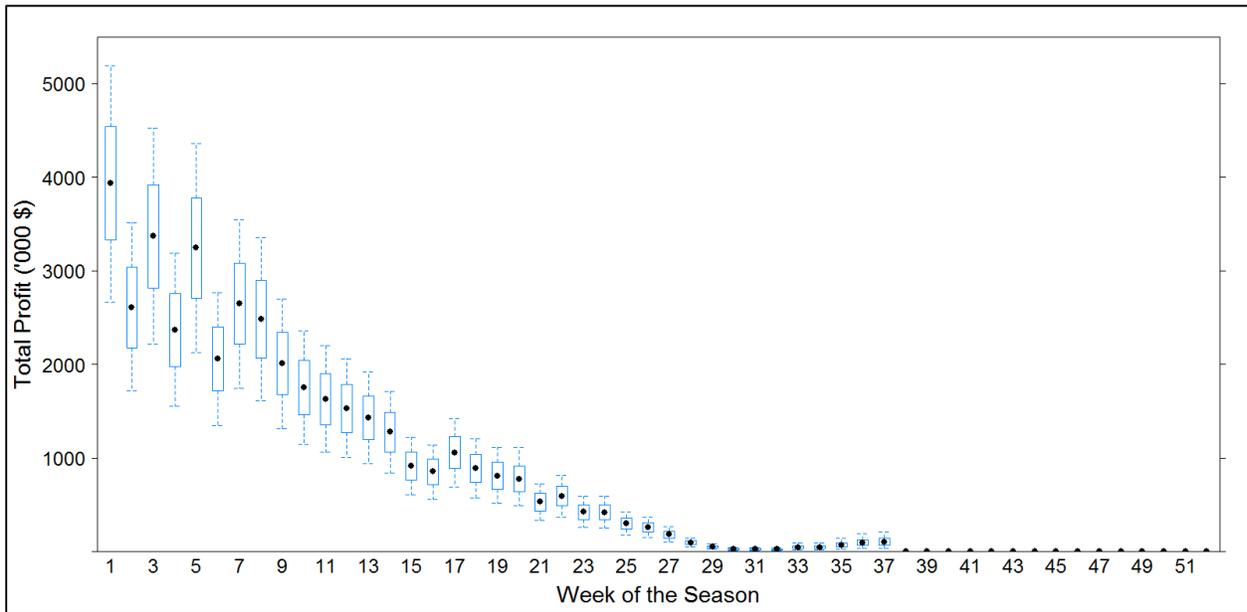


Figure 4.23: Total profit in the base simulation.

Figure 4.24 shows the distribution of profits on a subfleet basis. The subfleets with the greatest initial capacity- the crable and saltun fleets also earn the highest levels of profit. The shrimp and crable fleets exit the fishery relatively early and the open access and saltun fleets earn more profits later in the season as a result.

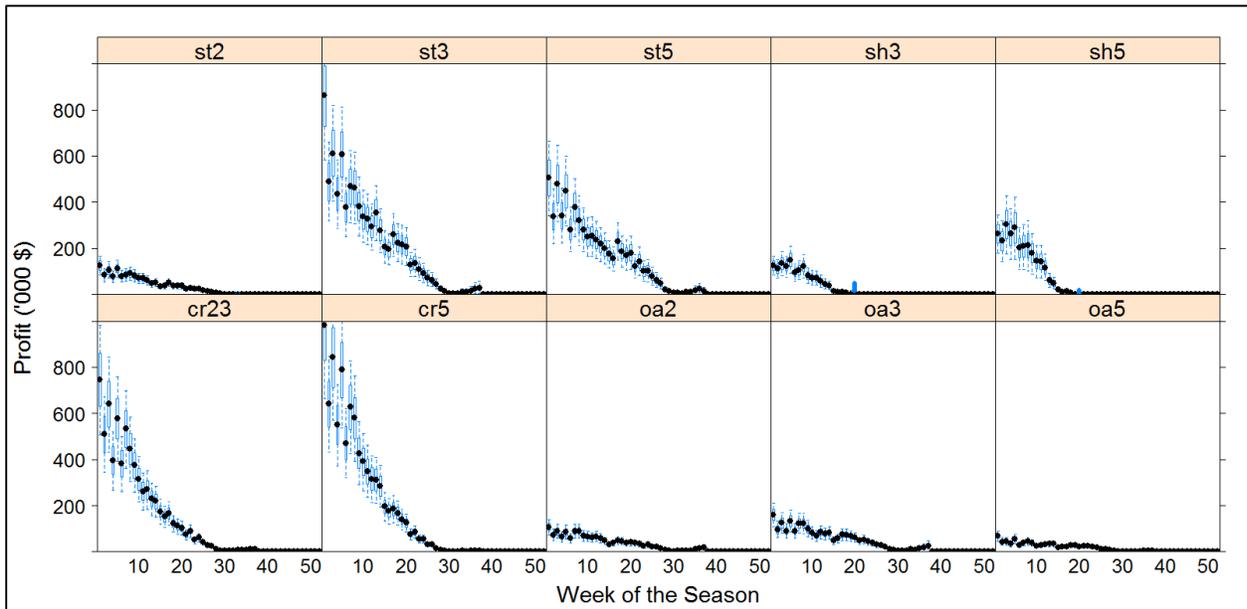


Figure 4.24: Operating profit by sub-fleet in the base scenario simulation.

4.6 Results

The results of our simulations indicate that the mortality of soft shell crab due to handling in the Dungeness crab fishery under the traditional season structure has a negative but relatively small effect on catch and profit in the fishery. While closing the season earlier than the traditional August 14th closure date would likely result in increased levels of biomass of legal size harvestable crab, the amount of this increase that is due to handling mortality of soft shell crab is relatively small. Furthermore, unless the soft shell crab handling mortality rate is at least approximately 24% of capture, there would likely be no increase in average total profit by implementing an early season closure. When handling mortality rates are above 24%, the closure date that results in the highest average profit occurs around week 29 (~June 15th), which is the time when the cohort of softshell crab is increasing at its fastest rate, on average. However, even when there is a positive difference in total profit in the fishery due to an early season closure, this difference is relatively small, on the order of less than 1% of the level of total profit. Finally, our model predicts that while the effects of an early season closure on total profit in the fishery are generally negative, or small when they are positive, these effects would accrue unevenly on the fleet with vessels that exit the fishery earlier on average benefiting from the closure, and vessels who remain in the fishery longer losing out.

4.6.1 BIOLOGICAL IMPACTS

A priori, one would expect that implementing an early season closure will reduce effort late in the season, reduce handling mortality of both sub-legal (SL), and softshell (LS) crab, reduce catches of harvestable (LH) crab, and that these mortality reductions would translate into higher availability (and hence catches) of harvestable crab during the subsequent seasons. Figure 4.26 shows the distribution of levels of harvestable crab at the beginning of each simulated season. The later the season is closed, the less crab are available to harvest on average but this decrease is relatively small. Closing the season on April 15th instead of August 14th each year results in an average increase of 720,610 lbs of LH crab, or a 2.67% increase in harvestable crab.

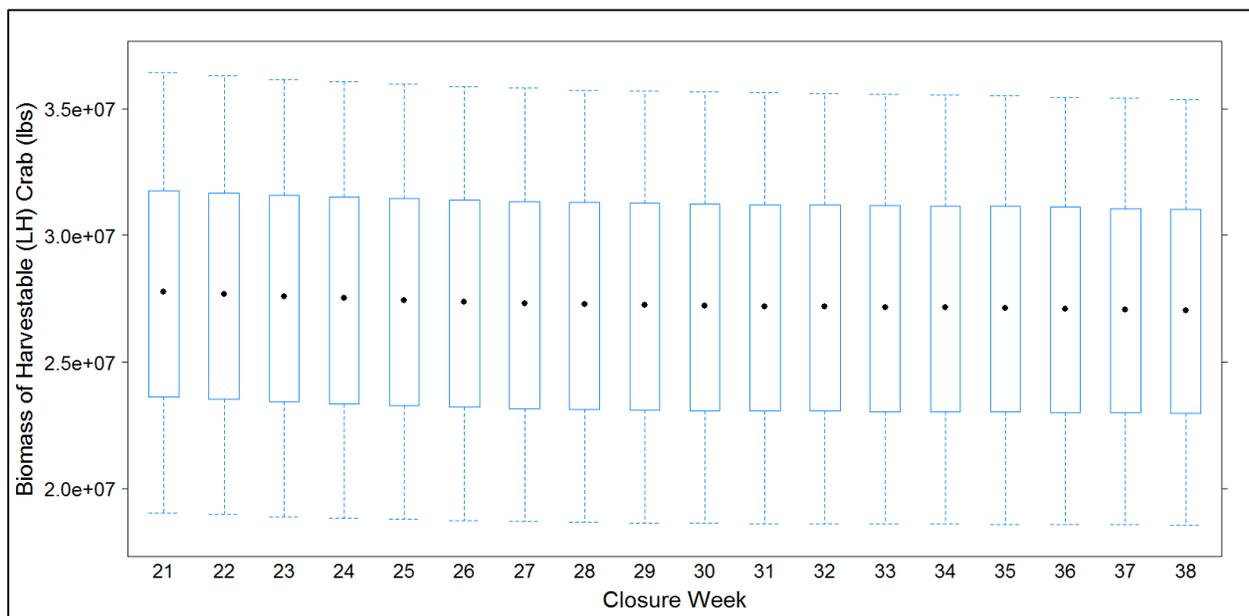


Figure 4.26: Predicted change in starting biomass of the LH cohort.

As expected, the higher the level of recruitment in the fishery, the higher the starting biomass of harvestable crab (figure 4.27).

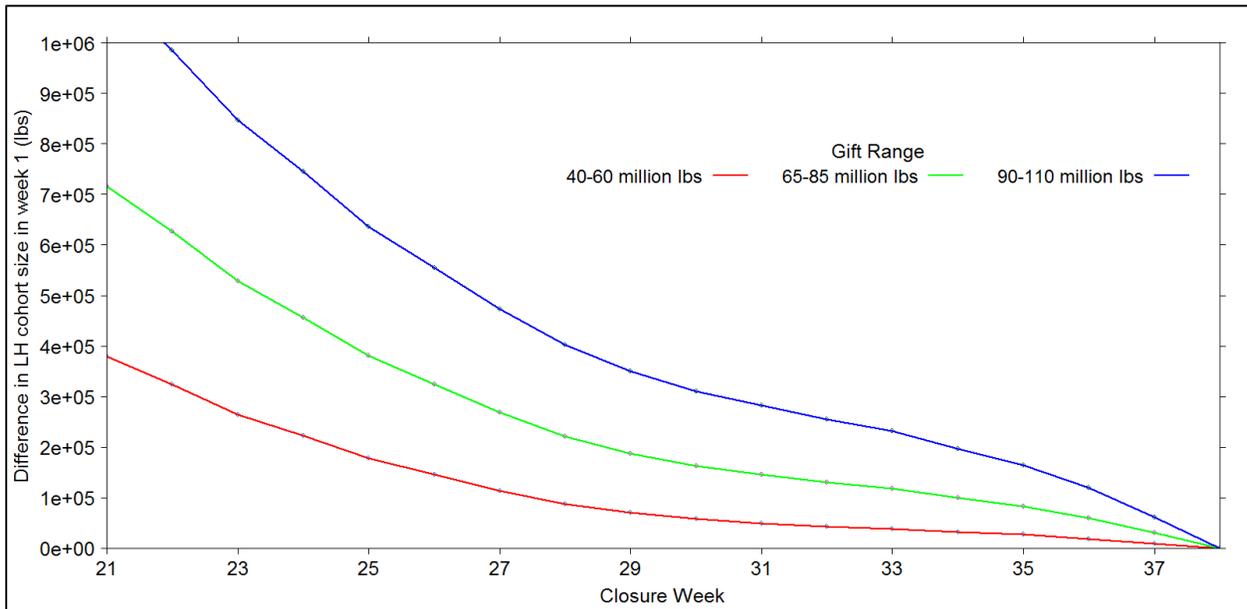


Figure 4.27: Predicted average effect of the level of the ‘gift’ on the starting biomass of the LH cohort in each season due to an early season closure.

Figure 4.28 shows the differences in total annual handling mortality of softshell crab of closing the season in week-increments starting on April 15th (week 21). Handling mortality decreases the earlier the season is closed due to reduced susceptibility of softshell crab to fishing mortality although the amount of decrease is relatively small. Note that the total amount of the decrease in mortality does not enter the LH cohort in the next season- natural mortality from the week of closure until the end of the season must be subtracted first. Assuming the base handling mortality rate of 9%, average total handling mortality avoided is approximately 100,000lbs if the season closure is around July 15th, and approximately 238,849 lbs if the season is closed around April 15th. Note that this amount of avoided handling mortality, after the base rate of natural mortality is taken into account, translates into approximately 128,488 lbs of crab that is added to the population of harvestable crab at the beginning of the next season. Avoided handling mortality of the SL cohort from closing in week 21 is on average 76,790 lbs, which translates into an addition of 41,309 lbs into the LH cohort in the next season after natural mortality is taken into account. The average balance of 550,814 lbs is due solely to reduced harvest of the LH cohort.

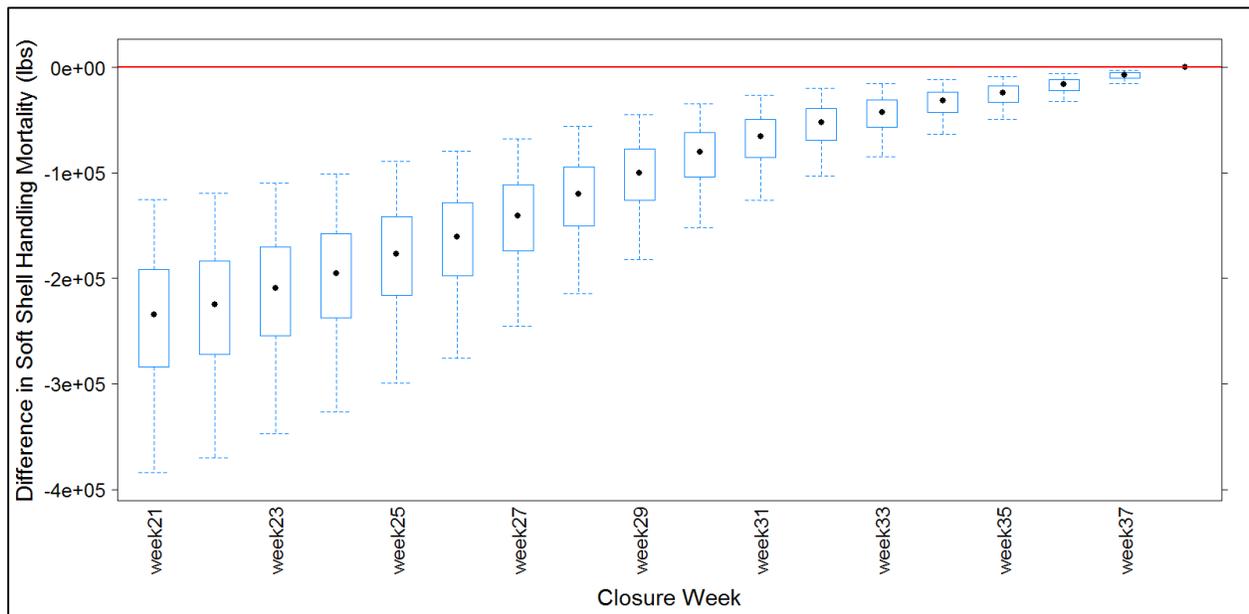


Figure 4.28: Predicted differences in the total amount of soft shell crab handling mortality.

4.6.2 ECONOMIC IMPACTS

Our model predicts that implementing early season closures will have a small but positive effect on the available biomass of harvestable crab although most of this effect, assuming a 9% rate of soft shell handling mortality, is due to decreases in the catch of hard shell crab that survive and are available for harvest in the subsequent year. The effects on total fleet profit of implementing early season closures, however, are generally negative. Figure 4.29 shows the effect on total fleet profit of implementing early season closures in the ODC fishery. Closing the season earlier than the traditional week 38 date results in an average loss of profit to the fleet due to foregone catches of harvestable crab after the season is closed. These foregone catches are not offset by the relatively small ‘stock’ effect where reduced handling mortality and catches of the LH cohort contribute to a larger stock of harvestable crab in the subsequent season. Price at the beginning of the season is also lower than at the end of the season which contributes to this effect.

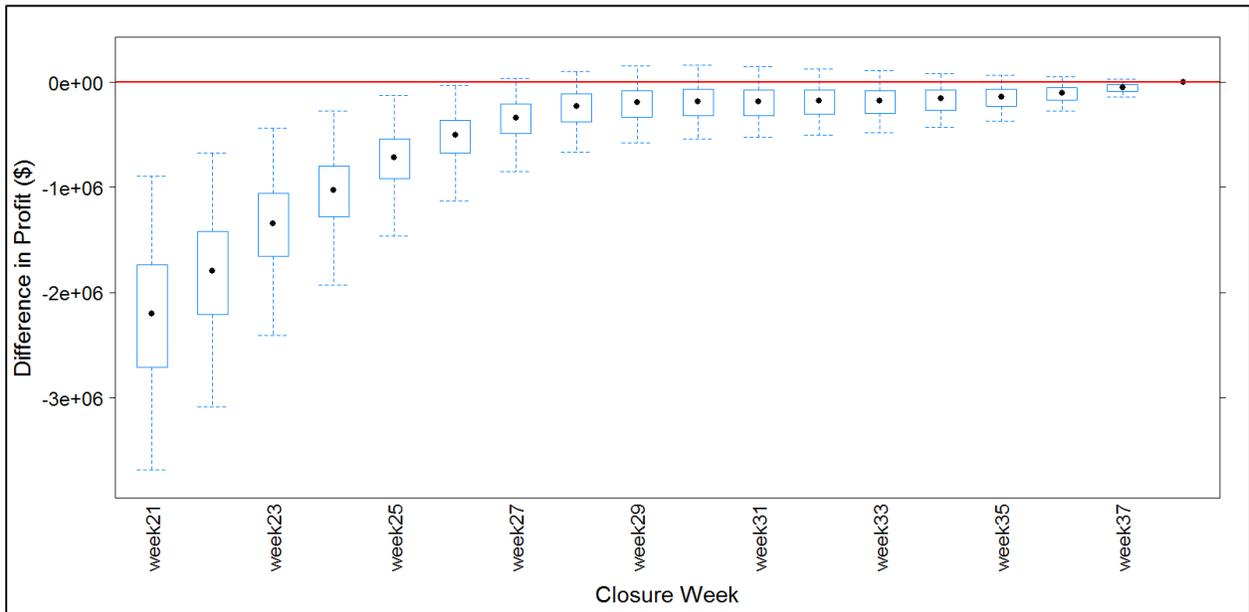


Figure 4.29: Differences in predicted profit from the traditional (week 38) closure date.

Figure 4.30 illustrates the profit effects on a subfleet basis. The shrimp subfleets, which exit the fishery before any of the closure dates examined always benefit from early season closures. The cr5 fleet also derives benefits when the season is closed earlier, especially if the closure occurs after week 25.

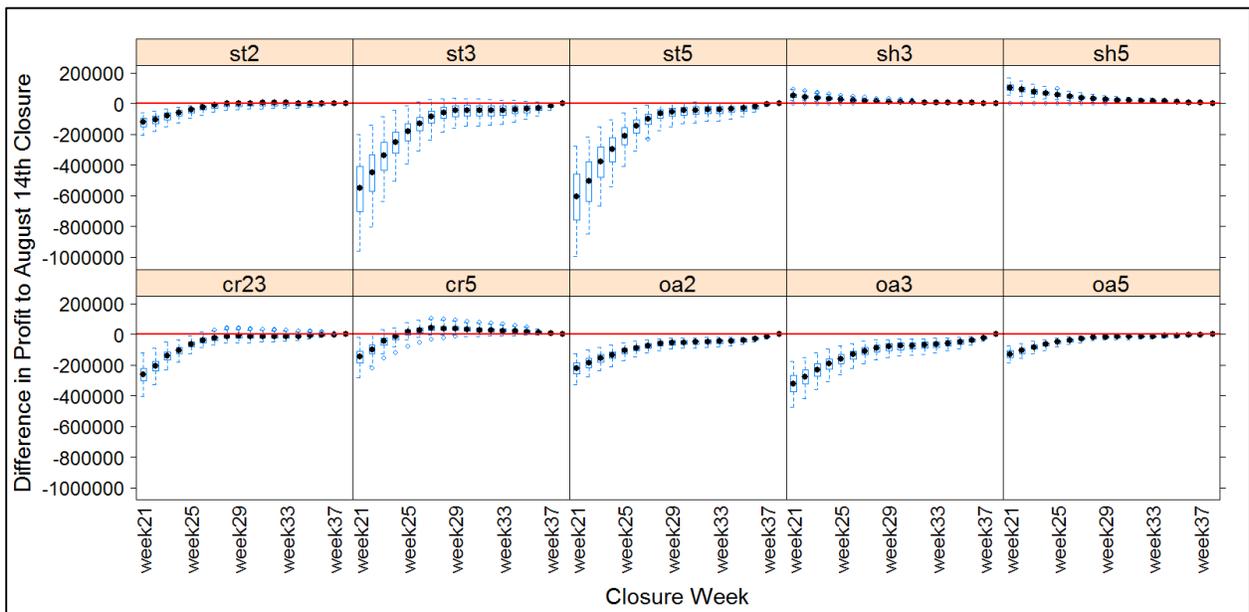


Figure 4.30: Difference in profit by sub-fleet of implementing a range of early season closures.

Figure 4.31 shows that while there is an average profit loss of implementing any early season closure, depending on the value of recruitment to the fishery, closing the season either in week 28, 29, or 30 compared to week 38 results in higher total profit for between .5 and 9% of the 1000 years in the simulation. This behavior is due to the interaction between effort levels (which are higher in week 30 than later in the season), and the increased availability of LH crab due to implementing an early season closure (the ‘stock’ effect). The earlier the season is closed, the higher the biomass of LH crab available in the shortened season (figure 4.26). However, if the season is closed earlier than week 28, the foregone profits from late season fishing outweigh the potential profits gained through the stock effect in 100% of the iterations. For closures in weeks 28, 29, and 30, increased average levels of the LH cohort increase catches and profits early in the season and this increase in profit outweighs the foregone profit from late season fishing in at least some of the iterations. For closures after week 30 while the available stock of LH crab increases with later closures, the marginal difference is relatively small (the base line in figure 4.27), and the foregone profits from fishing late in the season are not outweighed by the stock effect on profit.

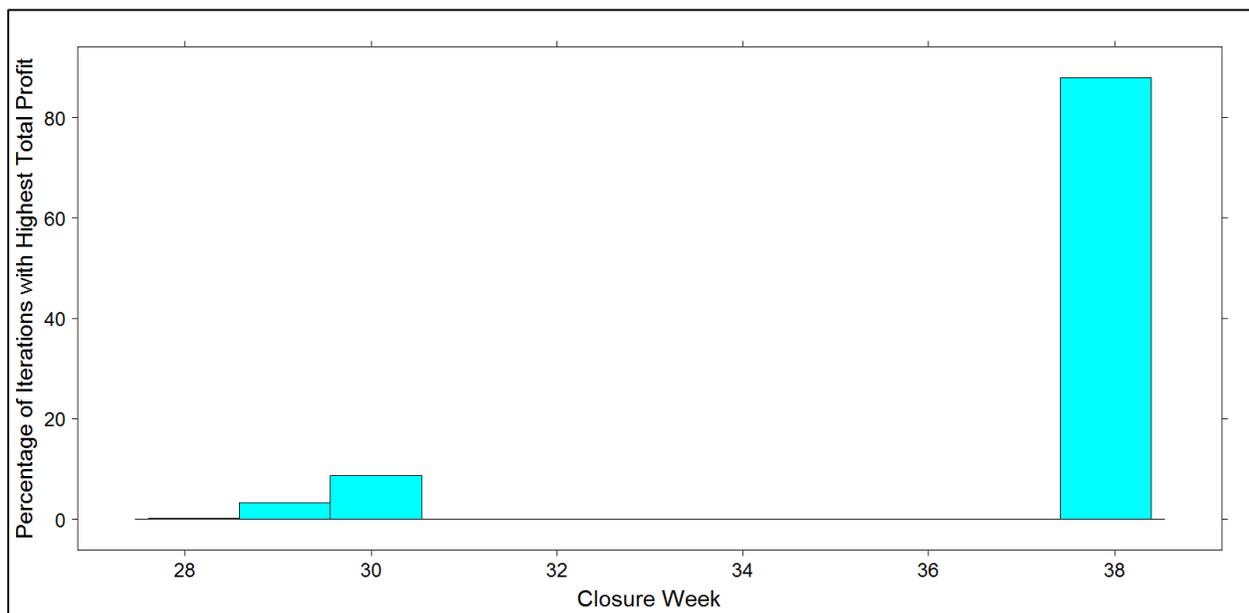


Figure 4.31: Percentage of the 1000 iterations for each closure date that results in highest total profit.

The years where total fleet profit are higher when season closures are implemented in weeks 28, 29, or 30 occur when the recruitment level is relatively low. When the level of recruitment is low, catch, effort, and profits from fishing late in the season are also relatively low which implies that the marginal effect on profit of closing the season a week earlier is also low. Figure 4.32 shows the average predicted profits for scenarios

with a low range for recruitment variation and a high range for recruitment variation. Higher levels of recruitment thus exacerbate the negative economic consequences of closing the season early.

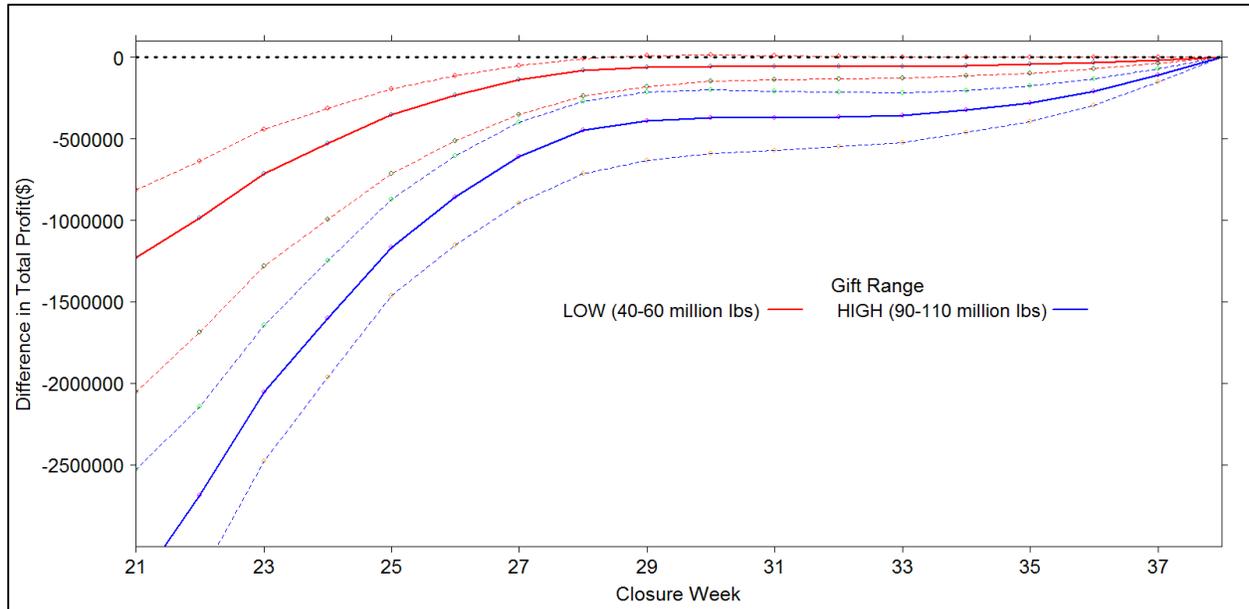


Figure 4.32: Difference in average total profit for two ranges for the ‘gift’. 1) a high range of 90-110 million lbs, and 2) a low range of 40-60 million lbs are examined. The dotted lines indicate the minimum and maximum predictions for each scenario.

Figure 4.33 shows these effects on profit on a subfleet basis. When recruitment is low an early season closure can benefit some fleets that do not benefit on average. For example, the 200 and 300 tier saltun fleets benefit on average from a season closure in week 30, something that does not occur given the full range of variability in the gift. In contrast, fleets that exit relatively earlier benefit from early season closures more with higher recruitment.

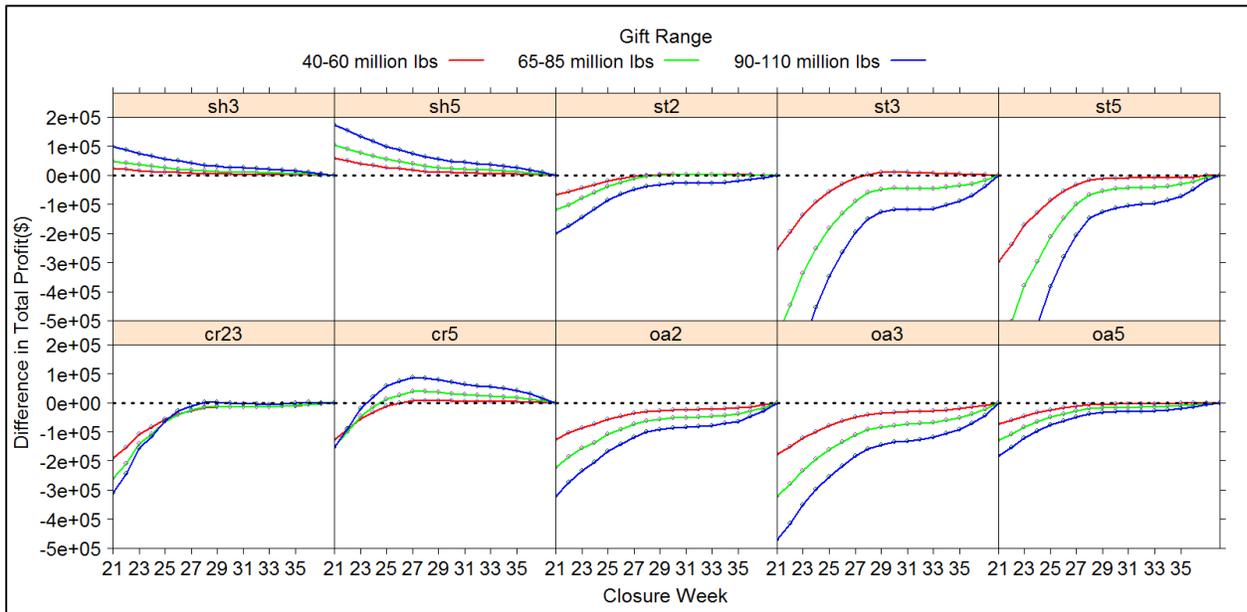


Figure 4.33: Difference in mean predicted total profit by sub-fleet for a range of early season closures versus the traditional season closure for three ranges for the ‘gift’. 1) a high range of 90-110 million lbs, 2) a medium range of 65-85 million lbs, and 3) a low range of 40-60 million lbs.

Figure 4.34 shows the percentage of iterations in the Monte Carlo simulation that total fleet profit is higher when the season is closed at earlier dates. A week 30 closure results in the highest percentage of iterations where total profit is higher than the traditional season closure (~12%). The traditional season closure date thus results in higher total profit a minimum of ~88% of the time.

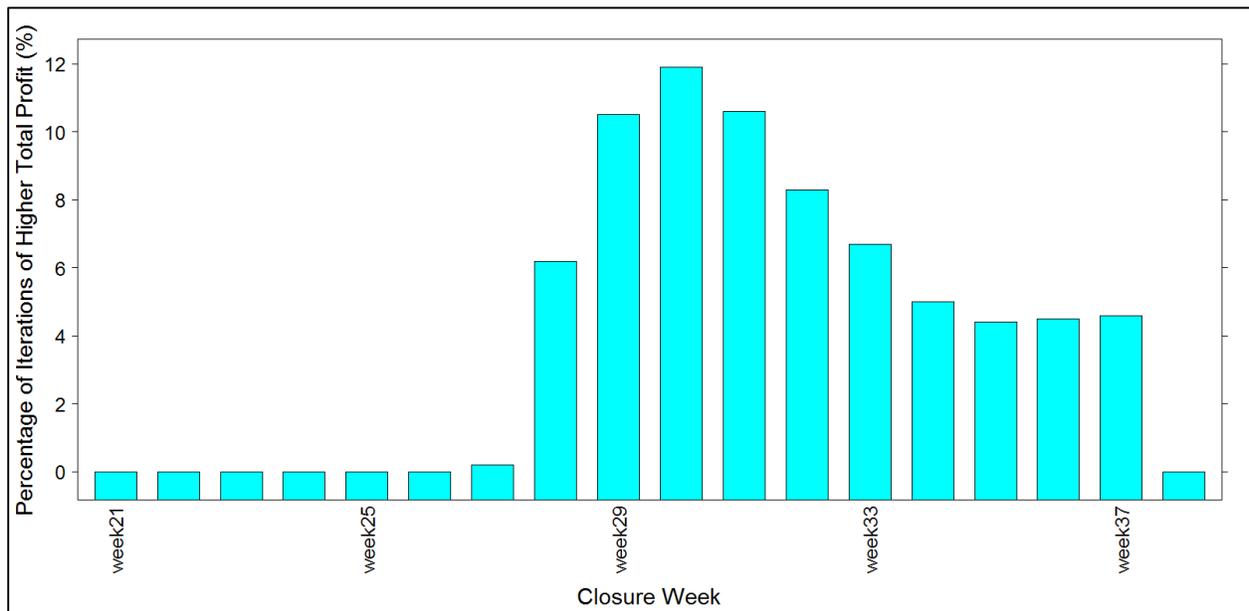


Figure 4.34: Percentage of iterations that a closure week results in higher profit than the traditional closure date.

The proportion of years that the shrimp fleets benefit from early season closures is 100%. Large crab-LE vessels with 500 pot tier limits also benefit 100% of the time if the season is closed after week 27, although this proportion goes to zero if the season is closed before week 22. In general the probability that fleets that exit late will benefit from an early season closure is much lower than fleets that exit the fishery earlier (figure 4.35).

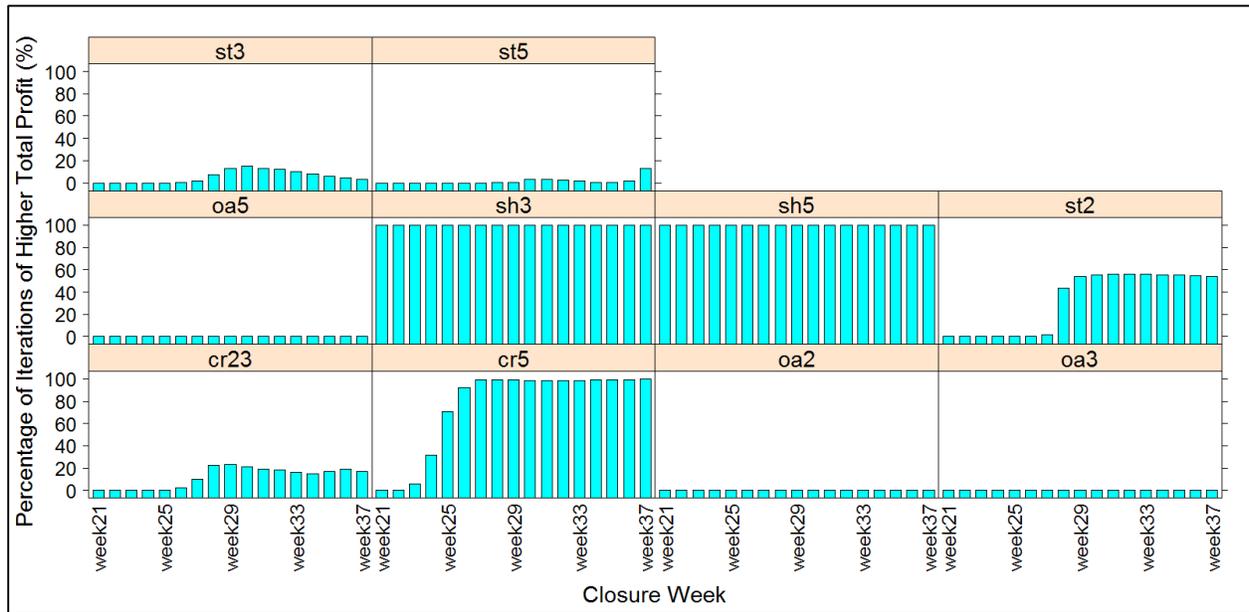


Figure 4.35: Percentage of iterations that each closure week results in higher profit than the traditional closure date by sub-fleet.

4.6.3 EFFECTS OF CHANGING THE HANDLING MORTALITY RATE

Figure 4.36 shows the effects of handling mortality rate of soft shell crab on the availability of legal-sized hard shell crab on December 1st of each year for a range of closure dates. When there is no handling mortality of soft shell crab, closing the season around April 15th results in an average of approximately 600,000 lbs of additional harvestable crab at the beginning of each season (figure 4.36). However, in this case that amount can only be attributed to the amount of harvestable (LH) crab available at the end of the season that is not caught and is available to the fishery in the next season. As the handling mortality rate of softshell crab increases, the differences in LH cohort size due to early season closures also increase due to the additional effect of handling mortality of soft shell crab due to late season fishing. These differences become more pronounced the earlier the season is closed but are less than 100,000 lbs if the season is closed less than 6 weeks early.

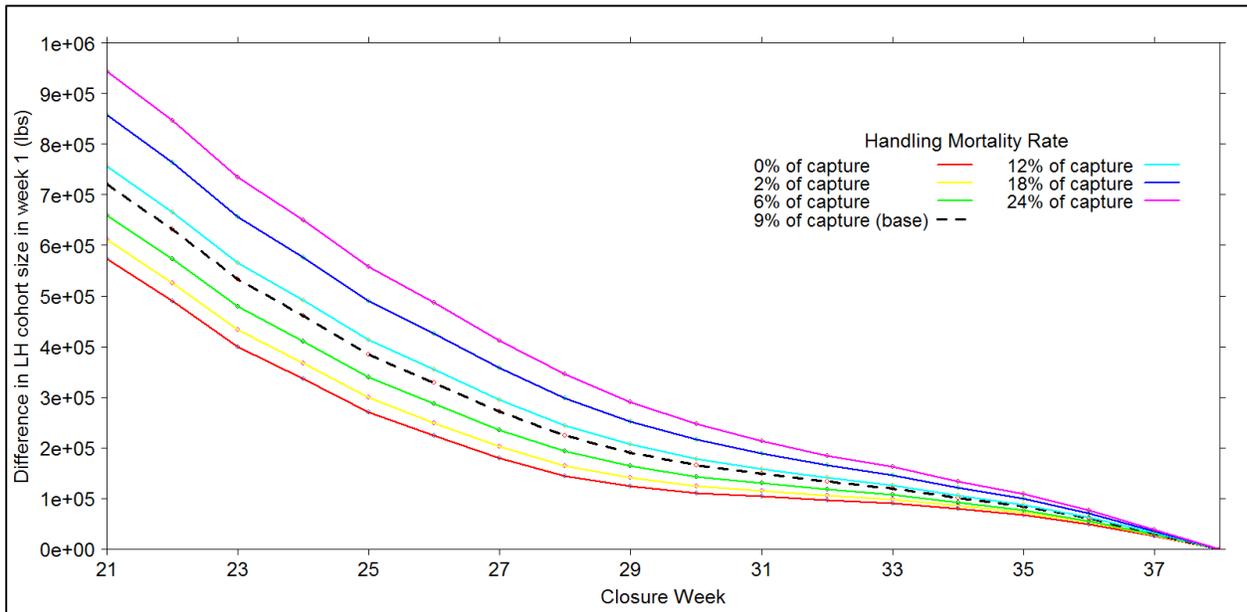


Figure 4.36: Differences in the biomass of the LH cohort for a range of season closures.

Figure 4.37 shows how the assumption on handling mortality rate affects the difference in total profit of implementing early season closures. As the handling mortality rate of softshell crab increases the relative benefits (in terms of total fleet profit) of closing the season earlier compared to the traditional closure date also increase. The mechanism for this is that closing the season early prevents fishing mortality of softshell crab. The crab which are ‘saved’ then re-enter the population of harvestable crab in the next year. When the softshell crab handling mortality rate is high enough, the contribution to fleet profits of the ‘saved’ crab outweighs the foregone profits from restricting effort leading to higher total average profits. In general, the higher the handling mortality rate, the earlier the closure that results in maximum total profit. However, average profits from implementing an early season closure are not predicted to be positive for any early closure date until the handling mortality rate reaches 24%.

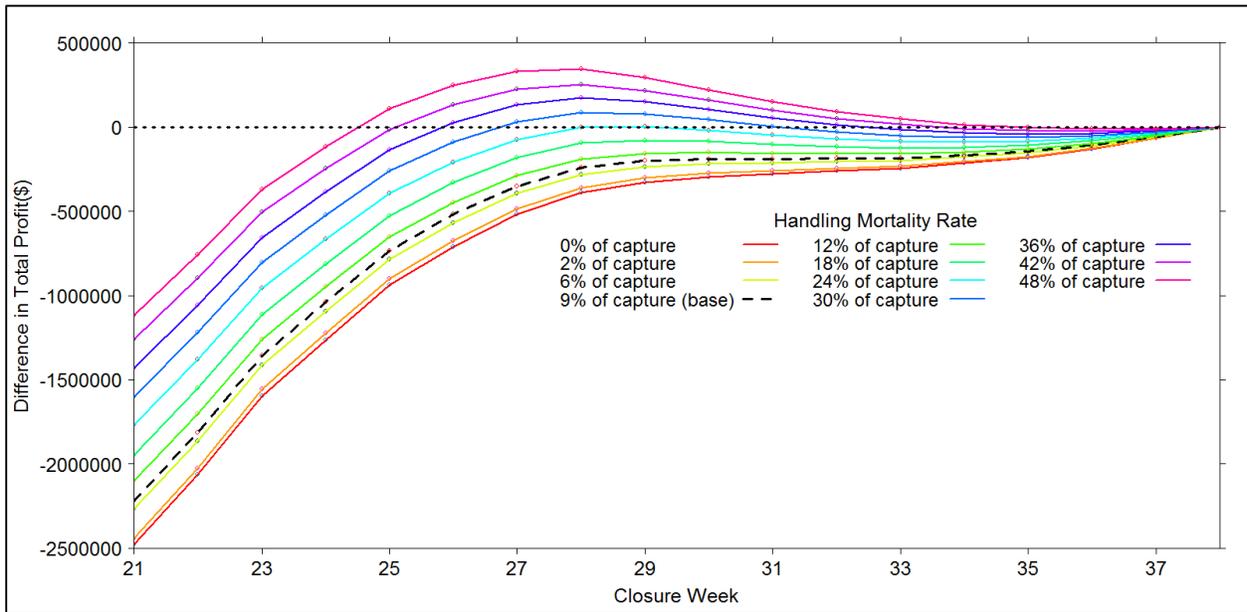


Figure 4.37: Impact of soft shell handling mortality rates on differences in average profits.

Figure 4.38 shows the effect of handling mortality rate on the distribution of profits across fleets. The pattern of profits is similar under the range of handling mortality rates examined. In general, the higher the handling mortality rate, the higher the benefits of implementing an early season closure. The shrimp and crable fleets, which exit relatively sooner than the saltun and open access fleets, benefit more from early season closures. The open access fleets do not benefit from an early closure under any assumption on handling mortality rate.

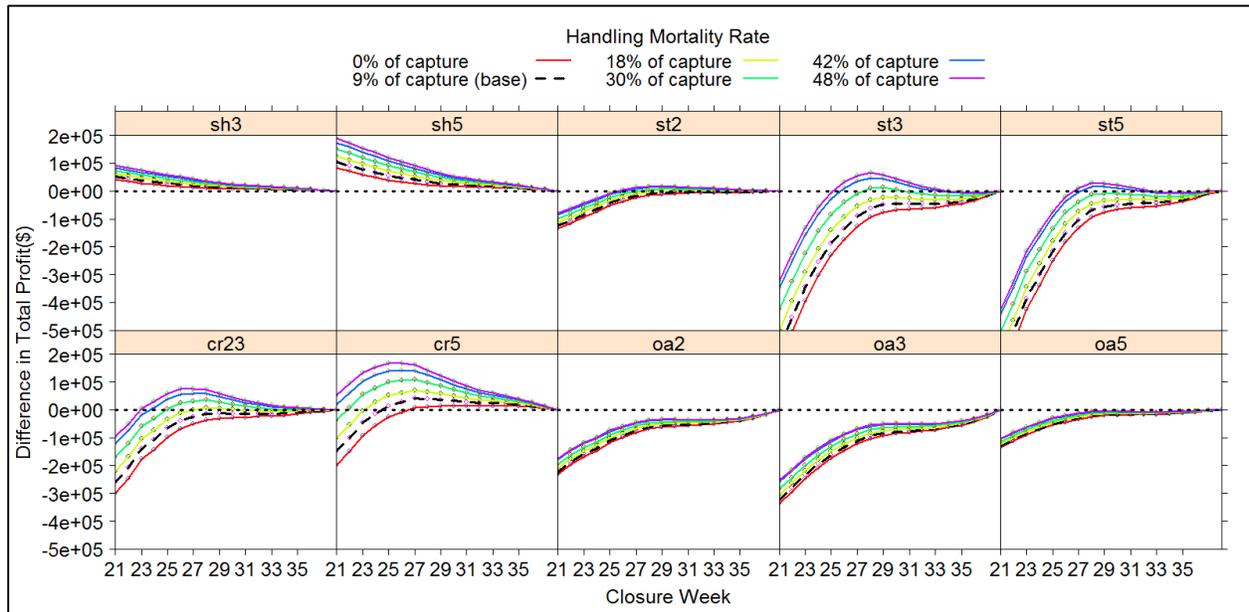


Figure 4.38: Impact of soft shell handling mortality rates on differences in average profits by subfleet.

4.6.4 CHANGES IN MOULT TIMING

Figure 4.39 illustrates the base pattern of moulting throughout the season. The changes in moult timing we examined were scenarios where the moult started earlier or later than the base case although the overall pattern of the moult did not change. Note that the ‘start’ of the moulting process occurs when 2% of the available crab in the LH and LS cohorts moult. Prior to this week 0.1% are allowed to moult (see table 4.14).

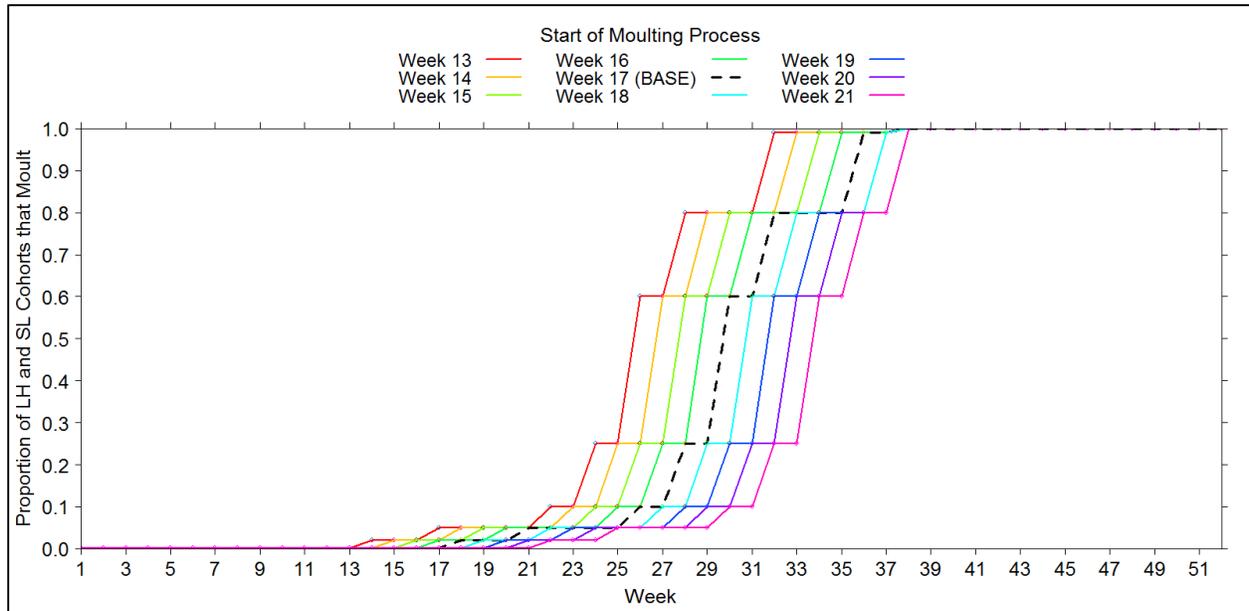


Figure 4.39: Moulting patterns examined. The pattern of moulting implied by the base moulting parameters (dotted line), and the range of ‘start’ dates that were examined.

A general pattern that emerges is that the earlier the moult starts to occur, the higher the average biomass of harvestable crab available at the beginning of the season. This is due to landings of the LH cohort decreasing earlier in the season as more of them move to the softshell cohort. At the base handling mortality rate of 9% the increase in softshell crab mortality is not enough to offset this effect. Revenues thus decrease at an earlier point in the season, total effort decreases in response, and more crab are available for capture the following season. When the moulting process starts later than average, there are less harvestable crab available at the beginning of the next season although differences are not as pronounced as is the case with an early moult. Figure 4.40 illustrates the average difference in harvestable crab from implementing early season closures for the range of moult timings that we examined.

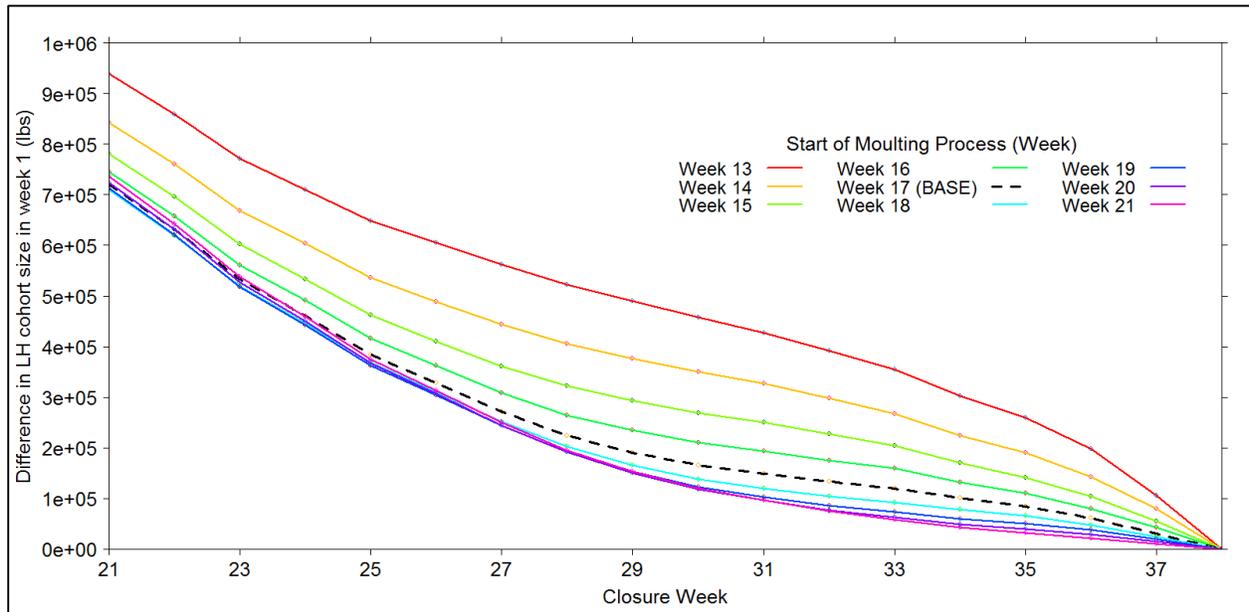


Figure 4.40: Predicted differences in LH cohort biomass for different moult timings.

While the available biomass of harvestable (LH) crab increases the earlier the moult occurs, the effect of an early moult on total fishery profits has the opposite effect. When crab in the LH cohort moult earlier than usual they are removed from the harvestable population at an earlier date and less crab are available when effort is still relatively high in the fishery. Moulded crab remain in the soft shell cohort for 12 weeks and then re-enter the population of harvestable crab. Although some crab moult throughout the year, the earliest that a significant proportion (>10%) of the SL and LH cohorts moult is in week 22, meaning these crab do not enter the LH cohort until week 35 at the earliest. Effort in the late stages of the season is generally low (figure 4.41) and the combination of high prices and increased availability of crab does not translate into profit increases that outweigh foregone profit given up earlier in the season due to the early moult.

If early season closures are implemented in the model, late moult timing ameliorates the generally negative effects on profit in the fishery, especially if the closure occurs between week 27 and 37. When the moult occurs later than usual, the LH cohort is subject to fishing mortality for a longer time period when effort is relatively high. This results in decreased average levels of crab that moult into soft shell crab and thus levels of the LH cohort at the beginning of the next season. However if a season closure occurs after week 27, the late moult means that the abundance of LH crab is higher for a longer period of time. This higher temporal abundance (even though average total abundance is lower) means that higher catches and profits occur in

the several weeks prior to the closure. The late moult therefore helps to lessen the negative effects of the early season closure.

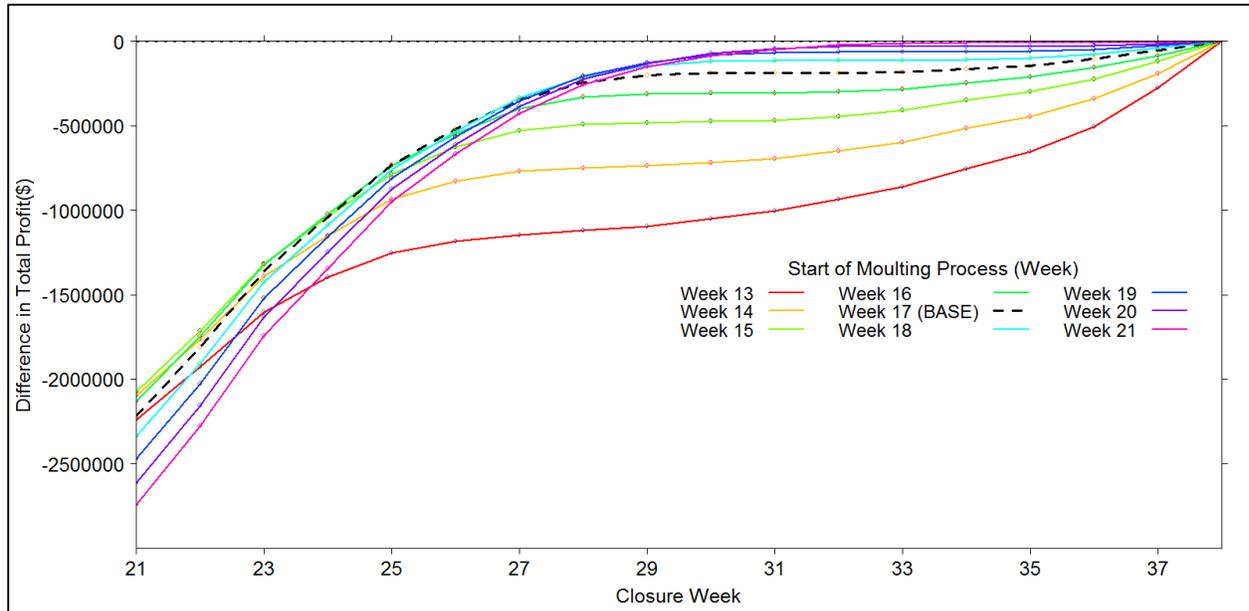


Figure 4.41: Effects of moult timing on differences in total profit.

The shrimp fleets benefit from an early moult in the range examined. Shrimp vessels generally leave by week 20 and an early moult implies that less crab are available for the rest of the fleet to harvest after this date. This translates into higher LH biomass at the beginning of each season when shrimp vessels do participate and when their effort is relatively high. This effect is the same for the large (500 tier) crabble fleet vessels who exit the fishery earlier than most of the other fleets. The saltun, oa, and smaller crabble vessels do not benefit from an early moult as effort for these fleets is spread out more throughout the season. Foregone profits in the part of the season after week 20 outweigh any potential stock effect from the early moult.

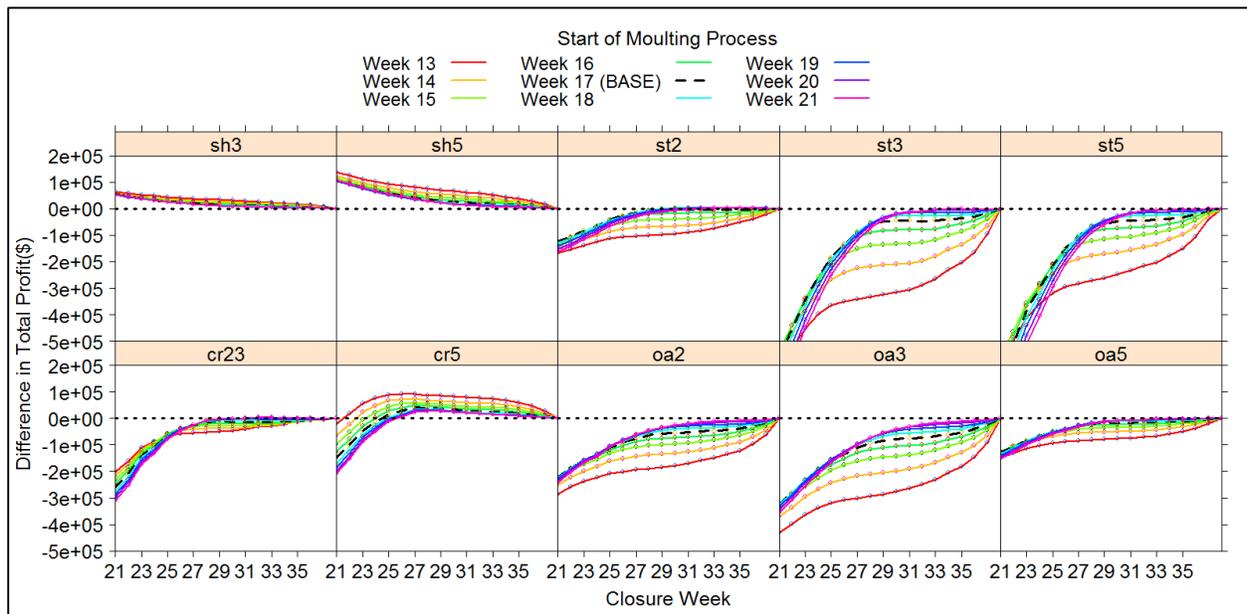


Figure 4.42: Effects of moult timing on the difference in sub-fleet profit.

4.7 Discussion

Our results illustrate the potential biological and economic effects of adjusting the season closure date in the Oregon Dungeness crab fishery. We demonstrate how our simulation framework can be used to explore some of the relationships between fishermen and the resource that have important implications for fishery managers, and that would otherwise not be obvious. For example, our model predicted under the base scenario that implementing an early season closure in the ODC fishery would likely have positive impacts on the average population of harvestable crab, as expected, but under the set of base assumptions regarding moult timing, handling mortality rate, price- and cost-structure, early season closures would likely have negative effects in terms of average total fleet profit. While this is true for the base scenario, we showed how our assumptions on softshell crab handling mortality rate, the timing of the moult, and the level of recruitment in the fishery would affect the direction and magnitude of the effect. In particular, early season closures become relatively more attractive from a profit perspective if: 1) the handling mortality rate of crab increases, 2) the moulting process occurs later than the base assumption of week 17, and 3) if the average level of recruitment is relatively low. These observations have important implications as they may be used by fishery managers in making determinations on season length in the future, especially if more information is collected in the future regarding these processes.

Our results also indicate a pattern where, in situations where early season closures provide a positive average change in profit to the fishery, the season closure date that maximizes profits occurs around the time when the biomass of softshell crab is increasing at its fastest rate, which in the base case occurs at the beginning of June. Figure 4.43 illustrates this effect using a scenario where handling mortality is high (36% of softshell capture), and the level of recruitment is low (40-60 million lbs per year). The later the moulting process starts, the later the season closure date that results in maximum total annual profit. Note that even for these extreme values for handling mortality and recruitment, for very early starts to the moulting process the traditional season closure date (week 38) results in maximum profits most of the time.

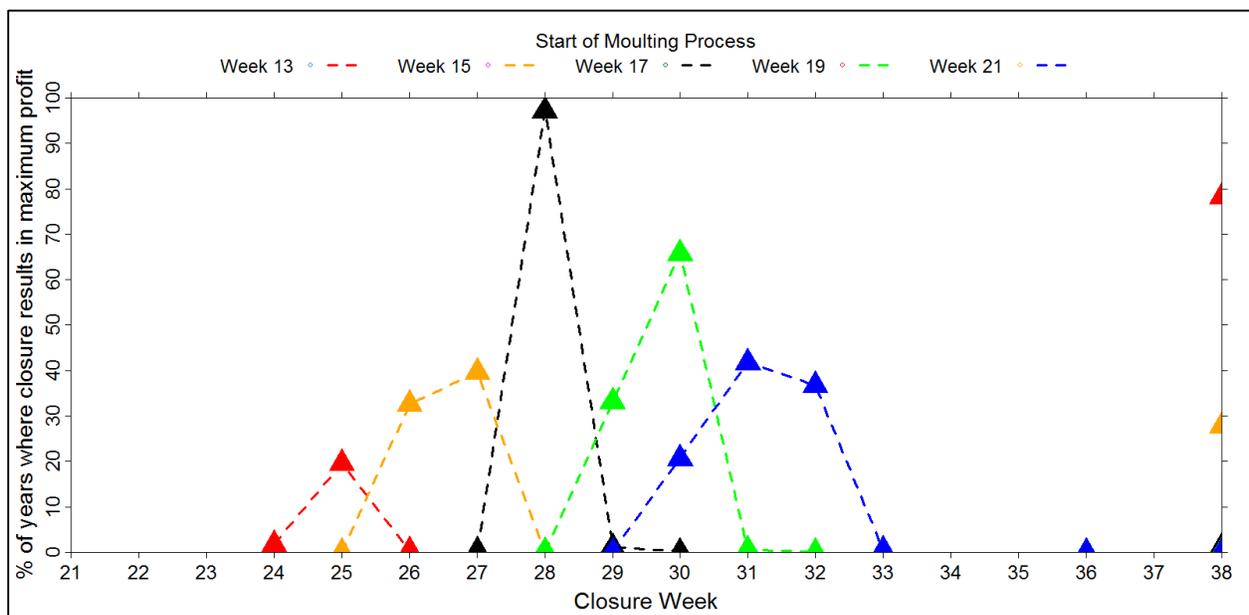


Figure 4.43: Illustration of the percentage of years that a particular closure week results in maximum fishery profit. A parameterization where recruitment is low (40-60 million lbs), and the assumed handling mortality rate of soft shell crab is high (36%) is used.

The later the moulting process occurs, the later the closure date that results in maximum fleet profits. In other words, if a season closure is going to be implemented, our model predicts that it is better to close the season at the beginning of the moulting process rather than later on in the process. This is due to the fact that between June and August fishing effort is generally low. This leads to relatively low levels of harvest and profit for vessels remaining in the fishery after June, but also relatively low levels of handling mortality of softshell crab. For closure dates after week 30 (for the base parameter scenario), the level of profit foregone directly by these summer vessels is greater than the potential gain in profits through an indirect 'stock' effect, where the mortality of soft shell and harvestable crab contribute to a larger stock size in the

next season. However, if the season is closed within the week 28-30 range, the indirect stock effects on total fleet profit are more likely to outweigh the foregone profits from the vessels that traditionally fish in the summer months. Finally, if the season is closed before week 28, foregone profits from vessels that would traditionally fish after the closure date again outweigh the positive indirect 'stock' effects on profit. These timings change with the timing of the moult- in general a later moult results in a later closure date that results in maximum total fleet profit.

Our model indicates the importance of our assumptions on the soft shell crab handling mortality rate on model predictions. We showed that as the rate of soft shell crab handling mortality increases, benefits to the fishery of any season closure date decrease. Future applications of this simulation model could shed light on the implications of reducing the soft shell handling mortality rate on the level of profits in the fishery under the traditional management structure. Similarly, the rate of handling mortality of the SL cohort was fixed in these simulations and even though the handling mortality rate that is thought to apply to sub-legal hard shell crab is relatively low (around 1-2%), high cohort biomass at the beginning of each season coupled with high effort levels leads to a potentially important effect on model predictions. These considerations are especially pertinent given the reluctance to adjust the season structure in the ODC fishery. By innovating new ways to reduce handling and discard mortality in the ODC fishery, benefits to the fishery could be created without the negative distributional impacts of adjusting season length. An examination of this question will be considered in future work.

The general pattern of effects of early season closures on total fleet profits is not observed for all of the subfleets. The earlier the season is closed, the more harvestable crab are available at the beginning of the next season so vessels that exert higher effort levels at the beginning of the season benefit disproportionately more than smaller vessels with a lower capacity for effort. In addition, subfleets that exit earlier on average give up proportionately less than subfleets that exit later in terms of foregone profits from late season fishing. For example, vessels that are part of the shrimp subfleet exert high levels of effort per trip at the beginning of the season (figure 4.18), and exit the fishery generally before week 20, which is before any of the season closure dates examined in the simulation. Vessels that are part of these subfleets therefore always benefit from an early season closure. As a general rule, the subfleets that are relatively better off under an early season closure are also those subfleets that exit the fishery sooner and traditionally exert less effort late in the season. Figure 4.44 shows the distribution of vessel lengths by subfleet aggregated over all seasons. Vessels in the shrimp subfleets are the largest on average, and vessel length is correlated with the pot tier permit that a vessel holds. The open access (oa2, oa3, oa), and saltun (st2, st3, st5) subfleets are

composed of smaller vessels on average and these are also the vessels that are more likely to lose out if an early season closure is implemented. This observation cuts to the heart of the issues regarding early season closures- that distributional concerns are paramount. There is currently friction between fishermen in the ODC fleet regarding the question of implementing early season closures- the larger vessels who exit earlier are more likely to agree with implementing an early season closure than smaller vessels who remain in the fishery longer (ODCC 2016b). Our model illustrates that this friction has a bioeconomic basis. Under a wide range of handling mortality rates and moult timings, vessels that are part of the open access fleets and salmon-tuna fleets will likely be the losers from an early season closure, while larger vessels that are part of the shrimp and limited entry groundfish fleets are the likely winners.

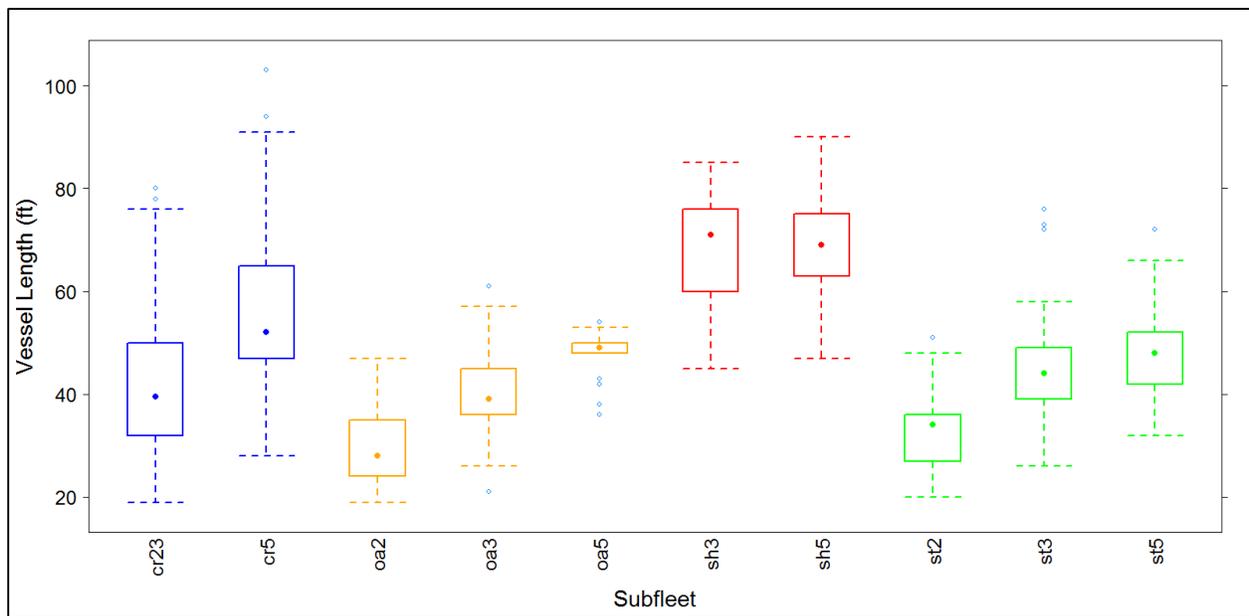


Figure 4.44: Box and whisker plots of the range of vessel lengths by subfleet. The dot in each box represents the median length, the box limits represent the 25th and 75th percentiles of length, and the whiskers are a measure of the range of the data.

While we incorporated a wide range of handling mortality rates and moult timings into the simulations, the way that these parameters are incorporated into the structure of the simulation model partly determines the structure of the results. For example, we assume that the handling mortality rate of softshell crab is constant throughout the year. In reality, the rate of handling mortality could change temporally as a result of changes in the physical environment (water temperatures, dissolved oxygen), the abundance of large male crab (that results in changes in the rate of cannibalism), or the migratory behavior of predators. An increase in handling mortality rates in the summer months would likely increase the relative benefits of closing the

season early while a decrease in the summer handling mortality rate would have the opposite effect. The overall effect of these changes cannot be easily investigated without the aid of a simulation model. In the case of the structure of the moulting process, we assume that 100% of the hard-shell crab in the model moult into the softshell cohort by the end of every year, and that most of the crab moult in the space of a two month period. While the frequency of moulting is high for young crab, and the assumption that all SL (3 year old) crab moult within a year may be reasonable (Rasmuson 2013), crab moult with a lower frequency as they get older. The effects of a different moult structure on model results are not readily apparent. On the one hand a reduction in the proportion of crab that are soft shelled would reduce handling mortality levels, and have a positive benefit on the population, but on the other hand any harvestable crab that don't moult would likely be caught anyway (although they would also be sold and provide benefits to the fisherman). If the moulting process occurred more gradually it is possible that a higher relative proportion of soft shell crab earlier in the season would mean an early season closure would provide increased benefits to the fishery, but more crab hardening later in the season would mean the level of foregone profits from an early closure would also increase. These points help to illustrate that while general results that apply over the full range of parameter values can't be derived easily (as is the case in many analytical models), one of the main advantages of simulation models is that they provide insight into situations that are too complex to grasp without expository help, and allow hypotheses to be explicitly formulated and explored (Hilborn and Walters 1987). They also point to areas where additional research would be valuable- in our case exploring factors affecting the timing and structure of the moult, and the effect of fishing on mortality of crab that are discarded.

We have used our model to elaborate on the patterns of bioeconomic effects that may occur if an early season closure is implemented in the ODC fishery. However, these patterns are predicated on the assumptions that we have made regarding the behavior of the vessels in the ODC fishery in response to such an action. Our use of a duration model that predicts the exit behavior of in-season exit behavior of fishermen constitutes a novel application in itself, and we know of no study that has combined a duration model into a bioeconomic fisheries simulation model. Our study has illustrated the usefulness of duration analysis for analyzing the factors affecting the in-season exit behavior of fishermen, something that has only been demonstrated for long term exit decisions (Smith 2005; Holloway and Tomberlin 2006; Cerdón Lagares and García Ordaz 2015) and trip level cessation decisions (Ran, Keithly, and Yue 2014). We showed that while ODC fishermen behave in remarkably stable patterns over time, they take their portfolio of alternative fishing activities into account when deciding when to exit the fishery. *Ceteris paribus*, an

increase in the relative value of alternative activities compared to ODC fishery participation leads to a higher rate of exit in the fishery. In addition, larger vessels exit earlier than small vessels even if their available alternatives were similar. This emphasizes the need for fishery managers to take both heterogeneity in fishermen's characteristics and their range of opportunities into account when analyzing the potential level and distribution of impacts of management actions.

While the application of a duration model into a bioeconomic simulation model is novel, incorporating the predictions of a statistical model of fisherman behavior into a fisheries simulation model is a relatively common method for determining the temporal and spatial distribution of fishing effort. For example, Holland (2000), Hutton et al. (2004), and Andersen et al. (2010), all estimate various specifications of random utility models and incorporate estimated effects into simulation models that explore alternative management actions. Allowing effort to respond to fishery conditions using an empirically estimated relationship provides a level of defensibility to model predictions, but is not without its practical issues -- mismatches between the scales of the simulation and estimation models may increase modeling complexity. For example, Hutton et al. (2004) found that after estimating their well-specified RUM only some of the results could be incorporated into the overall simulation model due to differences in model formulation. Ulrich et al. (2007) find similar restrictions when designing a generic spatial bioeconomic simulation model for evaluating management measures. In this case fishing effort was distributed spatially by multiplying calculated choice probabilities by an overall effort level. However, the set of explanatory variables that could be included in the model inputs was restricted by the fact that biological information was available at a much coarser scale than information on fleet behavior. These scale considerations forced the authors to use a reduced set of explanatory variables to generate bioeconomic simulation model predictions. In deciding on our model formulations and estimation procedures for the duration and Zero-Inflated Poisson (ZIP) models (that together determine the temporal distribution of fishing effort in the model), we explicitly took these considerations into account by specifying a discrete time structure where time intervals were the same for both the biological and economic components, and by specifying a subfleet structure for both the estimating models and the simulation model. Specifying matching temporal scales for our bioeconomic simulation model and the estimation model was a simple and logical step. However, the fact that our observations on the number of trips taken and fishery participation came from a longitudinal data set posed potentially serious theoretical complications for our estimation strategy. Observations on the same vessel in different years are not independent over time and if this non-independence were to be ignored, biased parameter estimates and elevated rates of type 1 errors (wrongly rejecting the null hypothesis) could result

(Barber et al. 2000). However, estimating the model for each subfleet separately, incorporating fixed effects for vessel class, and using a robust covariance estimator clustered on individual vessels at least partly addresses these issues. While estimating the effects of variables describing fishery conditions using a conditional fixed effects model is perhaps more likely to result in unbiased parameter estimates, including these results into a simulation model is complicated by the fact that the effect of time invariant variables can't be estimated (Agresti and Kateri 2011), and a control for time itself can't be included (Allison and Christakis 2006).

Whatever the specification for the empirical estimation, parameters estimated using data for a particular fishery over a specific time period reflect the behavior of fishermen over that particular time period and fishery, and are based on the economic, social, and biological structure of the fishery at the time. While the advantage of using behavioral economic models as a foundation for estimation is precisely that the response of individuals to policies can be predicted even if the policies were not in place during the period modeled (Wilén et al. 2002; Hutton et al. 2004), our duration model falls somewhere short of being a true behavioral model. We do not specify an explicit mechanism to describe why fishermen exit and what they do when they exit, but rather estimate an average temporal trend for exit and then how changes in fishery conditions cause deviations from this trend. Indeed, the main behavioral assumption that we make in specifying a duration model is that the relationship between fishermen's exit behavior and historical conditions in the fishery will not change due to an early season closure. In particular, this assumption implies that a fisherman's behavior in the part of the season before an early closure date will not change due to the imposition of that closure date and we argue that this assumption is not unreasonable. There is a theoretical amount of weekly effort that maximizes an individual fisherman's profit given competition for the resource and the availability of crab. At the beginning of the season when crab availability is high, effort is likely to be limited by physical or time constraints such as the number of pots available for use or the time it takes to haul pots and deliver crab to port. Given the high value of the crab fishery compared to most other West coast fisheries a reasonable assumption is that fishermen will try and maximize their effort levels given these constraints and an impending closure would have no behavioral effect. Later on in the season, given competition for not just the crab resource but resources in alternative fisheries, our assumption is then that fishermen's optimal effort levels do not change as a result of the season being shortened. Another implicit assumption is that the effects of an early season closure will not induce ODC fishermen to change their long term decisions on whether to remain in the fishery, or permanently exit the fishery. While economic theory would predict that the higher the profits in the fishery compared to alternative opportunities, the

more likely vessels are to remain in the fishery from season to season, our model predicts profit effects of early season closures to be felt unevenly among the fleet, with some vessels gaining and others losing out. Predicting long term exit and entry behavior is therefore complex and given that our model predicts effects on profit of implementing early season closures that are relatively small we did not incorporate this aspect into the simulation model. However, future research could shed light on this issue, possibly using a duration analysis framework as in Smith (2004) and Holloway or Tomberlin (2006).

The pattern of Dungeness crab moulting throughout the season is thought to be in a South-North direction-crab found further South are thought to moult sooner than crab found further North along the coast (Didier 2002; Rasmuson 2013). In addition, there is some anecdotal evidence that soft shell crab are found more frequently in shallow water (ODCC 2015). There is also a spatial component to fishermen's effort decisions in that they make a decision on where to fish from their homeport, and the choices they have are heterogeneous in both Dungeness crab abundance and costs of fishing. While incorporating a spatial component into the model would have allowed us to examine the bioeconomic impacts of spatial management measures as well as temporal measures, this is an area for future research, and one that may best be examined using a random utility framework (Smith 2004). Regardless of which additional parameters, dimensions, or environmental processes are incorporated into future work, the current simulation framework has provided a starting point for learning and thinking about how the complex interactions between fishermen and the environment can potentially impact fishery management measures, impacts that can only be readily exposed using a bioeconomic simulation framework.

4.8 Conclusion

Bioeconomic simulation models are important tools for informing fishery managers about the interactions between fishermen and the resource that are likely to affect the intended impacts of management measures. We combine a duration model of in-season fishery participation with a count model that predicts fishing effort into a greater bioeconomic model of Oregon's Dungeness crab fishery. This fishery has not previously been examined from a bioeconomic perspective and the state of knowledge regarding the structure and economic behavior of the fleet, as well as the population dynamics of the crab stock, is limited. In this paper we first developed a biological model that describes the salient stock dynamics of Dungeness crab in Oregon. We then examined the factors that affect fishermen's participation and effort level decisions. Finally we incorporated these estimated relationships into a bioeconomic simulation framework and explored the biological and economic impacts of implementing early season closures in the fishery. We

found that under a range of parameter values there would likely be either a negative impact, or relatively small positive impact on total fishery profits, and that these impacts would accrue unevenly on the fleet. We found that large vessels that exit the fishery relatively early for valuable alternative fishing opportunities are more likely to benefit than smaller fishing vessels that remain in the fishery longer. Due to a lack of knowledge regarding stock biomass levels, handling mortality rates, and moulting process characteristics, we were unable to make predictions regarding the level of biological and economic effects from implementing early season closures in the fishery. However, we were able to illustrate that the impacts of early season closures are sensitive to assumptions regarding the handling mortality rate of soft shell crab, the timing of the moulting process, and the level of recruitment in the fishery and showed that if an early season closure is implemented, closing the season before the main moulting process occurs would likely result in higher fishery benefits than later closures. These are all areas where research is needed in order to shed light on the impacts of not just season closures, but any fishery management measure considered for use in this fishery.

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5. CONCLUSION

Bioeconomic simulation models of fishery systems are generally complex enterprises that require a significant investment in time and other resources in order to undertake. While models that can be solved analytically are preferred to models that can't, the complex nature of the interactions between fishermen and the resource, and between difference components of the ecosystem, mean that the use of bioeconomic simulation models that incorporate a high level of complexity is becoming more common. In the U.S., a new Ecosystem-Based Science and Management (EBSM) paradigm, as well as the constant search for new scientific frontiers by the fisheries science community, are driving the demand for models that are capable of representing complex ecosystems. While the components of such models are often many and varied, this thesis has made contributions in incorporating a higher degree of realism to the 'fisherman' component of bioeconomic simulation models.

The structure of all bioeconomic simulation models is determined by the researchers who design and build them. Models that are built by biologists or ecologists generally place more weight on the biological or ecological component than the economic component and the opposite is true for models built by economists. In both cases omitting certain aspects of the fisheries system has implications for a model's behavior and predictions that are often not well understood. There has been recent interest in biological models that are designed to test the performance of alternative harvest control rules in fisheries. Although the spatial and temporal pattern of mortality in a fishery is determined by the behavior of fishermen, most of these models either omit this component, or calculate effort dynamics using a sub-model that is not based on an economic theory of fishermen behavior. This may be due to a perceived complexity on the part of biologists of incorporating a model of fisherman behavior into such simulation models. This thesis has demonstrated that incorporating a degree of realism in fishing behavior into simulation models yields insights that can inform management, drive future hypothesis formation, and stimulate thinking about the complex interactions between fishermen and the rest of the fishery ecosystem.

The first manuscript in this dissertation (chapter 2) illustrates that incorporating fishermen behavior into a 'biology focused' research topic does not necessarily have to be a complex undertaking and that important insights can be gleaned from doing so. For example, changing harvest limits for a single species in a multi-species fishery has impacts on both the age-structure and health of the target stock, but also on the other stocks in the fishery. These impacts are case-specific and depend on both biological and economic behavior and are best explored using a bioeconomic modeling framework. The second manuscript (chapter 3) introduces a novel game theoretic method for distributing fishing effort spatially in bioeconomic simulation

models. Perhaps the most commonly used method for distributing effort spatially, the ‘gravity’ model is not based on an explicit theory of how fishermen behave in space. While the implications of choice of model on model results depend on the particular situation that the model is applied to, the behavioral differences between the gravity model and the game theoretic method are described in a simple simulation framework. The third manuscript (chapter 4) documents the design and application of a bioeconomic simulation framework to the Dungeness crab fishery in Oregon, U.S.A. An application of a duration model to describe the in-season exit behavior of fishermen is made and incorporated with a population dynamics model to examine the potential economic and biological impacts of a suite of management measures designed to limit discard mortality in the fishery. This manuscript demonstrates how, in a fishery where information on stock dynamics is extremely limited, two statistical models that together determine how effort levels change in response to fishery conditions, can be combined into a bioeconomic framework that can be used to analyze potential effects of management actions.

Bioeconomic models are built because all individuals care about fishery ecosystems for various reasons and they are generally too complex to analyze without help from mathematics, statistics, programming, and the substantive efforts of previous researchers. Further improving our state of knowledge regarding the interacting processes that comprise fishery ecosystems by designing and improving bioeconomic simulations is a valuable exercise, and one that has the potential to improve the welfare of not only the current generation, but generations to come.

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