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Title: Two Essays on the Management of the West Coast Salmon Fishery

Abstract approved: ______________________________

Gilbert Sylvia

The West Coast salmon fishery presents several complexities that have received little attention in the fisheries economics literature. Two of those complexities are reviewed and analyzed in this dissertation. The first, salmon fishermen participate in alternative fisheries within a season demonstrating a complex switching behavior between different species. Second, the fishery is based on a mixed-stock system where many re-productively isolated sub-populations are harvested simultaneously.

In the first essay, I used unique and comprehensive vessel-landing level data describing fishing trips of salmon troll vessels from 2005 to 2014 in a Random Utility Maximization framework. An empirical model is used to determine the effect of closures on the salmon fishery including the distribution of fishermen across fishing locations and alternative fisheries. The results suggest that fishermen respond to area-temporal closures in the salmon fishery by reallocating across space and/or alternative fisheries. This research contributes to the literature by illustrating the importance of fishermen behavior when rent differentials exist across space and species, leading to a complex distribution of effort.

In the second essay, I present a spatially explicit mixed-stock system that characterizes the West Coast salmon fishery. I used model simulations to explore the effect that monitoring regimes at different spatial scales of mixed-stock harvest composition have on achieving weak stock escapement goals and economic benefits for the fishery.

Results suggest that spatial management of mixed-stock harvest composition allows for higher profits for the fleet -while meeting conservation goals- only when it takes place at fine spatial scales. In general, results of both essays illustrate that ecosystem-based fishery management requires managers to account for the complex behavior of harvesters and the dynamic spatial and ecological interactions of resources.

Two Essays on the Management of the West Coast Salmon Fishery

by
Smit Vasquez Caballero

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APPROVED:

Major Professor, representing Applied Economics

Head of the Department of Applied Economics

Dean of the Graduate School

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.

Smit Vasquez Caballero , Author

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CONTRIBUTION OF AUTHORS

All authors played a role in reviewing the manuscript of their respective chapters. Smit Vasquez Caballero is primarily responsible for model design, data analysis, interpretation, and writing of the manuscript of both essays presented in this dissertation. Dr. Gil Sylvia and Dr. Dan Holland supervised both manuscripts and provided critical feedback and helped shape the research, analysis, and manuscripts. Detailed contributions are listed next.

Chapter 2 titled Fishery Participation and Location Choice Model for the West Coast Salmon Fishery is authored by Smit Vasquez Caballero (SVC), Gilbert Sylvia (GS), and Daniel Holland (DH). SVC and GS conceived the original idea of modeling the location choice behavior of salmon fishermen. DH encouraged the investigation of the fishery participation behavior. SVC designed the econometric model, obtained permission to use dataset, performed data analysis and regression analysis, and wrote the manuscript. DH provided entire fish ticket data that served as the primary source for this study. Both DH and GS supervised model development and findings.

Chapter 3 titled Ecological-Economic Model of a Mixed Stock Fisheries is authored by Smit Vasquez Caballero (SVC), Gilbert Sylvia (GS), and Daniel Holland (DH). GS as a member of the Collaborative Research on Oregon Ocean Salmon (Project CROOS) motivated the original idea of developing a bio-economic model that characterizes the West Coast salmon troll fishery and that includes the use of Genetic Stock Identification data as a means to improve management practices in the fishery. SVC designed the model, performed numerical simulations, and wrote the manuscript. DH encouraged the use of utility score framework as a way to model effort allocation in the economic part of the model. GS and DH supervised all stages of this research.

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To Kathy for your invaluable support

&

to Marie for your love and care.

Two Essays on the Management of the West Coast Salmon Fishery

1 General Introduction

The study and management of fisheries reveals that fisheries across the globe are extremely diverse and complex. Fortunately for economists, the fisheries economics discipline is an integrated body of research that provides strong theoretical foundations and a rich and diverse methodological approaches that can address many of these complexities. The threads of the literature include fishermen behavior (Bockstael and Opaluch 1983; Eales and Wilen 1986; Holland and Sutinen 1999; Smith and Wilen 2003; Abbott and Wilen 2011), ecological dependence (Hannesson 1983; Flaaten 1991), multi-species and bycatch (Androkovich and Stollery 1994; Boyce 1996; Bisack and Sutinen 2006), spatial dimensions (Sampson 1994; Sanchirico and Wilen 1999; Abbott and Wilen 2011), and many others themes. In this dissertation, I make use of existent bodies of work on fisheries economics to study the complexities of the West Coast commercial salmon fishery. Two complexities are addressed in this research; the switching behavior of salmon fishermen across different fisheries and the migratory and multi-stock nature of the fishery.

Modeling fishermen spatial behavior has been a recurrent topic in the fisheries economics literature. Applications include the pink shrimp fishery off the coast of Northern California (Eales and Wilen 1986), the groundfish fishery in New England (Holland and Sutinen 2000), the sea urchin fishery in Northern California (Smith and Wilen 2003), the Bearing Sea pollock fishery (Haynie and Layton 2010), and the Gulf of Mexico reef-fish fishery (Zhang and Smith 2011), among others. While this literature has presented models of fishermen behavior, the location choice behavior has usually modeled decision-making in isolation of fishermen participation in other fisheries. A complexity observed in the West Coast commercial salmon fishery is the switching behavior of fishermen between the salmon fishery and other fisheries including crustacean, highly migratory, and groundfish fisheries. While past research has shown the effects that spatial closures have on fishing location choices (Smith and Wilen 2003), broader effects on the salmon fishery and other fisheries have not been investigated when fishermen manage a portfolio of fishery participation choices.

The complexity of the multi-species and bycatch aspects of fisheries has been studied in the literature. Early work has been motivated by the North Atlantic cod and haddock fisheries (Androkovich and Stollery 1994), the bycatch of dolphin in the eastern tropical Pacific Ocean tuna purse seine fishery (Bisack and Sutinen 2006), the flatfish fisheries in the Eastern Bering Sea (Abbott 2009), amongst others. The West Coast salmon fishery presents a somewhat different set of multi-species and bycatch management challenges. The fishery is a multi-stock fishery where several re-productively isolated sub-populations are aggregated in the same fishing grounds, and where each stock follows a unique migration pattern. The simultaneous harvest of several stocks in the salmon fishery presents another dimension of the bycatch problem; specifically, how to manage a fishery when stock composition is unknown to both the harvesters and the regulatory agency.

Based on these two dimensions of the West Coast salmon fishery, that is, the multi-target behavior of the fishermen and the multi-stock nature of the fishery, I seek to explore two questions in this dissertation. In Chapter 2, I investigate the question of how West Coast commercial salmon fishermen respond to area-temporal closures in the fishery. In Chapter 3, I seek to shed light on the question of whether fine-scale monitoring of weak stocks distribution can be used to achieve both conservation and fishery benefit objectives?

To answer the first question, I model fishery participation and location choice of salmon fishermen. The model is built using the framework developed to understand fishermen behavior where Random Utility Maximization (RUM) models can be used to empirically estimate fishermens discrete choices based on fishermens characteristics and choice alternative attributes. After estimating parameters of the fishery participation and location choice model using vessel-landing level data, I carried out simulation scenarios of area-temporal closures that allowed me to evaluate how fishery participation and location choice behavior responds to a closure in the salmon fishery.

To answer the second questions, I developed a stylized spatially explicit model that characterizes the spatial in-season dynamics of the stocks, the behavior of the fleet, and the area-temporal closure tool employed by the fishery regulator to achieve conservation objectives. I used the stylized model to carry out simulation of different management regimes, where each regime is characterized by the spatial level at which the manager is able to monitor spatial distribution of stocks. In each management regime, the regulator uses area-temporal closures at the spatial level at which the monitoring takes place in order to avoid harvest of weak stocks.

Results from Chapter 2 suggest that salmon fishermen respond to area-temporal closures by reallocating effort across space while continuing to target salmon, or by switching to alternative fisheries. Further, the responses to area-temporal closure depend upon the fishery portfolio of individual fishermen and the availability of alternative fisheries. My research shows that fishermen manage a portfolio of fishery participation decisions within a single salmon season. The management of portfolios of fishery participation options is observed in the switching behavior across fisheries during salmon seasons. The switching behavior of fishermen across fisheries due to in-season regulation is a topic that has not well explored in the fisheries literature. My work introduces fishery participation decisions as an important element to consider in spatial choice research. The results of Chapter 2 also provide a contribution to the literature in that spatial policies intended to protect species in one fishery may have spillover effects on other fisheries. For fisheries management, this finding is important since spatial policies are used in many fisheries across the globe.

The major contribution of Chapter 3 to the fisheries economics literature is the evaluation of the scale effect of spatial management decisions when harvest composition of target and non-target stocks is unknown to both the harvester and the regulator. The stylized simulation uses the characteristics of the West coast salmon fishery to structure the model. The model identifies critical economic and ecological interactions that affect fisheries economic performance. For example, the model shows that management of mixed-stock fisheries is complex given that spatial abundance and harvests are determined by the degree of concentration and migration patterns of individual stocks which change on a constant basis. Simulation results also show that management of weak stocks can be improved if the manager has the ability to monitor distribution of weak stocks at finer spatial scales. The implications of this work are policy relevant given ongoing efforts to reduce harvest of ESA listed salmon stocks which has resulted in area-temporal closure significantly affecting the livelihoods of salmon fishermen.

The dissertation has been organized as follows: Chapter 2 presents the essay titled Fishery Participation and Location Choice Model for the West Coast Salmon Fishery, as a standalone manuscript that includes an introduction, background, literature review, model, results and conclusions. Chapter 3 presents the essay titled Ecological Model of a Mixed-stock Fisheries which includes an introduction, background, literature review, mixed-stock fishery model, simulation scenarios, results and conclusion. An overall conclusion to the dissertation is provided in Chapter 4.

2 Fishery Participation Location Choice Model for the West Coast Salmon Fishery

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Abstract

The West Coast salmon troll fishery has experienced partial or total closure due to concerns on ESA listed stocks. We use rich vessel-landing level data describing fishing trips from West Coast salmon troll vessels from 2005 to 2014 on a random utility maximization framework to determine the effect of closures on the salmon fishery on the distribution of fishermen across fishing locations and alternative fisheries. The empirical model used expected revenue for different alternatives and vessel characteristics to predict fishery and fishing location choices. Our results suggest that fishermen respond to area-temporal closures in the salmon fishery by reallocating across space and across alternative fisheries. The responses depend on fishermens portfolio of fisheries. Our work also suggests that ignoring the ability of fishermen to move between fisheries may lead to both poor characterization of fishing behavior and poor prediction of the effect of spatial management policies.

[1]With Gil Sylvia and Dan Holland. This study was supported and monitored by National Oceanic and Atmospheric Administration (NOAA) under LMRCSC AB Grant 14-02. Data was used with the permission of the California Department of Fish and Wildlife, Oregon Department of Fish and Wildlife, and Washington Department of Fish and Wildlife.

2.1 Introduction

Spatial management measures are frequently used in fisheries. An extensive literature in fisheries economics focuses on how fishermen's behavior responds to changes in spatial policies and highlights the potential benefits of controlling spatial margins (Smith and Wilen 2003). Random Utility Maximization (RUMs) models are commonly used for modeling fishermen spatial behavior. In general, empirical work has found that fishermen respond to profits differentials across space, a result consistent with seminal fisheries economic theory (Gordon 1954). The majority of fishermen behavioral models are developed by modeling one fishery in isolation of other fisheries. Although unspoken, there is an assumption that changes in spatial policies of one fishery do not affect what occurs in other fisheries. However, a fisherman responses to spatial policies in one fishery may spill over to or be affected by other fisheries, especially in cases where fishermen participate across several fisheries on a seasonal or daily basis.

This research addresses the issue of modeling fishermen spatial behavior in consideration of other fisheries by developing a model of Fishery Participation and Location Choice (FPLC) and conducting an empirical investigation on how spatial and temporal closures, intended to protect species in one fishery, may affect fishermen's targeting behavior across space and across different fisheries. In particular, using a RUM framework a FPLC model is presented for the West Coast salmon fishery where concerns about ESA listed stocks or other weak stocks have driven routine closures of one, or many, salmon management areas and where fishermen participate in the salmon fishery along with potential participation in other fisheries including Dungeness crab, groundfish, albacore tuna, and/or other fisheries throughout the same fishing season.

Empirical results from the FPLC model are used to conduct policy simulation of salmon fishery area-temporal closures and are used to predict fishermen's responses in targeting salmon in open management areas or switching targeting to other available fisheries. This research fills a gap recognized in the ecosystem-based management literature, which calls for shifting the traditional paradigm of single-species modeling and management to paradigms that acknowledges the existence of multi-species interactions at the biological and economical level. This work highlights the importance of recognizing that spatial linkages are not only dictated by biological systems but also by economic conditions and fishermen's targeting behavior (Smith and Wilen 2003; Wilen et al. 2002).

The remainder of this manuscript is organized as follows. The next section provides background information about the West Coast troll salmon fishery and highlights the multiple fishery targeting and switching behavior of fishermen. Section 2 also describes the fishery participation and location choice data used in this work. Section three presents a literature review on fishermen behavioral models. Section four presents a behavioral model that characterizes the West Coast salmon fishery. The section also describe the choice set, the representative utility and the estimation and results of the expected revenue used to estimate parameters of the FPLC model. Section 5 presents results of the FPLC model and evaluates the effect of closures in the salmon fishery on the behavior of fishery participation. Conclusions are summarized in section 6.

2.2 Background

2.2.1 The West Coast Salmon Fishery

The West Coast ocean commercial salmon troll fishery is managed by the Pacific Fishery Management Council (PFMC hereafter) under the federal Magnuson-Stevens Fishery Conservation and Management Act. The PFMC develops commercial salmon regulation measures including fishing areas, seasons, quotas, legal gear, landing restrictions, and minimum lengths for salmon taken in the U.S. exclusive economic zone (3200 NM) off Washington, Oregon, and California. The management measures are intended to prevent overfishing and to apportion the ocean harvest equitably among treaty Indian, non-treaty commercial, recreational fisheries, Pacific Salmon Treaty, and ESA consultation (Council 2014). Commercial salmon fisheries management measures are defined at the following seven different management areas 1) NO: US/Canada Border - Cape Falcon, 2) CO: Cape Falcon Humbug Mt, 3) KO: KMZ Oregon Humbug Mt OR/CA border, 4) KC: KMZ OR/CA border Horse Mt, 5) FB: Horse Mountain Point Arena, 6) SF: Point Arena - Pigeon Point, and 7) MO: Pigeon Point USA/Mexico Border; management areas are depicted in Figure 2.1.

The commercial season usually starts at the beginning of May and ends in September/October of every year. The season length and management area-specific regulations are published by the National Marine Fisheries Services in the Federal Register at the beginning of March of each year. Furthermore, in-season closures and adjustments are common in the fishery. Concerns on ESA listed stocks [2] have led the PFMC to implement partial or total management area closures; the closures are either announced at the beginning of the season or established as an in-season action. For instance, in 2008 all management areas south of Cape Falcon were completely closed to commercial fishing due to concerns on escapement levels of the Sacramento River Fall Chinook and Klamath River Fall Chinook (Council 2009).

West Coast commercial salmon fishermen target two main species of salmon, Chinook (*Oncorhynchus tshawytscha*) and Coho (*Oncorhynchus kisutch*), using troll and gillnet gear methods. Salmon fishermen troll with a number of lures or baited hooks through the water using ”cannon balls” and spreader rigs at depths of up to 80 fathoms (PSMFC 2000). Many West Coast salmon troll fishermen also participate in other fisheries such as Dungeness crab (*Cancer magister*), highly migratory species such as albacore tuna (*Thunnus alalunga*), and the multi-species groundfish fishery.

The crab fishery usually opens early December in West Coast states and contin-

[2] Current ESA listed Chinook (*Oncorhynchus tshawytscha*) includes: Upper Columbia spring, Sacramento River winter-run (endangered), Snake River spring and summer, Snake River fall, Upper Willamette spring, Lower Columbia, Puget Sound, and California coastal (threatened)(Council 2014).

ues through August of the following year. Crab pots are used for most all commercial crabbing. The fishery is characterized by extremely high effort in the first part of the season, followed by a rapid decrease in effort as catch per unit effort decreases (PSMFC 2000). Crab season opening and closing dates, along with other regulations are established by California, Oregon, and Washington fish and wildlife agencies through the Dungeness crab tri-State process under the Pacific States Marine Fisheries Commission (PSMFC) [3]. Since 1995, the fishery has operated under a state managed limited entry permit system which capped the number of vessels allowed to participate in the fishery.

The Highly Migratory Species (HMS) fisheries are regulated by the PFMC and are among the few remaining open access fisheries on the West Coast. The Albacore tuna, the HMS species targeted by salmon fishermen, is harvested with troll gear and spreader rigs similar to salmon trolling. There are no seasonal restrictions in the albacore tuna fishery, however, the fishery generally starts in July and ends late September or early October when the fish are present (PSMFC 2000).

The groundfish fisheries include a number of species such as cod, rockfish, sole, flounder, and Pacific whiting. Most of the groundfish are harvested by trawlers using midwater or bottom trawl nets. However, black code (also known as sablefish) and some rockfish species are harvested by long-lines, pots, and other hook and line gear. The fishery is regulated by the PFMC and is composed of a limited entry and an open access sector. The fishery is managed through a number of measures including quotas, trip and landing limits, area restrictions, seasonal closures, and gear restrictions; management measures are implemented for a two-year period and adjusted through routine in-season actions.

[3] PSMFC website provides detail information on West Coast Crab fishery management `http://www.psmfc.org/program/tri-state-dungeness-crab-tsdc`

2.2.2 Data Description

To model West Coast salmon fishery participation and location choice behavior, Fish Ticket data was obtained from the Pacific Fisheries Information Network (PacFIN) with the permission of California Department of Fish and Wildlife, Oregon Department of Fish and Wildlife, and Washington Department of Fish and Wildlife. Fish tickets (FTs) are issued by a processor (or buyer) to a vessel selling its catch. On the West Coast, each state compiles and administers FT information. Copies of data are sent to the Pacific Fisheries Information Network who in turn standardizes FT entries.

FT information used in this analysis includes the fish ticket identifier, vessel identifier, landing date, landing port, species group identifier, quantity landed, unit price, and ex-vessel revenue. The data obtained from PacFIN corresponded to FTs associated to salmon trollers that landed 95 % of the total salmon troll fishery ex-vessel revenue per year during the years of 2005 to 2014. The complete number of FTs in the dataset total 268,741 associated with 619 vessels.

An individual fish ticket may record species from different fisheries if multiple species were landed and sold by the same vessel. For the purpose of this analysis, each individual fish ticket is assumed to describe attributes of a single fishing trip that target species from a single fishery. 6.5% of FTs in the dataset recorded species from multiple fisheries; of these FTs only entries from the species groups with the highest ex-vessel revenue were retained [4]. Information collected from FTs allows for the examination of fishery participation and location choice of salmon trollers, both described in the following subsections.

[4] To justify this selection criterion it is assume that the target species group of a fishing trip was the species group with the highest landing revenue; all other species landed were captured as bycatch.

2.2.2.1 Fishery Participation and Location Choice

FTs show that salmon fishermen participate in the salmon fishery but also in the following fisheries: crab, groundfish, highly migratory species (mainly albacore tuna), coastal pelagic, shellfish, shrimp, and others. Figure 2.2 displays weekly fishery participation for a random sample of 60 vessels for three arbitrary years [5]. The figure shows that the salmon fishermen fishing annual cycle appears to begin prior to the beginning of a calendar year by participating in the crab fishery, the months of November or December. The first fishery switch occurs when fishermen leave the crab fishery and start participating in the salmon fishery sometime during the month of May. A possible third switch occurs during the month of July when salmon fishermen start participating in the albacore tuna fishery. The fishery switch between the salmon fishery and the groundfish fishery is less obvious. Recall that the groundfish fishery operates all year round and does not have an opening and closing date as other fisheries. An additional observation from figure 2.2 is that no-participation behavior (represented in the figure as empty spaces) is highly recurrent among all vessels. The months of October and November appear to be an idle period for most of the vessels.

Figure 2.2 also suggests that fishery participation across fisheries is highly diverse, neither all vessels target a single fishery nor the majority participate in all fisheries. The figure shows that some vessels only target salmon and some others participate in two or more combination of fisheries. Table 2.1 shows the percentage of vessels that participate in the most representative combinations of fisheries across all years. For instance, only 14% of vessels in the sample participated only in the salmon fishery, while 23%, 16%, 11%, 9%, and 7% participated in the following fisheries

[5] Individual Fish Tickets were aggregated on a weekly basis to create a panel dataset that record observed fishery participation for all vessels at the same time step. Panel data of weekly fishery participation allows for the creation of a "no-participation" choice for any one week interval in which a vessel did not record a single Fish Ticket. Furthermore, weekly fishery participation allows comparing expected revenues across fisheries with fishing trips of different lengths. While crab, groundfish, and salmon trips have a mean number of days fished close to one, albacore tuna trips have a mean number of days fished per week equal to 5.8.

combinations: salmon-highly migratory, salmon-highly migratory-crab, salmon-crab, salmon-crab-groundfish, and salmon-highly migratory-crab-groundfish respectively [6].

The switching behavior of vessels that participate in any combination of two fisheries is depicted in Figure 2.3 and the behavior of vessels that participated in three fisheries is depicted in Figure 2.4. From figures 2.3 and 2.4 one can see that as the salmon season opens, fishermen that also participate in the crab fishery start leaving the crab fishery to participate in the salmon fishery. In some cases, fishermen continue participating in the crab fishery after participating in the salmon fishery; this participation behavior appears to be the exception rather than the rule. Fishermen that participate in the highly migratory fishery also follow the same pattern; first they participate in the salmon fishery early in the salmon season and then switch to the highly migratory fishery early July. For vessels that participate in both the salmon and groundfish fishery, the switching behavior is more intermittent. Once a vessel starts participating in the salmon fishery it will most likely continue to participate in the groundfish fishery as well. While figures 2.3 and 2.4 show the switching behavior of vessels in 2014, the behavior is consistent across all years in the sample.

Fish tickets provide area catch information at a coarse spatial scale that differs across fisheries. Unlike some other fisheries, there are no logbooks showing catch location in the salmon fishery. Because catch-area information does not allow forming mutually exclusive fine-scale fishing location choices common to all fisheries, landing location was used as a proxy for fishing location choices. Each landing port and its corresponding fishing trips were assigned to a unique salmon management area that included the port area. Although salmon management areas provide only a coarse-scale fishing location choice, they are the best available first-approximation choice for modeling the effects that spatial-temporal closures in the salmon fishery have across space and participation on other fisheries.

[6] A vessel was considered participant of a given fishery (other than the salmon fishery) if at least on 5% of the its total choice occasions, during the entire period of 2005-2014, the vessel chose to participate in such fishery. 5% threshold was chosen arbitrarily.

Observed weekly fishery participation and location choice serves as the main data for modeling the behavior of the West Coast salmon fishermen. For the purpose of this work, a choice occasion is defined as every observed weekly choice made by 1,371 salmon vessels from 2005 to 2014. In particular, observed weekly choices (i.e. weekly aggregated fish tickets) are used to create variables that record past behavior, such as last choice indicator, and expected revenue variable. In conjunction with fish ticket data PFMC records were used to create a dataset that records commercial salmon opening and closing days, as well as in-season closures, for all management areas for 2005 to 2014. A summary of actual commercial non-Indian troll salmon fishing regulations are published by the PFMC in its yearly Stock Assessments and Fishery Evaluation (SAFE) documents [7].

2.3 Literature Review on Fisherman Behavioral Models

Fishermen make decisions affecting their livelihoods and their lives daily and even hourly (Holland 2008). In the economics literature these decisions are often represented with a set of discrete alternatives, which fishermen evaluate with rich - though incomplete and imperfect- information and then choose a single option among the alternatives. Some of alternatives that determine fishing behavior include: when to go fishing (entry/exit fishing participation), what species to target (fishery choice), how to fish (gear choice), and where to fish (fishing location choice). These discrete decisions are determinants of fishing effort and understanding fishing effort is critical to the successful management of fisheries (Wilen et al. 2002).

For policy purposes, effective modeling of marine ecosystems may only be achieved when resource user behavior is included (Putten et al. 2012). Thus, a central motivation for modeling fishermen behavior is help fishery managers predict how fishing fleets will respond to new management policies or changes in other environmental

[7] www.pcouncil.org/salmon/stock-assessment-and-fishery-evaluation-safe-documents/

and economic factors. For example, understanding how fishermen respond to spatial policies, such as marine reserves, allows fishery managers to predict the redistribution of fishing effort across space after forming marine reserves (Smith and Wilen 2003; Wilen et al. 2002). Modeling fishermen behavior allows us to answer questions such as: will fishermen respond to new policies by changing entry/exit behavior, switching fishing locations, and/or targeting different species? Do adjustments in behavior significantly minimize/maximize potential losses/gains in resource rents? Or could behavioral changes result in unintended consequences? As an academic research, understanding behavior allows researches to inquire whether open access inefficiencies cuts across all aspects of fishermen decision-making, and whether fishery rents are dissipated, or not, due to inefficiencies in species targeting, gear choice, location choice or other types of behavior.

The purpose of this literature review is to describe the set of empirical applications that have been used to explain behavior, specifically empirical applications that characterize behavior as fishermen use of information to choose across discrete alternatives. The review provides an introduction to methods of estimation of discrete choice models, identify key drivers that have been considered in the empirical application of these models, and surveys the contribution of these methods.

2.3.1 Economic Modeling of Fishermen Behavior

In the natural resources economics literature, models representing fishermen decision-making are based on a foundation of microeconomics. Fishermen are considered rational decision makers that use available information to construct estimates of the expected utility of choices they face and select the choice with the highest expected utility (Wilen et al. 2002). To study behavior as a decision-making process of choosing across a set of discrete alternatives, researchers have relied on expected utility theory and a wide array of discrete choice models, known as Random Utility Models (RUMs). In RUMs, fishermens discrete decisions are statistically related to a set of variables characterizing alternatives attributes as well as fishermen characteristics.

Discrete choice models were first used to model travel choice (McFadden 1974). Soon after McFadden 1974 pioneering work, the RUM framework was used to model fishery choice under uncertainty (Bockstael and Opaluch 1983), fishery entry-exit decision (Eales and Wilen 1986), fishing location-species choice (Holland and Sutinen 1999; Zhang and Smith 2011), and fishing location choice (Smith 2005; Smith and Wilen 2003; Smith 2002; Haynie and Layton 2010). In general, these studies have found fishermen behave consistent with economic theory by making choices among discrete alternatives that optimize their expected utility of returns.

2.3.2 Theoretical Basis to Model Fishermen Behavior

To describe the RUM literature in detail, first one needs to describe the structural model that is common to all applications. The basic structure of a RUM is derived as follows: Lets denote the utility that a fisherman n obtains from alternative j at time t as U_{njt}. Where alternative j pertains to the set of discrete alternatives (i.e. $j \in 1, 2, ..., J$) and t pertains to the discrete time period $t = 1, ..., T$. The fisherman $n's$ problem in time t is to choose the alternative j that generates the highest utility, that is:

$$\max_{j \in \{1,...,J\}} \{U_{n1t}, ..., U_{nJt}\} \tag{2.1}$$

The fisherman $n's$ payoff at each time t will equal the utility of alternative j if and only if alternative j provides the highest utility among all alternatives (i.e. $U_{njt} > U_{nit} \forall i \neq j$). Utility, U_{njt}, is only known to individual fishermen but not to the researcher. However, researchers observe some attributes of the alternatives faced by the fishermen, named $\tilde{X}_{njt}$, as well as some attributes to the decision maker, $\tilde{Y}_{nt}$, and a vector of history of past choices, $\tilde{D}_{nt}$. Given observed attributes of choice occasions, researchers might specify a function that relates these observed factors to the fishermen utility with the following linear approximation of *representative utility*:

$$V_{njt} = \beta_1 \tilde{X}_{jt} + \beta_2 \tilde{Y}_{nt} + \beta_3 \tilde{D}_{nt} \tag{2.2}$$

where the vector of parameter, $\beta =< \beta_1, \beta_2, \beta_3 >$, are unknown and to be estimated statistically. Furthermore, we as researchers do not or cannot observe all aspects of utility (i.e. $U_{njt} \neq V_{njt}$), thus utility is decomposed as:

$$U_{njt} = V_{njt} + \varepsilon_{njt} \tag{2.3}$$

where ε_{njt} is a vector of unobservable not included in V_{njt}; ε_{njt} is simply defined as the difference between fishermen utility and the part of the utility that the researcher captures in the representative utility. The goal of RUMs is to represent the representative utility, V_{njt}, such that the unobserved part of the utility can be treated as purely random noise.

Given that researchers do not know ε_{njt}, the term is treated as random. Denoting the joint distribution of the vector $\varepsilon_n = \varepsilon_{n11}, ..., \varepsilon_{nTJ}$ as $f(\varepsilon_{njt})$, we can make probability statements about the fishermens choices. Following Train 2009 one can state that the probability that a fisherman n chooses alternative j at time t as:

$$\begin{aligned} P_{njt} &= Pr(\max_{j \in \{1,...,J\}} \{U_{n1t}, ..., U_{nJt}\}) \\ &= Pr(U_{njt} > U_{nit} \forall i \neq j) \\ &= Pr(V_{njt} + \varepsilon_{njt} > V_{nit} + \varepsilon_{nit} \forall i \neq j) \\ &= Pr(\varepsilon_{njt} - \varepsilon_{nit} < V_{nit} - V_{njt} \forall i \neq j) \end{aligned} \tag{2.4}$$

This cumulative distribution can be written as:

$$P_{njt} = \int_{\varepsilon} I(\varepsilon_{njt} - \varepsilon_{nit} < V_{nit} - V_{njt} \forall i \neq j) f(\varepsilon_n) d(\varepsilon_n) \tag{2.5}$$

where $I(\bullet)$ is the indicator function equal to 1 when the expression in parenthesis is true and 0 otherwise. Different choice models are obtained from different specifications of this density. All empirical discrete choice models that seek to explain fishermen behavior presented in this literature review are special cases of this RUM specification (equation 2.5) and seek to estimate parameters associated with the representative utility in equation 2.2. The estimation procedure however varied on the different assumptions about the distribution of the unobserved portion of the utility, ε_{njt}, as represented in the following equation:

$$\begin{aligned} U_{njt} &= V_{njt} + \varepsilon_{njt} \\ U_{njt} &= \beta_1 \tilde{X}_{jt} + \beta_2 \tilde{Y}_{nt} + \beta_3 \tilde{D}_{njt} + \varepsilon_{njt} \end{aligned} \tag{2.6}$$

2.3.3 The Early Work

The literature that seeks to explain fishermen behavior build up on Bockstael and Opaluch 1983 who developed a discrete choice model of fishery choice (what species to target) to study the role of uncertainty in behavior. In this context alternative j corresponds to a fishery alternative. In their work, the representative utility is a function of fishermans wealth, w_{njt}, and past behavior denoted by $D_{njt} = 1$ when fishery j was the alternative chosen by fisherman n at time $t-1$. Wealth is composed of initial wealth, W_{n0}, and the random return from the j fishery alternative denoted by R_{njt}. Expected revenue $E(R_{njt})$ is estimated based on a weighted average of observed lagged revenue. Risk preferences are evaluated by including a parameter on the variance of the expected revenue. Bockstael and Opaluch 1983 representative utility is written as:

$$V_{njt} = f(W_0, E(R_{njt}), Var(R_{njt}), D_{njt}; \beta) \tag{2.7}$$

where β is the vector of parameters associated with each of the observed components of the representative utility. By assuming that each unobserved parts of the utility, ε_{njt}, are independently, identically distributed Extreme Value [8], their discrete choice model follows the logit specification which conveniently has the following closed form expression:

$$\mathrm{P}_{njt} = \frac{e^{V_{njt}}}{\sum\limits_{i \neq j} e^{V_{nit}}} \tag{2.8}$$

[8] Bockstael and Opaluch 1983 erroneously called this distribution a Weibull distribution.

Given the form of this choice probability, the estimated vector of parameters β are further obtained by maximum likelihood estimation.

To estimate the fishery participation model, Bockstael and Opaluch 1983 use the fishery alternatives faced by New England fishermen. Their data consisted of yearly fishery participation during the years 1975 and 1976. In their work, the authors find evidence that relative returns affect the redistribution of effort. Additionally, they also found a strong bias among fishermen toward remaining within the same fishery over time.

The discrete choice model used by Bockstael and Opaluch 1983 is closely replicated to study day-to-day decisions of where to fish (i.e. fishing location choice) for the California Pink Shrimp Fishery (Eales and Wilen 1986). In this work, fisherman n chooses fishing location j at all times t. The representative utility is composed by proxies variables for expected profits, expected catch $E(C_{jt})$, and distance from homeport $(Dist_{jt})$, both alternative-specific variables.

Contrary to Bockstael and Opaluch 1983, Eales and Wilen 1986 expected catch is obtained with a linear regression of period t mean catches in alternative j against those same means for only 1 lag (i.e. period $t-1$) instead of a weighted average of past observations. Although no clear definition of the structure of the unobserved components of utility is provided, the authors employ a multinomial logit specification which assumes that unobservable errors are iid Type I Extreme Value distributed. To estimate their model, Eales and Wilen 1986 use daily location choice observations of the Pink Shrimp Fishery for the 1976 season. The authors' estimated RUM parameters support the hypothesis that fishermen behavior responds positively to expected profits across fishing grounds. Furthermore, the authors argue that their results provide evidence for short-run ground-specific rent dissipation which occur given the observed excessive moving in response to changes in profitable hot spots (Eales and Wilen 1986).

Along the same line of analysis of Bockstael and Opaluch 1983 and Eales and

Wilen 1986, Ward and Sutinen 1994 use a discrete choice model to estimate a fishery participation model (enter, exit, or remain in the fishery) using the case of the Gulf of Mexico shrimp fishery. Much like Bockstael and Opaluch 1983 work, Ward and Sutinen 1994 design their behavioral model recognizing that individual fishermen do not necessarily exploit a single stock of fish and choose the alternative that provides the highest benefits. However, contrary to past work, Ward and Sutinen 1994 develop a structural fishermen behavioral model that includes biological stock information. The model is structured according to the assumption that a fisherman n acts to maximize the present value of profits for all alternative, j, and that the shrimp stock declines according to a Ricker specification. The fisherman's problem is to maximize effort e_{nj} according to

$$
\begin{aligned}
U_{nj} &= \max_{e_{nj}} \int_{t=0}^{T} e^{\delta t} \pi_j dt \\
s.t.\ B_j(t) &= B_j(t)[g_j - m_i - f_i]
\end{aligned}
\tag{2.9}
$$

This specification introduces a number of new features to the decision-making process of the fishermen. For instance, the authors explicitly introduce total biomass $B_j(t)$ of fish stock in fishery j, individual growth rate $g_j(t)$, natural mortality m_j, and fishing mortality f_j which in turn depends on catchability of fishing gear and the total number of vessels participating in fishery j. The solution to the structural behavioral problem allowed Ward and Sutinen 1994 to define their representative fishery benefit, V_{njt} as follows:

$$
V_{nj} = \sum_{K} \beta_{kj} X_{kj} \ \ \forall j \in J \tag{2.10}
$$

where X_k is a vector of exogenous alternative-specific variables that includes exvessel prices, operating costs, stock abundance, and fleet size (which is intended to account for crowding externalities). Contrary to Bockstael and Opaluch 1983, the authors classify the observed choices (i.e. fishery chosen) to one and only one of the following outcomes 1) enter the shrimp fishery from some alternative fishery, 2) enter from outside the fishing industry, 3) remain in the shrimp fishery, or 4) retire from the fishing industry. This set of choices allows restating the fishery choice model as a participation model (i.e. entry/exit formulation). To estimate parameters in the representative fishery benefit function, the authors use a multinomial logit model consistent with equation 2.8.

Supporting the Bockstael and Opaluch 1983, Ward and Sutinen 1994 find empirical evidence that fishermen adjustments across fisheries are sluggish and that fishermen are more willing to enter the fishery in response to an increase in profits but less likely to exit when profits decline. The authors argue that this result is due to Bockstael and Opaluch 1983 claim of persistency for choosing the same alternative as past choices (i.e. state dependence). However, Ward and Sutinen 1994 do not explicitly use past behavior to characterize their representative utility function.

Ward and Sutinen 1994 work introduce evidence of two new elements in the decision making process, crowding externalities and stock abundance. According to their estimation, the probability of entry (exit) in the shrimp fishery is mitigated (enhanced) by the size of the fishing fleet. Increase in stock abundance is associated with a positive probability of entering the shrimp fishery. Although the authors advocate that introducing fleet size and stock abundance allows for a better characterization of behavior, one will assume that expected profits (or expected revenue, price, or catch) will be highly correlated with these two variables; the authors however do not account for this possible correlation across alternative-specific variables.

While Ward and Sutinen 1994 introduce a structural model to explain behavior that differs from model stated in equation 2.1, their discrete choice model (multinomial logit) is the similar to one derived from earlier specifications (equation 2.8). While Ward and Sutinen 1994 fisherman's problem formulation introduces fishery choice as a dynamic problem, their econometric specification is static in nature and not different than the discrete choice framework used in previous literature (Bockstael and Opaluch 1983; Eales and Wilen 1986).

On all the papers described above, the logit specification (equation 2.8) has been the framework to estimate parameters of the representative utility function. Additionally, theses early papers seek to explain behavior as a single level decision-making process. For instance, the choice of where to fish is analyzed in isolation from the choice of which species to target. This approach is valid if one argues that fishermen make fishery participation and fishing location choice across different time frames. For instance, entry/exit may often correspond to longer run time horizons while fishery choice may correspond to decisions made on shorter-run time horizons. On the other hand, fishing location choices may correspond to the shortest time frame, often day-to-day. While characterizing entry/exit, fishery choice, and location choice behavior in isolation may apply to many fisheries, there are some other fisheries where these choices are made jointly and within the same time frame. For example, fishermen may make a fishery and location choice decision on a trip-to-trip basis within the same fishing season. When this situations occur, a discrete choice modeling approach that models fishery and location choice separately may fail to explain observed behavior.

A second shortcoming of relying on the logit specification is derived from the assumption that each unobserved part of the utility function is independently identically distributed Type I Extreme Value. This independence assumption means that the unobserved portion of the utility of fisherman n for alternative j at time t is unrelated to the unobserved portion of the utility for the same fisherman n for any other alternative $i \neq j$. This assumption implies that the unobserved components of utility are uncorrelated across all fishermen, $n \in N$, and all time $t \in 1, 2, ..., T$. In a well-specified model, it is reasonable to assume that the unobserved part of the utility for one alternative does not provide any information about the unobserved part of the utility of any of other alternatives. Although this is a crucial element of the identification strategy none of the authors formally justify the independence assumption, it appears that logit model was chosen rather by convenience.

Using the logit specification also imposes a very specific substitution pattern across alternatives (Train 2009). It can easily be shown that the ratio of choice probabilities across two alternatives (i.e. P_{njt}/P_{nit} for $i \neq j$) remains constant no matter what attributes characterize the other alternatives; this is formally known as independence from irrelevant alternatives, or IIA. This property of the logit specification also suggests that the existence of fishery k does not change the substitution pattern between fishery j and fishery i. None of the authors in the earlier literature discussed how substitutability across alternatives can be assumed to be constant for all fishermen. Failing to justify the independence assumption and the existence of IIA property inherent to the logit model raises questions on the modeling strategy chosen on earlier studies.

2.3.4 Heterogeneity and Substitutability Patterns

Isolation of decision-making and IIA property is addressed in Holland and Sutinen 1999 whose behavioral model assumes that fishermen make a species and location choice on a trip-by-trip basis [9] motivated by the New England trawl fishery. Under their modeling approach, species and location choice is a multi-level decision process; the decision of what species to target on a given trip is typically made before leaving the port while the location choice is made during the trip. In this model, a fisherman n is assumed to first choose a species/zone combination $k \in K$. Once the alternative k has been chosen, fisherman makes a fishing location choice among the $j \in J$ alternatives [10], this sequence of hierarchical choices are made at discrete time t. The structure of this behavioral model required the representative utility to be decomposed as follows:

$$U_{njt} = \alpha W_{njt} + \beta Z_{nkt} + \phi Y_{nt} + \varphi D_{nt} + \varepsilon_{njt} \tag{2.11}$$

[9]A similar approach is presented in Smith 2002. In this work a fisherman n is assumed to first choose whether or not to participate in the California Sea Urchin fishery and then choose a fishing location choice each open season day.

[10]Examples of species/zone combinations are groundfish on George Banks or squid in Southern New England. Area choices are defined by three digit statistical areas within zones

where alternative-specific variables, X_{jt} in equation 2.4, are further decomposed into variables W and Z. The vector W contains variables that differ across fishing location j while the vector Z contains variables that are constants across fishing location but differ across species/zone combinations. By developing this multi-level decision making process the authors warrant that the IIA property holds only for location choice alternatives within a species/zone nest but not across location alternatives from different species/zone level $k \in K$. This implies that the unobservable part of the utility function, ε_{njt}, are correlated across fishing location alternatives within a species/zone nest but uncorrelated across fishing locations for different nest. Accounting for correlation across fishing locations within fishery/zone the author assume that the unobserved part of the utility are jointly distributed as a Generalize Extreme Value (GEV) distribution so that the choice probability can be written as follows:

$$\mathrm{P}_{njt} = \mathrm{P}_{n,j|k,t} \cdot \mathrm{P}_{nkt} \tag{2.12}$$

also known as nested logit specification. In this specification, the choice probability of choosing fishing location j is decomposed into a marginal, P_{nkt}, and conditional probability $P_{n,j|k,t}$ [11]. It is fundamental to note that what drives the choice probability to be specified as a nested logit is not the hierarchical structure of the decision-making process but the assumption about the correlation across the unobservable parts of the alternative's utility.

Holland and Sutinen 1999 also introduce a new set of factors to specify the representative utility. In addition to the traditional expected revenue variable, $E(R_{jt})$, the authors introduces: 1) lagged average revenue variables to account for both information sharing and the seasonality patterns across fisheries, 2) coefficient of variation of lagged revenues to account for riskiness in behavior, 3) lagged total effort to proxy for local stock abundance and depletion, and 4) individual historical fishery and location choices to account for past behavior (called *habits* variables). The novelty of the

[11] With this nested logit specification both the marginal and the conditional probabilities take the form of a standard logit specification (Train 2009)

introduction of a set of lagged variables is to fully account for the dynamics related to observed choices that enter the decision-making process; that is, the influence of past choices on current choice. The introduction of this set of *habit* variables improves the identification strategy given that it accounts for dynamics in observed behavior and for heterogeneity in taste. Furthermore, while including lagged variables allows accounting for both heterogeneity and state dependence it does not discard the possibility that unobserved attributes of utility may be correlated over time. Holland and Sutinen 1999 were unable to distinguish between heterogeneity and true state dependence with this approach.

Fishermen heterogeneity and risk preferences is studied under the random utility framework by Mistiaen and Strand 2000 whose develop a location choice model of the East Coast and Gulf longline. Their model build on the assumption that fisherman $n's$ utility of choosing alternative j in time t is defined according to equation 2.3. However, they allow for the possibility that fishermen tastes vary systematically with respect to observed variables. In such a case, the value that each individual fisherman places on the attribute of the representative utility varies over fishermen so that individual fisherman n utility of choosing alternative j in time t can be written as follows:

$$U_{njt} = \alpha_n X_{jt} + \beta_n Y_{nt} + \varphi_n D_{nt} + \varepsilon_{njt} \tag{2.13}$$

where $\alpha_n, \beta_n,$ and φ_n are parameters specific to each fisherman. Note that this representative utility is the same as equation 2.6 with the addition that parameters are allowed to vary across individual fishermen. Mistiaen and Strand 2000 argue that this utility function is particularly relevant when considering risk preferences which are not necessarily identical over fishermen when choosing fishing location. Following Bockstael and Opaluch 1983, Mistiaen and Strand 2000 utility function is defined as follows:

$$E(U_{njt}) = EU(\beta_n, X_{njt}) + \varepsilon_{njt} \tag{2.14}$$

where the vector X_{njt} includes expected profits and the variance of expected profits and β_n is a vector of fishermen specific parameters. As usual ε_{njt} is unobserved by the researchers but so are the β_n parameters. Although unknown to the researchers, they assume that individual preferences, β_n, follow a density of the form $f(\beta|\theta)$, where θ are the locations and scale parameters of the distribution. Given than both ε_{njt} and β_n are random terms if one assumes that ε_{njt} are distributed iid Type I Extreme Values one can integrate out β_n so that the probability that fisherman n choose alternative j at time t can be written as:

$$P_{njt} = \int \frac{e^{V_{njt}}}{\sum_{i \neq j} e^{V_{nit}}} f(\beta|\theta) d\beta \tag{2.15}$$

The authors used simulation methods to estimate parameters that characterize the distribution of the representative utility which they found to not be statistically significant, thus, the authors fail to reject the hypothesis that fishermen display heterogeneous risk preferences. Although their work introduces a new methodology to account for heterogeneity in taste, their specification only account for expected profits and it failed to account for other sources of variation that may explain fishermen behavior, such as state dependence variables as used in Holland and Sutinen 1999.

Smith 2005 presents a fishing location choice model that controls for and distinguishes state dependence from heterogeneity, allowing to examining the implication of ignoring one or both sources of unobserved heterogeneity. Smith 2005 work is facilitated by the availability of a time series data of repeated choices (needed to model state dependence) from multiple fishermen (needed to model heterogeneity) of the California sea urchin fishery. The representative utility includes a mixed logit specification to represent preference heterogeneity (Mistiaen and Strand 2000), and variables that describe past behavior (Bockstael and Opaluch 1983; Holland and Sutinen 1999). Build on the basic RUM specification as in equation 2.6, Smith 2005 alternative specific utility can be restated as:

$$U_{njt} = \beta_n X_{jt} + \delta D_{njt} + \varepsilon_{njt} \tag{2.16}$$

where the covariates X_{njt} are alternative-time specific variables that affect utility, such as expected revenue and a proxy for cost, and covariates in D_{njt} are individual-alternative-time specific variables that describe fishermen n past choices. The vector of parameters β_n are fisherman specific (i.e. varies across fishermen) and follows a multivariate normal distribution $\beta_n \sim MVN(\bar{\beta}, \Omega)$. In contrast to Holland and Sutinen 1999, who capture past choices as a set of dummy variables, Smith 2005 defines the state dependence covariate as a convex combination of previous periods decisions. Formally, state dependence is defined as a function that evolves according to the following equation:

$$D_{njt} = \alpha^{t-1}\tilde{D}_{nj1} + (1-\alpha)\sum_{\tau=2}^{t}\alpha^{t-\tau}y_{nj\tau-1} \tag{2.17}$$

where α operates like a discount factor of past choices, $\tilde{D}_{nj1}$ is a set of initial conditions for all $n \in N$ and $j \in J$, τ is an index of time. To estimate parameters of the representative utility the author assumes that the unobservable part of the utility ε_{njt} are iid Type I Extreme Value distributed so that the choice probability takes the usual logit specification as in equation 2.7. However given that alternative-specific parameters are assumed to be random, the deterministic portion of the representative utility is integrated over the random parameter distribution so that the choice probability can be written as:

$$P_{njt} = \int \frac{e^{\beta_n X_{jt} + \delta(\alpha^{t-1}\tilde{D}_{nj1} + (1-\alpha)\sum_{\tau=2}^{t}\alpha^{t-\tau}y_{nj\tau-1})}}{\sum_{i\neq j} e^{\beta_n X_{kt} + \delta(\alpha^{t-1}\tilde{D}_{nk1} + (1-\alpha)\sum_{\tau=2}^{t}\alpha^{t-\tau}y_{nk\tau-1})}} f(\beta|\theta)d\beta \tag{2.18}$$

To estimate the choice probability, the author estimates $\alpha, \beta s$, and δ jointly with simulated maximum likelihood, and the initial conditions are estimated exogenously (which the authors recognize is a caveat in their estimation approach).

Smith 2005 comparison across different specifications ignoring heterogeneity or state dependence or both provides provoking results. The results suggest that serial correlation among observed choices can be reduced by accounting for both heterogeneity and state dependence. However, modelling only for heterogeneity and excluding state dependence may magnify the apparent preference heterogeneity; as the author points out the potential spurious preference heterogeneity arises when state dependence is not modeled. This could be viewed as the converse of the problem explored in Heckman 1981, where the emphasis was on the emergence of spurious state dependence if heterogeneity is not modeled.

Sorting models have recently arisen in the fisheries economics literature as an alternative to model fishermen behavioral heterogeneity. Particularly, the work of Zhang and Smith 2011 draws from the industrial organization literature to incorporate observable heterogeneity in the representative utility function to model repeated choices of fishery choice (what species to target) jointly with fishing location choice (where to go fishing). Their model builds on the standard utility function as stated in equation 2.6. Suppose that the value that fishermen place on the alternative-specific attributes varies over fishermen, much like in Mistiaen and Strand 2000 and Smith 2005, thus one can write the utility function as follows:

$$U_{njt} = \alpha_n X_{jt} + \beta Y_{nt} + \varepsilon_{njt} \tag{2.19}$$

where the vector parameter associated with alternative-specific characteristics, α_n, varies over fishermen; reflecting difference in taste with respect to alternative-specific attributes. For instance, in the fishing location choice problem, fishermen with small vessels are likely to travel shorter distances (i.e. prefer fishing location choices closer to home port) than fishermen with larger vessels. In such case, one will assume that the value of the effect of travel distance, denoted by α_n, varies with the size of the vessel (called $Lenght_n$) owned by fisherman n, but nothing else, thus one can write the relation as follows:

$$\alpha_n = \gamma Length_n \tag{2.20}$$

γ captures the marginal effect of that length has on the value that fishermen n place on travel distance. Substituting this relationship in original utility function 2.19 produce:

$$U_{njt} = \gamma Length X_{jt} + \beta Y_{nt} + \varepsilon_{njt} \tag{2.21}$$

Under the assumption that unobservable part of utility are iid Type I Extreme Value distribute, a standard logit (equation 2.7) can be used to infer structural parameters that characterize behavior and that account for preference heterogeneity. The basic principle of this sorting approach is to include a wide array of observable features that distinguish fishermen (i.e. sorting) to characterize sources of heterogeneity. Under this modeling method utility of alternatives are expressed as a function of fishermen characteristics interacting with alternative-specific characteristics.

The work of Zhang and Smith 2011 make use of survey data on individual fisherman along with observed daily trip information to model species and location choice in the Gulf of Mexico reef-fish fishery. They characterize the representative utility as a function price, CPUE, distance as a proxy for travel cost, and whether the alternative was a marine reserve; all those are alternative-specific variables. To fully account for observed heterogeneity the authors interact survey data (e.g. vessel speed, vessel length, fisherman income, and age) with species-location specific variables to estimate parameters of the representative utility (equation 2.19). Estimated parameters along with observed individual attributes are used to evaluate the estimated distribution of individual preferences.

While Zhang and Smith 2011 use sorting models to account for observable heterogeneity, the work fails to account for unobservable heterogeneity that may be correlated over time and across choices. Recall that a logit fails to be a correct specification when there is a heterogeneity in fishermen preference that cannot be observed, causing the unobservable component of the utility, ε_{njt}, to be serial correlated so that the iid assumption does not hold. An extension to Zhang and Smith 2011 sorting approach is to include habit variables in a richer representative utility to control for unobservable heterogeneity due to state dependence.

2.3.5 The Dynamic Approach

State-of-the-art discrete choice modeling in fisheries economics has focused on fully accounting for the dynamic behavior of fishermen. In most models, fishermen have been assumed to be myopic and dynamic behavior has been modeled by accounting for the effects that past choices have in predicting current choices. However, the underlying behavioral model that generates observed choices can be described as dynamic not only if the representative utility contains past choices, or if the unobservable part of the representative utility is serial correlated, but also if one assumes that fishermen are forward looking. Provencher and Bishop 1997 and Robert L Hicks and Schnier 2006 move away from the traditional modelling of myopic behavior by characterizing fishermen participation in a dynamic framework, Huang and Smith 2014 also do so in a game setting to account the decision by other fishermen.

In the RUM static models described above there was no connection between the current decision and future utility, except for framework described by Ward and Sutinen 1994. However, one can argue that fishermen make choices as part of temporal strategic behavior that accounts for future benefits as well as current benefits so that fishermen can be considered to display forward looking behavior. Consistent with the RUM framework, a fisherman n receives a utility U_{njt} from choosing alternative j at time t. Assuming that alternative j generates the highest utility at time t (consistent with equation 2.1) and that fisherman n considers the impact of current choices on future payoff, following Huang and Smith 2014 one can define fisherman n objective at time period t as choosing alternative j to maximize the following expected utility:

$$\max_{j_t \in J} E\left[\sum_{t=\tau}^{T} \lambda^{\tau-1} \left(U_{nj\tau} | S_{nj\tau}\right)\right] \tag{2.22}$$

where $E[\bullet]$ represents fisherman $n's$ expectation operator, U_{njt} is the alternative-specific utility that provide the highest utility in period $t = \tau$, λ is the discount factor, and S_{njt} is the vector of state variables that affect maximum utility at $t = \tau$. The state space at t consists of the same elements as in the static model, $S_{njt} = \{X_{jt}, Y_{nt}, \varepsilon_{njt}\}$.

Let $\bar{V}_t(S_{njt})$ be the maximum expected present discounted value of remaining lifetime utility at $t = 1, ..., T$ given the state space S_{njt} and discount factor λ,

$$\bar{V}_t(S_{njt}) = \max_{j_t \in J} E\left[\sum_{t=\tau}^{T} \lambda^{\tau-1} \left(U_{nj\tau} | S_{nj\tau}\right)\right] \tag{2.23}$$

This value function, $\bar{V}_t(S_{njt})$ can be written as the maximum over all j alternative specific value function, $\bar{V}_t(S_{njt})$ for $j \in 1, ..., J$, that is

$$\bar{V}_t(S_{njt}) = \max\left[\bar{V}_{1t}(S_{n1t}), ..., \bar{V}_{Jt}(S_{nJt})\right] \tag{2.24}$$

Under this formulation, each of this alternative-specific value functions represents the utility for each alternative, V_{njt}, as defined in equation 2.2. The crucial difference is that representative utility in the dynamic case also accounts for future benefits. Following the principle of optimality, each of the alternative-specific value function obeys the Bellman equation:

$$\bar{V}_{jt} = U_{njt} + \lambda E\left[\bar{V}_{t+1}(S_{t+1}) | S_t\right] \tag{2.25}$$

The expectation is taken over the distribution of random components of the state space at $t+1$ and ε_{njt+1} conditional on the state space elements at t. To calculate these alternative-specific value function one needs to be able to calculate $E\left[\bar{V}_{t+1}(S_{t+1}) | S_t\right]$ at all values of the observable part of the state space, $S^{-}_{njt+1} = \{X_{jt+1}, Y_{nt+1}\}$, that may be reached from the state space elements at time t. A full solution of the dynamic programming problem consists on finding

$$E\bar{V}_\tau(S_{njt}) = E \max\left[\bar{V}_{1t}(S_{n1t}), ..., \bar{V}_{Jt}(S_{nJt})\right] \tag{2.26}$$

for all values of S^{-}_{njt+1} at all $\tau = \tau + 1, ..., T$.

Similar to the static discrete choice model, the dynamic discrete choice model can be used in the estimation of the structural parameters defined in the representative utility; however, given the dynamic nature of the model one also is interested in estimated transition probabilities for the state variables, X_{jt} and Y_{nt}. As in the static model, the estimation criterion is based on the assumption regarding the unobservable part of the state space, ε_{njt}.

Huang and Smith 2014 dynamic discrete choice model uses daily fishing participation choices of the North Carolina shrimp fishery. In this work, the fishermen act at every time step t and make a binary choice of whether to fish or not to fish. The utility derived from participating in the fishery is assumed to be defined by the revenue generated by the expected harvest, h_{nt}, minus the cost of fishing. Variables in the expected harvest and the cost of fishing correspond to the state variables, $S^{-}_{njt} = X_{jt}, Y_{nt}$. These variables are alternative-specific state variables, X_{njt} (such as price, wind speed, wave height, fuel price, stock index, and number of vessels fishing) and fishermen specific state variables Y_{nt} (such as length of the vessel and individual catchability coefficient).

In contrast to the static approach, in a dynamic settings a transition function must be defined for each of the state variables. Huang and Smith 2014 model the state variables as stochastic exogenous variables, except for the endogenous stock index (which is modeled as a discrete time stochastic difference). To define the alternative-specific expected utility of fisherman n, the authors also account for the actions of other fishermen (i.e. alternative chosen). To estimate both transition probabilities and parameters of the representative utility, the authors follow a two-stage estimation (Aguirregabiria and Mira 2007). The first stage consists of estimating parameters of all state equations for the observable states, S^{-}_{njt}, and then estimate the conditional choice probabilities. In the second stage, the authors simulate the dynamics of the observable state space and evaluate choice-specific value functions, $\bar{V}_t(S_{njt})$. In this second stage, by assuming that the unobserved component of utility are additive and iid Type I Extreme Value distributed, the choice probability of participation (given the value function) has a close form solution. This choice probability is the standard logit model in equation 2.7, except that the representative utility is replaced by the value function; such that

$$P_{njt} = \frac{e^{\bar{V}_{njt}}}{\sum_{i \neq j} e^{\bar{V}_{nit}}} \tag{2.27}$$

where the value function takes the form in equation 2.25. The solution to dynamic discrete choice fishery participation model allows Huang and Smith 2014 to demonstrate that individual fishermen exert more effort than the level of effort that is socially optimal. The authors also find that the congestion externality is costly instantaneously but beneficial in the long run because reduces effort and mediates the stock externalities.

2.3.6 Literature Review Summary

While the review highlights key work relevant to this research, the review leaves out some relevant research looking at fishermen behavior using different approaches (Berman 2006; Weninger and Perruso 2013) or extension of the RUM framework less relevant to our research (Haynie and Layton 2010). Overall, this literature review demonstrate that RUM has been the primary framework for modelling fishermen behavior. While RUM provides the structural framework to understand behavior, assumptions regarding the distribution of the unobservable part of the utility drive the estimation of structural parameters using a wide range of discrete choice models. Even though the availability of discrete choice model is extensive (e.g. multinomial logit, multinomial probit, nested logit, mixed logit, paired combinatorial logit, generalize extreme value models, mixed probit, etc.) the vast majority of models have used a conditional logit which is a form of multinomial logit that allows choices to vary conditionally based on the attributes of the choices as represented in equation 2.7. Almost all models assume that fishers share information on fish distributions in some way rather than relying solely on their own information.

Empirical results of fishermen behavior suggest that fishermen respond positively to the increase on the expected utility of returns associated with different discrete alternatives. In particular, in the short-run, fishermen are very responsive to economic incentives (Eales and Wilen 1986). However, in the long-run, adjustments to fixed and quasi-fixed factors appear to be more sluggish (Bockstael and Opaluch 1983). Additional key drivers of fishermen behavior are: the variance of expected utility (usually measured by proxies for expected profits, revenues, or catch and that serves as a measure of risk), environmental factors (such as weather and wind speed) (Smith and Wilen 2003; Wilen et al. 2002), proxy measurements for congestion and information sharing (Ward and Sutinen 1994; Holland and Sutinen 2000; Huang and Smith 2014), and individual vessel characteristics (such as vessel tonnage, length, horse power, and age) (Zhang and Smith 2011; Huang and Smith 2014). Fundamental to all the location choice literature is the strong evidence that behavioral patterns of fishermen are responsive to, and predicted by, relative differences in proxies for expected profits.

The literature review also suggests that the advances in modeling fishermen are channeled toward accounting for heterogeneity across fishermen, correlation across alternatives and serially correlated errors. The overall goal of more newly developed models is to define the representative utility such that the unobservable part of the utility are truly reduced to white noise that follows an independently identical distribution. Cutting edge modeling seeks to fully account for the dynamics of fishermen behavior by assuming fishermen display a forward looking utility function as compared to the static framework and to account for the behavior of other fishermen.

2.3.7 Literature Review Conclusions

The logit specification is by far the most widely used discrete choice model for studying fishermen behavior. Logit and any of its variations are derived under the assumption that the unobservable part of the utility, ε_{njt}, is i.i.d. Extreme Value distributed. The independence assumption means that the unobserved part of the utility are uncorrelated across fishermen, $\forall n \in \{1, ..., N\}$, across alternatives, $\forall j \in \{1, ..., J\}$, and across time, $\forall t \in \{1, ..., T\}$. However, it is a reasonable assumption that unobserved factors related to one alternative may be similar to those related to another alternative. For example, a fisherman who dislikes participating in a given fishery because of dangerous conditions might have a similar response to other fisheries that have the same dangerous attributes. Assumption of independent errors over time is severe (i.e. $\text{cov}(\varepsilon_{njt}, \varepsilon_{njt-\tau}) \neq 0$). In general, if one assumes that observed state variables are dynamic (Huang and Smith 2014), then one may expect dynamics in the unobserved factors as well. Often, however, this correlation is overlooked when assuming a logit specification.

While nested logit, mixed logit specifications, and the addition of habit variables are used to ensure that unobservable are truly uncorrelated, there has been little effort to formally account for correlation of errors while estimating parameters of the representative utility. This shortcoming is primarily due to the fact that when one accounts for the correlation across errors, and/or heteroscedasticity, the multidimensional integral over the density of the unobserved portion of utility (equation 2.5), does not have a closed form and must be evaluated numerically. The logit specification provides a convenient form for the choice probability given that it has a closed form solution and estimation of parameters of representative utility is straightforward using maximum likelihood techniques. It appears that in some cases the logit specification is used for computational convenience without justification that the unobservable part of utility truly reflects the property of the logit; such as independence assumption and the IIA property.

The shortcomings of using logit specification, or any of its alternatives, as de facto discrete choice model are even more severe in the presence of panel data. In using logit for panel data one needs to assume that unobserved factors that affect fishermen decisions are independent over repeated choices. Although a series of choice situations are generated by the same fishermen, each choice situation becomes a separate observation. Thus, one assumes that there is essentially no difference between treating the data as cross-sectional or panel data. One can expect that unobserved factors that affect the choice in one period would persist, at least, into the following period introducing unobserved dependence among the choices over time.

While there are some efforts in the literature to specify the representative utility so that sources of unobserved dynamics are independent over time, there has not been any work that seeks to fully account for the dynamics of the unobservables by placing a structure on the covariance of the errors over time and over alternatives. Addressing correlation across errors over time may lead to a choice probability that does not have close form solution, however, the literature shows that one can use numerical approximations to solve choice probabilities with intractable solutions (Huang and Smith 2014). Future research that seeks to explain fishermen behavior will need to move toward novel simulation techniques to fully account for serially correlated errors that are the feature of panel data.

2.4 Model

The West Coast salmon fisherman behavioral model represents fisherman n decision making process at time t. The decision making process is defined as follows: at each time t a fisherman n makes a jointly decision whether go fishing, which fishery to participate, and where to go fishing. To use the RUM framework to model West Coast salmon fishermen behavior, one must first define the set of alternatives as derived from weekly fishery participation and location choice observations. Then, the representative utility, V_{njt}, must be described for each alternative as a function of alternative specific attributes using available Fish Ticket data. Finally, after assuming a specific distribution for the unobserved part of the utility, parameters can be estimated for the representative utility.

2.4.1 The Choice Set

Given observations from observed weekly choice occasions as described in section 2, the complete set of fishery-participation-location-choice (FPLC) alternatives are defined as: participating in salmon fishery at one of the management areas (NO, CO, KO, KC, FB, SF and MO [12]) as shown on Figure 2.1, the Dungeness crab fishery, the highly migratory fishery, the ground fish fishery, other fisheries [13], or to "no-participate" in any fishery [14]. The full set of alternatives observed on weekly choice occasion are depicted in Figure 2.5.

One can define a common choice set for all vessels, however, as shown in figures 2.2, 2.3, and 2.4 not all vessels participate in all fisheries. To address this issue, mutually exclusive choice sets were created with alternatives from the full set to represent observed behavior made by troll salmon fishermen. For example, for vessels that participate only in the salmon fishery, the choice set is given by the no-participation alternative along with the salmon alternative in combination with all available management areas (a total of 8 alternatives). For vessels that participate only in the salmon fishery and the crab fishery the choice set is given by the no-participation, the salmon along with all management areas, and the crab fishery (a total of 9 alternatives). Recreation and transportation demand literature has shown that neglecting or misspecification of individual choice sets may lead to biased parameter estimates in RUM (Manski 1977; Robert L. Hicks and Strand 2000; Parsons et al. 2000). To avoid biased, one must estimate parameters of the representative utility per different choice sets [15].

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[12] NO: US-Canada border to Cape Falcon OR, CO: Cape Falcon OR to Humbug Mt. OR, KO: Humbug Mt. OR to OR-CA border, KC: OR-CA border to Horse Mt. CA, FB: Horse Mt. CA to Point Arena CA, SF: Point Arena CA to Point Pigeon, and MO: Point Pigeon CA to US-Mexico border respectively.

[13] Where other fisheries aggregate participation in the shell fisheries, coastal pelagic, shrimp, or other.

[14] For the purpose of this work, location choices were defined only for the salmon fishery in order to reduce computation time.

[15] Individual choice sets were defined based on observed past behavior (i.e. a deterministic process). Alternatively, one can define the choice set as stochastic process where the choice sets are created endogenously within the model (Ben-Akiva and Boccara 1995).

2.4.2 The Representative Utility

Consistent with the literature on modeling fishermen behavior (Bockstael and Opaluch 1983; Ward and Sutinen 1994; Eales and Wilen 1986; Smith and Wilen 2003; Holland and Sutinen 1999; Haynie and Layton 2010), the representative utility is defined as a linear function of alternatives-specific variables, X_{jt}, case-specific variables, Y_{jt}, and alternative-specific constant terms. The alternative-specific variables are expected revenues and state dependence variables while case-specific variables are vessel-specific attributes. Thus, the fisherman $n's$ representative utility of choosing alternative j at time t can be written as:

$$U_{njt} = \alpha_j + \beta_1 ER_{njt} + \sum_{i=1} \theta_i d^i_{nj\tau} + \sum_{m=1} \mu_m Y^m_{nt} + \varepsilon_{njt} \tag{2.28}$$

ER_{njt} represents the expected revenue [16]. This variable varies across fisherman, alternative, and time. $d^i_{nj\tau}$ are i number of state dependence variables that indicate the alternative chosen at time $t = \tau$ for $\tau < t$ (Bockstael and Opaluch 1983; Holland and Sutinen 1999). Two state dependence variables are used, an indicator for the alternative chosen at the last choice occasion (i.e. $\tau = t - 1$) and an indicator for the alternative chosen in previous years (i.e. $\tau = t - 52$). Y^m_{nt} are the m number of vessel-specific characteristics such as tonnage, length, and horsepower; these are alternative invariant variables. α_j are alternative-specific constants which capture unobservable fishery-location heterogeneity to address omitted variable bias. Note that the alternative-specific constants are fixed across fishermen and time, based on the assumption that other unobservable fishery-location attributes do not vary across time and fishermen. Finally, ε_{njt} indicates the unobserved part of the utility, which is fisherman-alternative-time specific component of the representative utility.

[16] I use expected revenue as opposed to expected catch (as commonly used in the literature) because of the different values by species and size of fish across different fisheries. The same approach has been previously used when modeling location choice in fisheries (Holland and Sutinen 1999).

2.4.3 Expected Revenue

2.4.3.1 Expected Revenue Estimation

In order to estimate the RUM (equation 2.28), the expected revenue variable ER_{njt} must first be estimated. Earlier RUM literature used several approaches to define the expected profit or a proxy for expected profits. For example, ER_{njt} has been defined as: the weighted average of actual returns over choices (Bockstael and Opaluch 1983), linear function of recent mean catches per alternative (Eales and Wilen 1986), function of further past periods mean catches at different spatial scales (Holland and Sutinen 1999; Abbott and Wilen 2011), and an expected function that is computed from a density function, with parameters that are jointly estimated with choice probabilities (Haynie and Layton 2010). To define the set of variables and functional form of the expected revenue function, this work closely follows the rational expectation approach implemented in Abbott and Wilen 2011 (hereafter A&W).

The foundation for the A&W expected revenue formulation builds on Wilson 1990 study on fishermen production knowledge regarding the location of fish. According to Wilson 1990, fishermens information can be categorized as fine and coarse-grained information. Fine-grained information is defined as the idiosyncratic and transitory information related to the immediate fish location. This information tends to be dispersed selectively rather than broadly. On the other hand, coarse-grained information is defined as information about the long-term patterns and tends to be widely and freely dispersed.

Based on this classification, A&W defined expected catch as a function of average catch rate at a site from members associated with explicit fishing institutions (fine grained information) and expected catch rate based on aggregate spatial and seasonal scale (coarse grained information). Furthermore, A&W also categorized fine-grained information as recent or older information depending on whether catch averages were calculated from the previous day's catch information or previous week's catch records. Following A&W, the expected revenue that fisherman n obtains by choosing a fishery-management area combination j at time t is defined as a function of different information signals:

$$E(ER_{njt}|I_1, ..., I_M) = \delta_0 + \delta_1 I_1 +, ..., +\delta_M I_M \tag{2.29}$$

where I_m, for $m \in \{1, ..., M\}$, represents information signals. Five classes (i.e. $M = 5$) of information signals are considered: coarse-scale information, fine old, fine recent, finest old, and finest recent information.

Coarse-scale information is defined as the general trends in revenue that a fisherman expects during a fishing season. To estimate these seasonal regularities, a linear regression of observed weekly revenues is estimated for each fishery as a function of the number of weeks since the fishery opened (a variable called *NumWeeks*), its quadratic term, and annual and spatial indicators, (D_{year}) and (D_{MA}) respectively. The *NumWeeks* variable takes the value of 1 when the fishery starts and consecutively increases by 1 unit per week until the next fishing season begins. The *NumWeeks* variable and its quadratic term are intended to capture the effect that time has on the expected revenue per fishery. Specifically, the coarse-scale information signal that fishermen n expects from alternative j at time t is defined using the following regression:

$$CS_{jt} = \alpha_1 + \beta_1 NumWeeks + \beta_2 NunWeek^2 + \sum_s \beta_s D_{year} + \sum_m \beta_m D_{MA} + \varepsilon_{species} \tag{2.30}$$

Observed weekly revenues per fisheries are used to obtain estimated parameters of equations. Further, estimated parameters are used to compute coarse-scale expected revenues for all years and all weeks of the season for all fisheries. The coarse-scale information obtained from equation 2.30 is the only signal permanently available to all fishermen at all times.

Contrary to coarse-scale information, fine-scale information is intended to capture information that is common only to members of a group of fishermen. Fine-scale information, both old and recent, account for the potential role of information sharing across different vessels [17]. These variables can be calculated by averaging revenue across formal or informal information sharing groups. For instance, fine-scale revenue information for fisherman n, that pertain to group G, for alternative j at time t is calculated as follows:

$$Fine_{Gjt} = \frac{\sum_{g \in G} R_{gjt-\tau}}{\bar{g}} \tag{2.31}$$

where g indexes a vessel that pertains to the same group to which vessel n is part, and $\bar{g}$ indicates the total number of vessels in the group G and τ indicates the time lag. Where $\tau = 1$ indicates last week's (recent) revenue information and $\tau = 52$ indicates last year's (old) revenue information. Group assignment is described in detail in the next section.

Recent finest-scale and old finest-scale information are intended to capture private information that is available only to individual vessels. For the purpose of calculating expected revenue, recent finest-scale revenue information is constructed using a vessel's previous week's revenue; no information from other vessels is required. On the other hand, old finest-scale revenue information is calculated using last year's revenue. These information signals reproduce approaches taken in early fishery RUM formulations to calculate proxies for expected profits (Bockstael and Opaluch 1983; Eales and Wilen 1986). More precisely, finest-scale revenue information for vessel n, alternative j at time t is given by:

$$Finest_{njt} = R_{njt-\tau} \tag{2.32}$$

where τ indicates the time lag according to whether information is recent or old. Note taht for a given vessel n, finest-scale information is presented only for the alternatives previously chosen by the vessel and the information is absent for alternatives that are not part of the vessel history of past choices.

[17] The role of information sharing in fisheries for addressing common-pool inefficiencies has been largely revised in the literature (Gilman et al. 2006; Haynie, Robert L. Hicks, et al. 2009; Evans and Weninger 2013)

The five variables previously described form the revenue information signals used to calculate the expected revenue for all PFLC alternatives. Given these five variables, one can restate expected revenue in equation 2.29 as:

$$E(ER_{njt}) = \delta_0 + \delta_1 CS_{jt} + \delta_2 Fine^{rec}_{Gjt} + \delta_3 Fine^{old}_{Gjt} + \delta_4 Finest^{rec}_{njt} + \delta_5 Finest^{old}_{njt} + \varepsilon_{njt} \quad (2.33)$$

Of all information signals, only the coarse-scale information is available to all fishermen at all times for all alternatives; its calculation is based on all observed choices. Finest-scale information and fine-scale information signals may be unavailable to a given vessel depending on its own and its information sharing group history of past choices. Table 2.5, describes all the potential information sets based on the information signals available. The expected revenue function needs to account for the potential lack of information signals. Therefore, equation 2.33 is rewritten as:

$$\begin{aligned} &E(ER_{njt}|d(njt)_1 I_1, ..., d(njt)_M I_M) = \\ &\quad \delta_0 + \delta_1\{d(njt)_1, ..., d(njt)_M\} I_1 + ... + \delta_M\{d(njt)_1, ..., d(njt)_M\} I_M + \varepsilon_{njt} \quad (2.34) \end{aligned}$$

where $d(njt)_m$ for $m = \{1, ..., 5\}$ is an indicator variable representing whether information signal m is available to fisherman n at time t about alternative j. With this formulation, information signal weights δ_m are fixed across fishermen that share the same information set (combination of available information signals) but vary depending upon information sets available at each alternative for each choice occasion. This formulation requires estimating $M \times k$ information signal weights, where m is the number of information signals and k is the total number of possible information sets.

In summary, the following sequence of steps need to be conducted in order to estimate the expected revenue variable used in the representative utility function (equation 2.28). First, observed weekly choices are used to estimate parameters of the coarse-scale information (equation 2.30), and the predicted values are used as coarse-scale information signals for all alternatives and for all choice occasions; the information is available to all fishermen for all alternatives j at all times t. Second, fine-scale and finest-scale information signals, recent and old, need to be calculated based on observed revenues according to equations 2.31 and 2.32 respectively. Third, based on all calculated information signals, information signal weights are estimated according to equation 2.34. Once information signals are estimated, they are used to predict values of the expected revenue function (equation 2.34). Predicted expected revenues then entered the representative utility function (equation 2.28).

2.4.3.2 Expected Revenue Results

Observed weekly revenues can only be used to calculate coarse-scale information if vessels were homogeneuos and had the same revenue generating capacity so that vessel $n's$ weekly revenue provides information on all other vessels' average weekly revenue rates. However, the presence of heterogeneous vessels calls for converting observed weekly revenues into a common index so that vessel $n's$ weekly revenue has the same meaning for vessels with different characteristics (Holland and Sutinen 1999; Abbott and Wilen 2011). Summary of statistics for vessel characteristics are shown in Table 2.2. To normalize revenue to a common basis, weekly revenue was modeled using a translog production function of logarithm levels, product, and cross-products of a vessels tonnage, length, and horsepower. In addition to vessel characteristics, annual, monthly, and salmon management areas indicators were included to account for temporal and spatial factors that influence average revenue rates.

Estimates of the OLS translog production function per fishery are shown in Table 2.3. Note that the relative low R^2s (0.182 to 0.295) indicate that much of the variance in the revenue rate remains unexplained. However, the validity of this approach to standardize revenue to account for vessel heterogeneity has been justified in the literature (Holland and Sutinen 1999; Abbott and Wilen 2011). Using estimated parameters of the translog production function, the log revenue for each vessel for all fisheries and temporal dummies was then estimated. The same operation was carried out for a baseline vessel; a vessel with characteristics at mean values as shown in Table 2.2.

To obtain the standardization factor, predicted weekly revenues for all vessel/spatial-temporal combinations was divided by the predicted value of the baseline vessel (Abbott and Wilen 2011). The distribution of the standardization factor is depicted in Figure 2.7. Note that the mean value of the standardization factor is 1.16 with a standard deviation of 0.53, suggesting a large degree of variation in the relative revenue efficiency of vessels. Vessel revenues were normalized to a common basis by dividing observed weekly revenues by the corresponding standardization factor.

Normalized weekly observed revenues were used to estimate coarse-scale regressions (equation 2.30). To carry out the estimation, observed weekly choice occasions were assigned to a set of spatial-temporal coarse-scale units. Coarse spatial units were applied only to the coarse-scale regression for the salmon fishery. The salmon, crab, and albacore [18] fisheries have a defined season starting, thus the variable *NumWeeks* counts the number of weeks since the fishery was opened. The groundfish and other fisheries operate year-round, thus the first week of the year was assigned as the beginning of the season on the *NumWeeks* variable.

Estimated parameters for the coarse-scale regression per fishery are provided in Table 2.4. Parameters were estimated using Poisson Quasi-Maximum Likelihood (Poisson QMLE) regression. This regression provides positive values of coarse-scale revenue information that are consistent even when the Poisson distributional assumption does not hold (Cameron and Trivedi 2010; Abbott and Wilen 2011). Table 2.4 shows that $NumWeek$, spatial, and year indicator variables are significant for all fisheries. In fact, all regressors are jointly statistically significant at 5% (the Wald Chi2 test statistic has a $p < 0.05$). Fitted values from these species-specific Poisson QMLE regression provide the values for the coarse-grained information used to estimate information signal weights (equation 2.34). Predictive values for coarse scale revenue information in 2014 for all fisheries are shown in Figure 2.8.

[18] The Albacore tuna fishery does not a defined opening data but the season typically begins on the first week of July.

As a second step, the following four variables were constructed to complement coarse-scale information signals: old fine-scale information, recent fine-scale information, old finest-scale information, and recent finest-scale information. Ideally, fine-scale information variables, recent and old, should be constructed with revenue information from members of information sharing groups including formal fishing organizations and cooperatives. However, from the available information at hand, one is unable to determine whether or not this type of information sharing institutions, formal or informal, exists within the salmon fleets.

As an approximation to developing fine scale information groups, vessels were classified into 10 different groups based on their characteristics, such that vessels in the same groups are of a comparable size. This groups were created using a k-mean clustering partition method which finds a partition in which vessels within each group are as close to each other as possible and far from vessels in other groups. Figure 2.9 depicts the categorization of vessels based on their characteristics as measured by tonnage, length, and horsepower. Table 2.6 provides summary statistics of vessel characteristics by group. Revenue information from vessels within a given group presumably provides meaningful information to vessels within the same group. Average revenue information among vessels with the same characteristics (equation 2.31), serves as a proxy for fine-scale information. Recent fine-scale information and old fine-scale information is computed by taking the average of observed weekly revenue per fishery and per groups at 1-week lag and 52-week lag as stated in equation 2.31.

Recent and old finest-scale information signals for vessel n are constructed with that vessel's last-week and last-year revenue respectively (i.e $\tau = 1$ and $\tau = 52$ in equation 2.32). This information is present only for those alternatives that were previously chosen by individual vessel and absent for alternatives that are not part of the vessel's history of past choices. As previously noted, only the coarse-grained information is permanently available to all fishermen at all times. Fine and finest-scale signals may be unavailable if the information sharing group, or the individual fisherman, has not participated in the fishery in the previous week and/or previous year. Table 2.5 lists the frequencies of observed information sets on observed weekly choices. Only 3.2% of the observed choices had only coarse-scale information, meaning there is no previous revenue information to inform expected revenue on the observed choice. Most of these choice occasions took place at the beginning of the fishing seasons. Note also, that about 23% of observed choices had all possible sources of revenue information to estimate the information weight.

The last step was to estimate information signal weights by regressing normalized observed weekly revenues on available information signals (equation 2.34). Recall that $d(njt)_m$ is an indicator variable that determines whether the information signal m about alternative j at time t is observed in the data at each observed choice occasion. The parameters δ_m represent information weights that must be estimated. The total number of information weights are shown in Table 2.5, where weights are equal to zero whenever the information signal is not part of the information set.

Tables 2.7 and 2.8 report estimated information weights for all possible information sets available. Column 1 in Table 2.7 shows the estimated information weight for the coarse-scale information only (no other information was available). Conversely, column 16 in Table 2.8 shows estimated parameters for all information weights, a situation observed in 23% of total choices (see Table 2.5). As in the case of estimating the coarse-scale information parameters, information weights were estimated via Poisson QMLE to ensure positive predicted expected revenues. As observed in tables 2.7 and 2.8, all of the estimated information signal weights are significant at the 95% level. The complete set of estimated weights is used to obtain expected revenue for each choice occasion, across all available alternatives, to estimate parameters of the Random Utility Maximization as stated in equation 2.28.

2.5 Results

2.5.1 Random Utility Maximization Estimation

A nested logit specification was used to estimate parameters of the representative utility [19]. Given the structure of the troll salmon fishermen behavior as depicted in figure 2.5, one can expect the unobservable attributes of alternatives within the salmon participation choice be highly correlated, thus, location choices for the salmon fishery alternative can be nested. Additionally, one can also assume the unobservable attribute between the alternatives in the salmon nest and all other alternatives be independent, therefore, the errors are assumed to be distributed as Gumbels Multivariate Extreme Value distribution (Train 2009) [20]. This distribution gives rise to the following choice probability:

$$P_{njt} = \frac{e^{V_{njt}/\lambda_k} \left(\sum_{i \in B_k} e^{V_{njt}/\lambda_k} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{i \in B_l} e^{V_{njt}/\lambda_l} \right)^{\lambda_l}} \tag{2.35}$$

where V_{njt} is the *representative utility* as defined in equation 2.28 and the parameter λ_k (also known as dissimilarity parameter) is a measure of the degree of correlation in the unobserved part of the utility among alternatives in nest k. B_k denotes the set of alternatives in nest k. Estimation of the parameters of the representative utility, as well as the dissimilarity parameters, are estimated using Full Information Maximum Likelihoods (Green 2008).

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[19] Discrete choice specifications (such as conditional logit, multinomial logit, nested logit, mixed-logit, and others) have been used in the literature to estimate parameters of the representative utility due to its ease of estimation, interpretation, and the ability to remove choice alternatives (Bockstael and Opaluch 1983; Eales and Wilen 1986; Smith and Wilen 2003; Holland and Sutinen 1999; Smith 2005).

[20] Specifically the vector of unobserved utility has a cumulative distribution $F(\varepsilon_{njt}) = e^{\left(- \sum_{k=1}^{K} \left(\sum_{j \in B_k} e^{-\frac{\varepsilon_{njt}}{\lambda_k}} \right)^{\lambda} \right)}$

2.5.2 Random Utility Maximization Results

Estimation of the *Expected Revenues* for all FPLC alternatives were carried out as described in section 2.4.3. The expected revenue for the no-participation alternative was omitted from its representative utility, so that the alternative specific constant accounts for the unobserved no participation opportunity cost. Last-week choice and last-year choice were defined with a dummy variables indicating the alternative chosen in the previous week and in the previous last year respectively. Vessel-specific tonnage, length, and horsepower are estimated as alternative specific variables. Table 2.9 shows parameters estimated from nested logit specification for selected variables and the following seven choice sets:

1. Participate only in the Salmon fishery in one of the management areas
2. Participate in the Salmon or CRAB fishery
3. Participate in the Salmon or HMS fishery
4. Participate in the Salmon or GRND fishery
5. Participate in the Salmon, HMS or CRAB fishery
6. Participate in the Salmon, HMS or GRND fishery
7. Participate in the Salmon, CRAB or GRND fishery

The estimated parameters of alternative specific variables are significant at the 5% level across all models. Some of the alternative specific constants are also significant. The alternative specific constants account for the average effect of unobserved factors on the utility of each alternative relative to the no-participation alternative.

The Nested logit specification is a non-linear model; thus, coefficients in Table 2.9 cannot be interpreted as marginal effects. However, coefficients' signs provide an interpretation in the direction of the effect of an individual variable on the probability of choosing an alternative. For instance, the positive sign in the *Expected Revenues* variable, across all choice sets, suggests that salmon fishermen are more likely to choose an alternative j when $j's$ expected revenues increases. The positive coefficients in the dummy variables *last week* and *last year* suggest that fishermen are more likely to choose the alternative that was chosen in the previous week and the previous year; this evidence of state dependence and sluggish behavior is consistent with finding from the literature (Bockstael and Opaluch 1983; Ward and Sutinen 1994; Holland and Sutinen 1999; Smith 2005). Note that the direction of the effect of alternative specific variables on the probability of choosing an alternative is the same across all models. The results are not surprising especially if one looks at individual models in isolation.

The dissimilarity parameter λ in a nested logit specification measures the degree of independence among alternatives within the same nest, a higher value of λ indicates greater independence. Furthermore, the statistic $1-\lambda$ measures the correlation across errors within the same nest. As λ rises, it indicates a greater independence and less correlation (Train 2009). Greater independence across alternatives within the same nest (no correlation) indicates a lower degree of substitution among alternatives. For example, a value of λ_{SAMN} closer to 1 on a FPLC model indicates a low degree of substitution among the alternatives within the salmon nest. Thus, a larger value of λ_{SAMN} indicates that a closure in a management area in the salmon fishery (i.e. eliminating the alternative) increases the probability of both remaining in the salmon fishery or switching fisheries. A value of λ_{SAMN} closer to 0 indicates a high degree of substitution across alternatives within the salmon nest. That is, when a salmon management area is closed, fishermen are more likely to switch to a different management area while remaining in the salmon fishery rather than switching fisheries.

The dissimilarity parameter λ_{SAMN} for the set of vessels that participated in the salmon and groundfish fisheries (column 4 in Table 2.9) has the lowest value among all models. The values of λ_{SAMN} indicates that the highest degree of substitution across salmon alternatives are for vessels that participate exclusively in the salmon and groundfish fisheries ($\lambda = 0.248$), followed by those that participate in the salmon, crab, and groundfish fisheries ($\lambda = 0.289$). Higher dissimilarity parameter values occur for the set of vessels that participate in the salmon and crab fisheries (column 3, $\lambda = 0.463$), and salmon and the albacore tuna fisheries (column 2, $\lambda = 0.393$). These higher values indicate that when an alternative in the salmon nest is eliminated due to a closure the probability of switching fisheries increases for vessels that participate in the salmon and crab or highly migratory fisheries [21].

Different values on the parameter λ_{SAMN} may indicate that fishermen's responses to a closure in the salmon fishery are heterogeneous and depend on their portfolio of fisheries. For instances, vessels that participate exclusively in the salmon and the groundfish fisheries are more likely to respond to a closure in a salmon management area by switching location and continue participating in the salmon fishery. On the other hand, vessels that participate exclusively in the salmon and the crab fishery are more likely to respond to a closure by switching fisheries. Estimated parameters will be used in section 5.2 to calculate changes in probabilities as a result of a closure to provide an illustration of these results.

2.5.3 Comparing Coefficients across Choice Sets

One must be careful in comparing coefficients of the representative utility across models (Train 2009; Karlson et al. 2012; Hoetker 2003). The fact that the magnitudes of the coefficients are different across models does not imply heterogeneous effects of each variable on choice probabilities. Estimated coefficients indicate the effect of each observed variable relative to the variance of the unobserved factors [22]. Absolute values of coefficients can only be compared if the amount of unobserved variation is the same across choice sets, an assumption that cannot be formally be verified. To show

[21] The comparison of dissimilarity parameters across different choice sets need to be stated with caution given that each choice set correspond to different data; we can not show statistically whether these value are different from each other.

[22] Generalize Extreme Value Models, such as the nested logit, normalize the scale of utility by normalizing the variance of the error term by $\pi^2/6$.

whether coefficients differ across choice sets, while treating the difference in residual variation as irrelevant, one can compare the impact of the state dependent variables relative to the *Expected Revenues* variable (Train 1998).

Table 2.10 shows coefficient ratios across choice sets. The values were calculated by taking the ratio of coefficients in Table 2.9 with respect to the *Expected Revenues* coefficient. The ratios on the state dependent variables provide a money metric value of prior experience for choosing an alternative. For example, the ratio for the last-week and last-year choice indicator are 9,537 and 4,241 respectively for the choice sets that participate only in the salmon fishery (Model 1). These ratios indicate that fishermen who participate only in the salmon fishery value last-week choice twice as much as the choice made last year. Note that this pattern is similar across choice sets (columns 2-7).

The highest values on the state dependent ratios are for salmon vessels that also participate the crab fisheries (choice sets 3, 5, 7). On the other hand, the lowest values are for vessels that participate in salmon, highly migratory species, and groundfish fisheries (choice sets 2, 4, and 6). Overall, these values indicate that salmon vessels that participate in the crab fishery are less likely to switch or exhibit a more sluggish response than vessels that switch between the salmon and the groundfish or highly migratory fisheries. These results support the observed behavior shown in Figures 2.3 and 2.4. The figures show that once a vessel switches from the crab to the salmon fishery it will most likely remain in the salmon fishery. Conversely, switching behavior between the groundfish and the salmon fishery is more intermittent.

2.5.4 Effect of Closures on the Salmon Fishery

2.5.4.1 Closure of a Single Management Area

Estimated parameters in Table 2.9 are used to compute predicted probabilities in the presence and absence of a closure for one of the salmon management areas. A closure in a given management area is imposed by removing the alternative from the choice set and calculating choice probabilities according to equation 2.35.

Table 2.11 displays the choice probabilities for an open and closed scenarios for two different dates. The open scenario has the following assumptions: 1) The representative fisherman can choose any of the FPLC alternatives and the no-participation alternative. 2) The *Expected Revenues* for all alternatives is set to a value for the second week of May 2014 (beginning of the salmon season) and second week of July (beginning of the albacore tuna season); values were calculated using coarse-scale information estimates from Table 2.4. 3) The alternative chosen in the previous week and previous year was to participate in the salmon fishery at the Horse Mountain Point Arena management area (alternative with the highest coarse-scale information, see Figure 2.8). 4) All FPLC alternatives are open. 5) Vessel characteristics are set to baseline values shown in Table 2.2. The closed scenario has similar assumptions as the open scenario except that the FPLC alternative previously chosen (salmon fishery at the Horse Mountain Point Arena management area) has been removed from the choice set while all other alternatives remain available. Choice probabilities are calculated for all different choice sets of vessels as classified in Table 2.9.

Table 2.11 shows that under the open scenario for the second week of May, the probability of choosing the alternative previously chosen is the highest among all choice probabilities. The exception is for salmon vessels that participate in the HMS fisheries where the highest choice probability is to not participate in any fishery; 0.48 for vessels that participate only in the salmon and the highly migratory species. Table 2.11 shows that for vessels that only participate in the salmon fishery, the probability of choosing the same alternative is 0.73 while the probability of not participating is 0.25. The table also shows that the probability of choosing the same alternative varies according to the portfolio of fisheries which they participate. For instance, the probability of choosing the same alternative for a salmon vessel that participates in the HMS fisheries is 0.29, while for vessels that also participate in the crab fisheries the probability is 0.71 and for those participating in the groundfish fisheries the probability is 0.70. These results show that as vessels have different portfolio of fisheries the probability of choosing the alternative previously chosen changes.

For the second scenario, when the salmon fishery is closed on the second week of May at the alternative previously chosen, the probabilities of remaining in the salmon fishery at a different location, switching fisheries, or no participating in any fishery are larger relative to when the alternative is available. For instance, for the set of vessels that participate only in the salmon fishery, the probability of remaining in the fishery but switching location is 0.43, while the probability of exit is 0.57. On the other hand, when a salmon vessel also participates in the crab fishery, the probability of switching location is 0.32, while the probability of no participation is 0.48, and the probability of switching to the crab fishery is 0.20 (compared to the 0.08 probability for the open scenario). For vessels that participate in the salmon and the highly migratory species, the probability of remaining in the salmon fishery after the closure is 0.38. On the other hand, the probability of no participation is 0.56 and the probability of switching to the highly migratory species changes slightly from 0.05 to 0.06.

For the particular case of a closure at the beginning of the salmon season, the higher probability of switching behavior corresponds to vessels that also participate in the crab fishery, while the lower switching rate occurs when the vessels participate in the salmon and the HMS and groundfish. The highest increase of no participation in any fishery occurs for vessels that participate in the HMS, reflecting the fact this alternative is not available early in the salmon season.

The same close and open scenarios are presented in Table 2.11 for the second week of July; at the beginning of the albacore tuna season. Note that when the alternative previously chosen remains open, a vessel that participates exclusively in the salmon and the highly migratory species has a probability of making the same choice of 0.28 (similar to the probability for the same case on the second week of May). However, the probability of switching fisheries from the salmon fishery to the highly migratory species is 0.14 (higher probability than in the second week of May).

When the alternative previously chosen is closed, the probability of switching fisheries increases from 0.14 to 0.17, while the probability of no participation increases from 0.42 to 0.49, and the probability of switching location decreases from 0.44 to 0.34. When a closure occurs at the beginning of the albacore tuna season, the higher probability of switching fisheries occurs for vessels that participate in the highly migratory species and groundfish fisheries. A summary of choice probabilities for both scenarios and both periods is shown in Figure 2.10.

2.5.4.2 Closure of Several Management Areas

In 2006 the ocean salmon fishery seasons were constrained by 1) endangered Sacramento River winter Chinook south of Point Arena; 2) Klamath River Fall Chinook from Cape Falcon south to Point Sur; 3) threatened Snake River and lower Columbia River (LCR) natural tule fall Chinook north of Cape Falcon; and 4) threatened LCR natural coho north of Humbug Mountain (Council 2006). Therefore most of the salmon management areas were partially or totally closed (see Figure 2.11). Table 2.12 shows observed choices at two different time points for the years of 2005 and 2006. The first time point is the first week of May, when the salmon fishery opened, while the second time is the first week of September, which represents a time when the salmon fishery is close to ending. Table 2.12 shows that in the first week of May of 2005 the alternative that was chosen the most was to participate in the salmon fishery at the CO management area, 152 vessels (43%), followed by the no participation alternative, 54 vessels (16%), and the crab fishery alternative, 49 vessels (14%). A similar proportion of vessels, 143 (41%), chose to participate in the salmon fishery at the same management area during the first week of September of the same year. However, a larger proportion of vessels chose to not participate in any fishery, 131 (37%). 9 (3%) vessels chose to participate in the HMS fishery.

Table 2.12 shows observed choices for 2006, when five of the seven management areas of the salmon fishery were closed. Note that due to the closure, none of the vessels chose to participate in the salmon fishery at the CO management area; the alternative with the highest choice rate in 2005 for both time frames, first week of May and first week of September. In 2006, during the first week of May, the alternative with the highest choice proportion was the no participation alternative, 250 (72%), follow by the crab fishery alternative, 60 (17%). Note that in the first week of May of 2006, the number of observed choices increased for the no participation, crab, and groundfish fisheries alternatives compared to observed choices in 2005. On the other hand, there was a decrease in the number of observed choices in the salmon fishery alternative at all management areas, including open management areas.

Table 2.12 also shows the observed choices on the first week of May of 2006 of vessels that participated in the salmon fishery at the CO management area in 2005. Of theses 152 vessels 135 (89%) vessels chose to not participate, 13 (8.5%) vessels chose to participate in a fishery different than the salmon fishery, and 6 (4%) vessels chose to participate in the salmon fishery at one of the open management areas, NO and MO. Observed choices in the first week of September of 2006 are shown on Table 2.12. As in the first week of May, the no participation alternative had the highest frequency of observed choices in the first week of September, 277 vessels (80%), followed by the highly migratory fishery and groundfish fishery alternatives, 33 (9.5%) and 23 (7%) respectively. Note the contrast with the first week of May on 2006 when the crab fishery was the second alternative with the highest frequency and when the highly migratory fisheries did not record any observed choices.

Compared to the same time period in 2005, in the first week of September of 2006 there was an increase in the number of vessels that participate in the highly migratory and groundfish fisheries, and an increase in the number of vessels that participate in the salmon fishery at the NO management area (one of the two areas open during season).

Table 2.12 shows that of the 143 vessels that chose to participate in the salmon fishery during the first week of September in 2005, 120 (83%) chose to not participate during the same week a year later, during the closures, 5 (3.5%) chose to participate in the salmon fishery on an open management area, while 18 (12%) chose to switch fisheries compared to their most recent previous year behavior.

Observed choices shown in Table 2.12 suggests that salmon vessels may change their behavior with respect to last year's behavior in response to closures in the salmon fishery. The table shows that when a salmon alternative previously available is closed, vessels may respond by either not participating, switching locations while remaining in the salmon fishery, or switching fisheries. The responses depend on the time of year and the availability of other fisheries.

Table 2.13 show the choice probabilities, as calculated using estimated parameters in Table 2.9, for all available alternatives, for all choice sets, at two different point times (first week of May and first week of September) during 2006. The choice probabilities were calculated with indicator variable equal to one for the salmon MO alternative, indicating that last year's choice was to participate in the salmon fishery at a management area closed during 2006. Further, the choice probabilities were calculated for different cases, each case indicating a different choice in the last week's choice occasion.

From Table 2.13 one can see that when the last week choice was to not participate and last year's choice was to participate in the salmon fishery at the CO management area (area closed during 2006), the no participation choice probability is the highest across all choice sets for both time periods, 85% and 82% for the first week of May and first week of September respectively. These probabilities resemble the proportion of vessels that choose to not participate as shown in Table 2.12, 88% and 83% for the first week of May and first week of September. Note also that the choice probabilities of available alternatives are similar between the two time periods for the same fleet. For instance, for vessels that participate only in the salmon fishery the probability of no participation is 0.92 at the beginning of the salmon fishery as well as during the first week of September. The exception is for vessels that participate in only the salmon and highly migratory species fisheries whose probability of no participation decreases from 0.91 to 0.87 from May to September.

Table 2.13 also shows that in the presence of a closure of several management areas, a vessel that in the most recent year participated in the salmon fishery at one of the management areas closed, provided that did not participate in any fishery prior to the beginning of the salmon season, the probability of entering the salmon fishery at an open managment area is low (between 0.01 to 0.09) and does not change during the the season for a given fleet. For instance, during the first week of May, vessels that participate in the salmon and highly migratory fisheries the probability of continuing to not participate is 0.91 while the probability of switching location (with respect to last year choice) is 0.07. Further, the probability of choosing to participate in the highly migratory fishery is 0.02. While the probability of not participating decreases and the probability of entering the highly migratory species during the first week of September increases, the probability of switching locations with respect to last year's choice remains the same between the two periods.

When the last choice was to participate in the crab fishery, the no participation probabilities are lower than when the last choice was to not participate. As one may expect, the highest probability is to continue participating in the crab fishery. The probability of continuing to participate in the crab fishery is specially high for vessels that participate exclusively in the salmon and crab fishery, a probability of 0.67 at the beginning of the salmon season. When vessels participate in the salmon, crab, and other fisheries such as groundfish fisheries the probability of continuing to participate in the crab fishery decreases from 0.66 to 0.48 for the first week of May scenario. Note that the highest probability of no participation occurs for vessels that participate in the salmon, HMS, and crab with a probability of 0.36 for the same period.

For vessels that participated in the highly migratory species at the last choice occasion, alternative available only during the after July, the probability of no participation and participating in the HMS fishery are the highest among all alternatives.

This pattern remains true across all choice sets. Table 2.12 shows that a higher proportion of vessels participate in the fishery later in the salmon season. Predicted choice probabilities in Table 2.13 also shows an increase in the probability of participating in the highly migratory fisheries later in the season, specially for vessels that have participated in the fishery earlier.

Surprisingly the choice probabilities between the two different time periods do not drastically differ for a given choice set when the last choice was to participate in the groundfish fisheries. For instance, during the second week of May a vessel that is part of the fleet that participates in the salmon, crab, and groundfish fisheries, has probabilities of 0.26, 0.07, 0.1, and 0.57 for the no participation, participating in the salmon, crab, and groundfish fisheries respectively. These probabilities differ only slightly for the scenario of the first week of September, 0.26, 0.07, 0.09, and 0.58 respectively. This pattern is the same across choice sets.

The two simulation cases, a single closure (Table 2.11) and closure of several management areas (Table 2.13), as well as observed choice in Table 2.12 show that in general, vessels that participate across multiple fisheries respond to a closure in the salmon fishery not only by switching location while targeting salmon, but also by switching fisheries or not fishing at all. Choice probabilities in Table 2.13 shows that vessels have heterogeneous responses to closures in salmon management areas. The effect of a closure depends upon a vessel's portfolio of fisheries, the availability of other fisheries, timing of closures, and the past behavior of the fisherman.

2.6 Conclusion

This work had two main goals. The first was to develop a behavioral model for West Coast salmon troll fishermen. The second was to explore the effects that closures in the salmon fishery has on their behavior. The first goal was accomplished by developing a model of Fishery Participation and Location Choice (FPLC) using a

Random Utility Maximization framework. The model represents the behavior of fishermen who make fishery participation and location choice jointly. Modeling location choice in isolation may not always be appropriate, especially for fleets that participate in multiple fisheries throughout the same season. While this FPLC model was developed to represent the behavior of West Coast troll salmon fishermen, a similar approach can be used to model behavior of multi-species fisheries. This model also suggests that the RUM models can be used to explore complex fishermen behavior that has not been previously studied in the literature.

Predicted probabilities obtained from the FPLC model suggest that West Coast troll salmon fishermen respond to closures in the salmon fishery by reallocating across open management areas, across fisheries, or by not participating in any fishery. Responses to a management area closure in the salmon fishery depend upon the fishery portfolio of fishermen as well as the seasonality of the fisheries. For instance, vessels that participate exclusively in the salmon fishery, will respond to a closure or closures by either switching location or by stopping fishing. However, if a vessel also participates in the highly migratory fishery, it may respond by switching fisheries rather than by switching locations. The response depends on whether the closure takes place at the beginning of the salmon season (when albacore tuna is not available) or halfway through out the season. Several factors affect fishermen responses to closures, including available fisheries, fisheries portfolio, time, and fisherman history of past choices. This heterogeneous effect of a closure has not been analyzed in previous published research.

In the context of ecosystem-based management our result suggests that spatial fishery regulations, such as selected openings and closures, need to account for the effect on alternative fisheries. Spatial measures that are intended to protect stocks in a particular fishery may have spillover effects on other stocks given that fishermen may address constrained spatial fishing opportunities by switching fisheries rather than by exiting or switching fishing locations. This study suggests that spatial policies need to account for the complex behavior of fishermen that affect linkages across stocks through fishermen substitution patterns across fisheries. In general, this work provides evidence that fishermen respond to rent differentials that exist across space but also across fisheries.

2.7 Tables

TABLE 2.1: Proportion of Vessels by Fishery Participation During all Years, 2005-2014

Fisheries				Proportions
SAMN	HMS			23.280
SAMN	HMS	CRAB		16.578
SAMN				14.109
SAMN	CRAB			11.287
SAMN	CRAB	GRND		9.347
SAMN	HMS	CRAB	GRND	7.407
SAMN	HMS	GRND		6.702
SAMN	GRND			6.526
OTHER				4.762

Notes. OTHER category comprise the all other possible fishery participation combinations

TABLE 2.2: Vessel Characteristics: Summary of Statistics

Characteristics	Min	Max	Mean	Baseline Vessel
Lenght	15	72	40	40
Tonnage	1	78	17	12
HPower	10	892	198	170

TABLE 2.3: Selected Results from OLS Estimation of Translog Production Function

	(SAMN)	(CRAB)	(HMS)	(GRND)	(OTHERS)
Constant	19.89***	16.22***	-4.819	-9.382***	36.31*
	(2.041)	(3.261)	(4.527)	(2.793)	(15.50)
$Length$	-9.977***	-4.553*	4.283	7.870***	-23.18*
	(1.201)	(1.845)	(2.505)	(1.481)	(9.134)
$Tonnage$	1.974***	1.487***	1.251**	-0.567*	6.279**
	(0.252)	(0.332)	(0.484)	(0.283)	(2.383)
$HPower$	0.117	-1.539***	0.00418	-0.00417	0.245
	(0.193)	(0.276)	(0.458)	(0.455)	(1.399)
$Length^2$	1.806***	0.664*	-0.0918	-0.691**	3.868**
	(0.185)	(0.282)	(0.365)	(0.239)	(1.359)
$Tonnage^2$	0.0815***	0.0722***	0.156***	0.0243	0.0840
	(0.0117)	(0.0114)	(0.0173)	(0.0149)	(0.0839)
$HPowersq^2$	-0.00496	0.0843***	0.0256*	0.150***	-0.145***
	(0.00508)	(0.00588)	(0.0123)	(0.0112)	(0.0378)
$Length \cdot Tonnage$	-0.667***	-0.388***	-0.566***	0.119	-1.881**
	(0.0750)	(0.100)	(0.137)	(0.0800)	(0.625)
$Length \cdot HPower$	-0.0384	0.249**	-0.0948	-0.394**	0.313
	(0.0592)	(0.0888)	(0.114)	(0.135)	(0.480)
$Tonnage \cdot HPower$	0.0261	-0.0296	0.0499*	0.0409	0.0809
	(0.0150)	(0.0170)	(0.0236)	(0.0313)	(0.163)
Management Area Dummies					
NO	0.393***				
	(0.0198)				
CO	0				
	(.)				
KO	0.123***				
	(0.0281)				
KC	0.589***				
	(0.0563)				
FB	0.925***				
	(0.0297)				
SF	0.764***				
	(0.0284)				
MO	0.493***				
	(0.0507)				
Temporal Dummies Omitted					
N	28169	31553	8399	11585	1735
R^2	0.206	0.268	0.182	0.207	0.295

Notes. Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 2.4: Species Specific Coarse-Information Signal Regression Estimates

	SAMN	CRAB	HMS	GRND	OTHERS
Constant	7.458***	9.953***	8.326***	7.147***	5.462***
	(0.000532)	(0.000357)	(0.000939)	(0.00106)	(0.00383)
$NWsince1W$	0.0336***	-0.171***	0.00963***	0.0781***	0.175***
	(0.0000634)	(0.0000184)	(0.000104)	(0.0000678)	(0.000237)
$NWsince1W^2$	-0.00113***	0.00323***	0.0000142***	-0.00141***	-0.00291***
	(1.98E-06)	(3.42E-07)	(3.53E-06)	(1.12E-05)	(3.95E-06)
2006.Year	-0.307***	0.0697***	0.0720***	-0.117***	0.0500***
	(0.000601)	(0.000375)	(0.000790)	(0.000812)	(0.00237)
2007.Year	-0.345***	-0.0615***	0.0361***	-0.0473***	0.117***
	(0.000546)	(0.000395)	(0.000773)	(0.000833)	(0.00201)
2008.Year	-0.562***	-0.270***	0.374***	-0.142***	0.170***
	(0.00122)	(0.000407)	(0.000770)	(0.000778)	(0.00193)
2009.Year	-0.594***	-0.0833***	0.136***	0.0158***	0.104***
	(0.00104)	(0.000387)	(0.000760)	(0.000733)	(0.00197)
2010.Year	-0.0564***	-0.0564***	0.203***	0.211***	0.386***
	(0.000572)	(0.000389)	(0.000754)	(0.000725)	(0.00201)
2011.Year	-0.139***	0.188***	0.394***	0.416***	0.820***
	(0.000543)	(0.000370)	(0.000713)	(0.000713)	(0.00185)
2012.Year	0.0253***	0.487***	0.486***	0.113***	0.764***
	(0.000456)	(0.000359)	(0.000700)	(0.000795)	(0.00181)
2013.Year	0.375***	0.192***	0.517***	0.00562***	0.961***
	(0.000401)	(0.000360)	(0.000722)	(0.000907)	(0.00180)
2014.Year	0.454***	0.0580***	0.434***	0.112***	0.960***
	(0.000401)	(0.000375)	(0.000731)	(0.000905)	(0.00185)
NO	0.239***				
	(0.000335)				
CO	0				
	(.)				
KO	0.177***				
	(0.000450)				
KC	0.575***				
	(0.000732)				
FB	0.798***				
	(0.000366)				
SF	0.664***				
	(0.000377)				
MO	0.521***				
	(0.000732)				
N	26790	34428	9485	11206	2001
$WaldChi^2$	0.0000	0.0000	0.0000	0.0000	0.0000

Notes. Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 2.5: Information Set

	Own vessel info		Group average			Observed Choices	
Info Set	FF^R	FF^O	F^R	F^O	CS	$Freq$	%
1	0	0	0	0	1	2675	3.20
2	1	0	0	0	1	1018	1.22
3	0	1	0	0	1	249	0.30
4	0	0	1	0	1	4534	5.43
5	0	0	0	1	1	1801	2.16
6	1	1	0	0	1	218	0.26
7	1	0	1	0	1	6068	7.27
8	1	0	0	1	1	556	0.67
9	0	1	1	0	1	288	0.35
10	0	1	0	1	1	1026	1.23
11	0	0	1	1	1	16849	20.19
12	1	1	1	0	1	383	0.46
13	1	1	0	1	1	742	0.89
14	1	0	1	1	1	18219	21.83
15	0	1	1	1	1	9637	11.55
16	1	1	1	1	1	19208	23.01

Notes. 1 = Information signal is present, 0 otherwise

FF^R: Finest recent, FF^O: Finest old,

F^R: Fine recent, F^O: Fine old, CS: Coarse-scale

TABLE 2.6: Summary of Statistics by Groups

Vessel Group	%	Length		Tons		Horse Power	
		Mean	Std	Mean	Std	Mean	Std
1	0.33	37.50	0.71	15.00	5.66	881.00	15.56
2	0.82	45.00	12.08	21.00	9.27	619.40	50.56
3	5.88	35.69	8.32	10.50	10.25	44.14	28.12
4	9.97	41.00	9.89	16.70	11.57	257.13	9.74
5	26.63	41.56	7.47	14.40	9.02	162.61	10.95
6	10.78	44.53	9.51	23.85	15.16	330.62	23.19
7	24.18	35.66	7.65	8.70	7.02	106.82	15.98
8	6.21	38.95	9.44	13.34	9.94	227.47	7.14
9	12.09	37.96	8.70	13.08	9.89	199.11	7.28
10	3.10	40.95	12.49	19.00	20.31	446.00	34.88
All	100.00	39.45	9.01	14.01	11.29	193.01	105.74

TABLE 2.7: 1-8 Information Weight Estimates

	1	2	3	4	5	6	7	8
1	7.247***	7.073***	7.823***	7.207***	7.344***	7.282***	7.173***	7.265***
	(0.000671)	(0.00152)	(0.00209)	(0.000562)	(0.000740)	(0.00218)	(0.000676)	(0.00168)
2	0.000281***	0.0000837***	0.000206***	0.000240***	0.000198***		0.00000808***	0.0000928***
	(1.57E-07)	(4.55E-07)	(5.14E-07)	(1.65E-07)	(1.43E-07)		(2.54E-07)	(4.31E-07)
3		0.000173***				0.000178***		0.000115***
		(2.24E-07)				(4.10E-07)		(2.97E-07)
4			0.0000338***			0.0000384***		
			(2.80E-08)			(1.03E-07)		
5				0.0000850***			0.000235***	
				(8.77E-08)			(1.50E-07)	
6					0.0000862***			0.0000577***
					(1.21E-07)			(E2.27E-07)
N	2779	1017	293	4927	1908	208	5753	565
R^2	0.15	0.28	0.25	0.14	0.19	0.53	0.23	0.12

Notes.
Variables, 1: Constant, 2: Coarse Scale (Seasonal Average), 3: Recent Finest (own), 4:Old Finest (own)
5: Recent Fine (Group Average), 6: Old Fine (Group Average)
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 2.8: 9-16 Information Weight Estimates

	9	10	11	12	13	14	15	16
1	7.939***	7.946***	7.253***	7.210***	7.374***	7.108***	7.670***	7.301***
	(0.00159)	(0.000750)	(0.000245)	(0.00240)	(0.00165)	(0.000349)	(0.000282)	(0.000355)
2	0.0000360***	0.0000769***	0.000176***	0.0000682***	0.0000127***	0.000127***	0.000116***	0.000104***
	(3.79E-07)	(1.06E-07)	(6.35E-08)	(8.11E-07)	(4.39E07)	(1.23E07)	(5.69E-08)	(1.12E-07)
3				0.0000919***	0.0000981***	0.000126***		0.000110***
				(4.52E-07)	(2.41E-07)	(5.63E-08)		(5.08E-08)
4	0.0000407***	0.0000257***		0.0000439***	0.0000373***		0.0000176***	6.60E-06***
	(3.56E-08)	(1.34E-08)		(2.46E-07)	(1.19E-07)		(4.70E-09)	(1.11E-08)
5	0.0000826***		0.0000774***	0.0000261***		-0.0000153***	0.0000746***	-5.59E06***
	(1.53E-07)		(4.80E-08)	(7.09E-07)		(1.14E-07)	(4.24E-08)	(1.08E-07)
6		0.0000869***	0.0000795***		0.0000645***	0.0000263***	0.0000741***	0.0000143***
		(1.14E-07)	(4.77E-08)		(2.55E-07)	(8.34E-08)	(4.76E-08)	(8.21E-08)
N	386	1203	18782	341	695	16239	12824	15990
R^2	0.46	0.18	0.22	0.21	0.18	0.21	0.20	0.20

Notes.
Variables, 1: Constant, 2: Coarse Scale (Seasonal Average), 3: Recent Finest (own), 4:Old Finest (own)
5: Recent Fine (Group Average), 6: Old Fine (Group Average)
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 2.9: RUM Model Results.

	S	S-H	S-C	S-G	S-H-C	S-H-G	S-C-G
Alternative Specific Variables							
$ExpectedRev$	0.000145***	0.000242***	0.000135***	0.000147***	0.000135***	0.000205***	0.000111***
	(0.0000247)	(0.0000168)	(0.00000695)	(0.0000318)	(0.00000601)	(0.0000269)	(0.00000941)
$LastWeek$	1.383***	1.384***	1.702***	1.283***	1.392***	1.355***	1.472***
	(0.0706)	(0.0371)	(0.0590)	(0.0890)	(0.0420)	(0.0476)	(0.0516)
$LastYear$	0.615***	0.533***	0.783***	0.579***	0.619***	0.536***	0.650***
	(0.0462)	(0.0271)	(0.0332)	(0.0487)	(0.0307)	(0.0483)	(0.0391)
Alternative Specific Constant							
SAMN NO	-0.165	-0.412	0.172	-2.565***	0.237	-0.408	-0.945
	(0.438)	(0.275)	(0.767)	(0.421)	(0.554)	(0.729)	(0.683)
SAMN CO	-0.534	0.127	-0.577	-1.358**	0.364	0.247	-0.234
	(0.320)	(0.191)	(0.552)	(0.521)	(0.432)	(0.575)	(0.714)
SAMN KO	0.455	1.200*	-1.218*	-0.755	0.295	2.018	1.748**
	(0.616)	(0.481)	(0.620)	(0.897)	(0.678)	(1.138)	(0.557)
SAMN KC	-2.049**	-2.734***	-1.012	-1.016	-1.234	-3.945***	-0.694
	(0.685)	(0.781)	(0.677)	(0.948)	(0.746)	(0.999)	(1.123)
SAMN FB	-1.649*	0.367	-0.236	-2.192**	0.148	-1.949	-2.641**
	(0.725)	(0.840)	(0.703)	(0.696)	(0.795)	(1.064)	(0.831)
SAMN SF	-2.168**	-0.712	-1.116	-2.140**	-0.114	-1.993	-2.266**
	(0.707)	(0.745)	(0.604)	(0.704)	(0.737)	(1.163)	(0.843)
SAMN MO	-1.113	-0.517	-1.686	-1.887*	-0.635	-2.419*	-2.005**
	(0.851)	(0.702)	(0.905)	(0.893)	(0.945)	(1.173)	(0.684)
CRAB			-0.255		0.646		-1.723*
			(0.403)		(0.503)		(0.816)
HMS		-1.487***			-1.558***	-0.210	
		(0.313)			(0.368)	(1.046)	
GRND				1.546**		-0.563	1.289*

Continuation of Table 2.9

	S	S-H	S-C	S-G	S-H-C	S-H-G	S-C-G
				(0.521)		(0.933)	(0.535)
Case Specific Variables -Tonnage, Tons and Horse Power - Omitted							
Dissimilarity Parameters							
λ_{NoPart}	1.000***	1.000***	1.000	1.000***	1.000	1.000	1.000
	(0.0129)	(0.0665)	(.)	(0.115)	(.)	(.)	(.)
λ_{SAMN}	0.333***	0.393***	0.463***	0.248***	0.371***	0.349***	0.289***
	(0.0354)	(0.0255)	(0.0348)	(0.0261)	(0.0198)	(0.0251)	(0.0201)
λ_{CRAB}			1.000		1.000		1.000
			(11.12)		(1.938)		(1.487)
λ_{HMS}		1.000**			1.000	1.000	
		(0.305)			(2.018)	(1.639)	
λ_{GRND}				1.000**		1.000	1.000
				(0.356)		(4.467)	(3.571)
N	131280	305370	195597	100251	303050	113740	181710
$WaldChi^2$	550.41***	2622.37***	1845.45***	3002.77***	2676.91***	3212.66***	1542.07***

Notes. Choice Sets: S: Salmon Only; S-C: Salmon/Crab; S-H: Salmon/HMS; S-G: Salmon/Groundfish; S-H-C: Salmon/HMS/Crab; S-H-G: Salmon/HMS/Groundfish; and S-C-G: Salmon/Crab/Groundfish.

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 2.10: Comparing Coefficients Ratios Across Fleets

Variables	S	S-H	S-C	S-G	S-H-C	S-H-G	S-C-G
Alternative Specific Variables							
ExpRev	1	1	1	1	1	1	1
LWeek	9537.9	5719.1	12607.4	8727.9	10311.1	6609.7	13261.2
LYear	4241.3	2202.4	5800	3938.7	4585.1	2614.6	5855.8
Alternative Specific Constants							
NO	-1137.9	-1702.4	1274.17	-17449	1755.5	-1990.2	-8513.5
CO	-3682.7	524.7	-4274.1	-9238.1	2696.2	1204.8	-2108.1
KO	3137.9	4958.6	-9022.2	-5136.1	2185.1	9843.9	15747.7
KC	-14131	-11297.5	-7496.3	-6911.5	-9140.7	-19243.9	-6252.2
FB	-11372.4	1516.5	-1748.1	-14911.6	1096.2	-9507.3	-23792.8
SF	-14951.7	-2942.1	-8266.6	-14557.8	-844.4	-9721.9	-20414.4
MO	-7675.8	-2136.3	-12488.9	-12836.7	-4703.7	-11800	-18063.1
CRAB			-1888.8		4785.1		-15522.5
HMS		-6144.6			-11540.7	-1024.3	
GRND				10517.1		-2746.3	11612.6

Notes. Choice Sets: S: Salmon Only; S-C: Salmon/Crab; S-H: Salmon/HMS; S-G: Salmon/Groundfish; S-H-C: Salmon/HMS/Crab; S-H-G: Salmon/HMS/Groundfish; and S-C-G: Salmon/Crab/Groundfish.

TABLE 2.11: Choice Probabilities for a Single Closure

		2nd Week of May		2nd Week of July	
Choice Set	Alternative	Open	Close	Open	Close
S	NoParticipation	0.25	0.57	0.24	0.56
	SAMN NO	0.00	0.08	0.00	0.08
	SAMN CO	0.01	0.24	0.01	0.24
	SAMN KO	0.00	0.01	0.00	0.01
	SAMN KC	0.00	0.01	0.00	0.01
	SAMN FB	0.73		0.74	
	SAMN SF	0.00	0.07	0.00	0.08
	SAMN MO	0.00	0.02	0.00	0.02
S-C	NoParticipation	0.20	0.48	0.19	0.48
	SAMN NO	0.00	0.04	0.00	0.04
	SAMN CO	0.01	0.13	0.01	0.13
	SAMN KO	0.00	0.06	0.00	0.06
	SAMN KC	0.00	0.03	0.00	0.03
	SAMN FB	0.71		0.72	
	SAMN SF	0.00	0.06	0.00	0.06
	SAMN MO	0.00	0.01	0.00	0.01
	CRAB	0.08	0.20	0.07	0.19
S-H	NoParticipation	0.48	0.56	0.42	0.49
	SAMN NO	0.07	0.15	0.06	0.14
	SAMN CO	0.09	0.19	0.08	0.17
	SAMN KO	0.00	0.00	0.00	0.00
	SAMN KC	0.00	0.00	0.00	0.00
	SAMN FB	0.29		0.28	
	SAMN SF	0.01	0.02	0.01	0.02
	SAMN MO	0.01	0.02	0.01	0.02
	HMS	0.05	0.06	0.14	0.17
S-G	NoParticipation	0.25	0.53	0.24	0.52
	SAMN NO	0.00	0.13	0.00	0.13
	SAMN CO	0.00	0.15	0.00	0.15
	SAMN KO	0.00	0.01	0.00	0.01
	SAMN KC	0.00	0.01	0.00	0.01
	SAMN FB	0.70		0.71	
	SAMN SF	0.00	0.05	0.00	0.05
	SAMN MO	0.00	0.02	0.00	0.03
	GRND	0.05	0.10	0.05	0.10
S-C-G	NoParticipation	0.19	0.41	0.19	0.41
	SAMN NO	0.00	0.04	0.00	0.04
	SAMN CO	0.00	0.08	0.00	0.08
	SAMN KO	0.00	0.04	0.00	0.04
	SAMN KC	0.00	0.01	0.00	0.01

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TABLE 2.11 – continued from previous page

		2nd Week of May		2nd Week of July	
Choice Set	Alternative	Open	Close	Open	Close
	SAMN FB	0.63		0.64	
	SAMN SF	0.00	0.05	0.00	0.05
	SAMN MO	0.00	0.01	0.00	0.01
	CRAB	0.07	0.15	0.06	0.14
	GRND	0.11	0.22	0.11	0.23
S-H-C	NoParticipation	0.29	0.48	0.27	0.44
	SAMN NO	0.00	0.03	0.00	0.03
	SAMN CO	0.01	0.15	0.01	0.14
	SAMN KO	0.00	0.03	0.00	0.02
	SAMN KC	0.00	0.01	0.00	0.01
	SAMN FB	0.54		0.53	
	SAMN SF	0.00	0.05	0.00	0.05
	SAMN MO	0.00	0.01	0.00	0.01
	CRAB	0.09	0.15	0.08	0.13
	HMS	0.06	0.10	0.10	0.17
S-H-G	NoParticipation	0.29	0.48	0.27	0.43
	SAMN NO	0.01	0.10	0.01	0.10
	SAMN CO	0.02	0.18	0.01	0.17
	SAMN KO	0.00	0.00	0.00	0.00
	SAMN KC	0.00	0.00	0.00	0.00
	SAMN FB	0.57		0.56	
	SAMN SF	0.00	0.03	0.00	0.03
	SAMN MO	0.00	0.01	0.00	0.01
	HMS	0.03	0.05	0.07	0.12
	GRND	0.08	0.13	0.08	0.13

Notes. Assumptions

Open:

- *Expected revenue* values are set to 2014 values
- All alternatives are available
- *Last Week* = *Last Year* = salmon fishery at the FB Management Area.

Closed

- Same as open scenario but salmon fishery at FB is closed.

Choice Sets: S: Salmon Only; S-C: Salmon/Crab; S-H: Salmon/HMS; S-G: Salmon/Groundfish; S-H-C: Salmon/HMS/Crab; S-H-G: Salmon/HMS/Groundfish; and S-C-G: Salmon/Crab/Groundfish.

TABLE 2.12: Observed Choices in 2005 and 2006

	Choice Sets							
Alt	S	S-C	S-H	S-G	S-C-G	S-H-C	S-H-G	Total
First week of May in 2005								
NoParticipation	1	15	5	2	11	17	3	54
SAMN NO	4	2	11	1	3	3	2	26
SAMN CO	26	9	53	13	7	27	17	152
SAMN KO	1	0	1	5	2	8	0	17
SAMN KC	0	0	0	0	0	0	0	0
SAMN FB	0	0	0	0	0	0	0	0
SAMN SF	1	4	2	1	3	2	1	14
SAMN MO	1	7	8	1	3	4	0	24
CRAB	0	23	0	0	13	13	0	49
HMS	0	0	0	0	0	0	0	0
GRND	0	0	0	3	5	0	2	10
Total	34	60	80	26	47	74	25	346
First week of September 2005								
NoParticipation	12	27	39	5	14	30	4	131
SAMN NO	0	0	2	0	0	0	1	3
SAMN CO	20	13	35	13	10	35	17	143
SAMN KO	0	4	0	2	7	0	0	13
SAMN KC	1	8	0	0	1	1	0	11
SAMN FB	0	5	1	2	4	0	0	12
SAMN SF	1	3	0	0	2	2	0	8
SAMN MO	0	0	0	0	0	0	0	0
CRAB	0	0	0	0	1	0	0	1
HMS	0	0	3	0	0	6	0	9
GRND	0	0	0	4	8	0	3	15
Total	34	60	80	26	47	74	25	346
First week of May 2006 (all observed choices)								
NoParticipation	33	28	72	22	23	52	20	250
SAMN NO	0	1	5	0	3	3	2	14
SAMN CO	0	0	0	0	0	0	0	0
SAMN KO	0	0	0	0	0	0	0	0
SAMN KC	0	0	0	0	0	0	0	0
SAMN FB	0	0	0	0	0	0	0	0
SAMN SF	0	0	0	0	0	0	0	0
SAMN MO	1	2	3	0	1	1	0	8
CRAB	0	29	0	0	13	18	0	60
HMS	0	0	0	0	0	0	0	0
GRND	0	0	0	4	7	0	3	14
Total	34	60	80	26	47	74	25	346

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TABLE 2.12 – continued from previous page

	Choice Sets							
Alt	S	S-C	S-H	S-G	S-C-G	S-H-C	S-H-G	Total
First week of May 2006 (Observed choices of vessels that chose SAMN CO on same week in 2005)								
NoParticipation	27	7	50	12	4	20	15	135
SAMN NO	0	0	3	0	1	0	0	4
SAMN CO	0	0	0	0	0	0	0	0
SAMN KO	0	0	0	0	0	0	0	0
SAMN KC	0	0	0	0	0	0	0	0
SAMN FB	0	0	0	0	0	0	0	0
SAMN SF	0	0	0	0	0	0	0	0
SAMN MO	0	1	0	0	0	1	0	2
CRAB	0	1	0	0	1	6	0	8
HMS	0	0	0	0	0	0	0	0
GRND	0	0	0	1	1	0	1	3
Total	27	9	53	13	7	27	16	152
First week of September 2006 (all observed choices)								
NoParticipation	34	60	58	21	28	59	17	277
SAMN NO	0	0	7	1	1	0	1	10
SAMN CO	0	0	0	0	0	0	0	0
SAMN KO	0	0	0	0	0	0	0	0
SAMN KC	0	0	0	0	0	0	0	0
SAMN FB	0	0	0	0	0	0	0	0
SAMN SF	0	0	0	0	0	0	0	0
SAMN MO	0	0	0	0	0	0	0	0
CRAB	0	0	0	0	1	2	0	3
HMS	0	0	15	0	0	13	5	33
GRND	0	0	0	4	17	0	2	23
Total	34	60	80	26	47	74	25	346
First week of Sept 2006 (Observed choices of vessels that chose SAMN CO on same week in 2005)								
NoParticipation	29	13	28	9	5	24	12	120
SAMN NO	0	0	3	0	1	0	1	5
SAMN CO	0	0	0	0	0	0	0	0
SAMN KO	0	0	0	0	0	0	0	0
SAMN KC	0	0	0	0	0	0	0	0
SAMN FB	0	0	0	0	0	0	0	0
SAMN SF	0	0	0	0	0	0	0	0
SAMN MO	0	0	0	0	0	0	0	0
CRAB	0	0	0	0	0	2	0	2
HMS	0	0	3	0	1	4	3	11
GRND	0	0	0	2	3	0	0	5

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TABLE 2.12 – continued from previous page

	Choice Sets							
Alt	S	S-C	S-H	S-G	S-C-G	S-H-C	S-H-G	Total
Total	29	13	34	11	10	30	16	143

Notes. Each entry indicates the number of vessels that participate in each alternative
Choice Sets:
S: Salmon Only; S-C: Salmon/Crab; S-H: Salmon/HMS; S-G: Salmon/Groundfish; S-H-C: Salmon/HMS/Crab; S-H-G: Salmon/HMS/Groundfish; and S-C-G: Salmon/Crab/Groundfish.

TABLE 2.13: Choice Probabilities for Several Closures

	Choice Sets						
Alt	S	S-C	S-H	S-G	S-C-G	S-H-C	S-H-G
First week of May in 2006 Last week choice = No Participation							
NoParticipation	0.92	0.89	0.91	0.86	0.79	0.84	0.85
SAMN NO	0.07	0.03	0.06	0.09	0.04	0.04	0.06
SAMN MO	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CRAB		0.07			0.07	0.07	
HMS			0.02			0.04	0.02
GRND				0.04	0.09		0.05
First week of May in 2006 Last week choice = CRAB							
NoParticipation		0.28			0.29	0.36	
SAMN NO		0.05			0.07	0.06	
SAMN MO		0.01			0.01	0.02	
CRAB		0.67			0.48	0.49	
HMS						0.07	
GRND					0.15		
First week of May in 2006 Last week choice = GRND							
NoParticipation				0.49	0.26		0.42
SAMN NO				0.18	0.06		0.12
SAMN MO				0.03	0.01		0.01
CRAB					0.10		
HMS							0.05
GRND				0.30	0.57		0.39
First week of September in 2006 Last week choice = No Participation							
NoParticipation	0.92	0.90	0.87	0.86	0.79	0.82	0.82
SAMN NO	0.07	0.03	0.06	0.09	0.04	0.04	0.07
SAMN MO	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CRAB		0.06			0.06	0.06	
HMS			0.06			0.07	0.05
GRND				0.04	0.09		0.05
First week of September in 2006 Last week choice = HMS							
NoParticipation			0.41			0.35	0.40
SAMN NO			0.12			0.06	0.12
SAMN MO			0.01			0.02	0.01
CRAB						0.10	
HMS			0.45			0.47	0.36
GRND							0.10

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TABLE 2.13 – continued from previous page

	Choice Sets						
Alt	S	S-C	S-H	S-G	S-C-G	S-H-C	S-H-G
	First week of September in 2006						
	Last week choice = GRND						
NoParticipation				0.49	0.26		0.39
SAMN NO				0.18	0.06		0.12
SAMN MO				0.03	0.01		0.01
CRAB					0.09		
HMS							0.09
GRND				0.31	0.58		0.38

Notes. Assumptions
-*Expected Revenue* values are set to 2nd week of August on 2006
- Salmon management areas CO, KO, KC, FB, and MO are closed as show in Figure 2.11
- *Last Year Choice* = Salmon at CO
Choice Sets:
S: Salmon Only; S-C: Salmon/Crab; S-H: Salmon/HMS;
S-G: Salmon/Groundfish; S-H-C: Salmon/HMS/Crab;
S-H-G: Salmon/HMS/Groundfish; and S-C-G: Salmon/Crab/Groundfish.

2.8 Figures

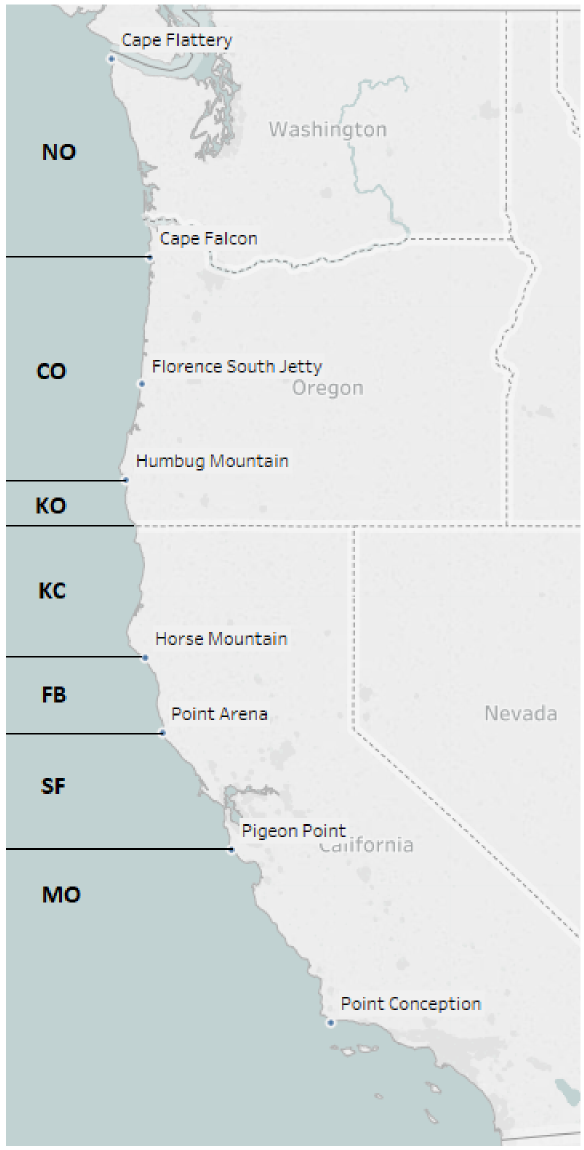

FIGURE 2.1: Salmon Marine Management Areas
Salmon management areas as defined by the Pacific Fishery Management Council (Council 2014).

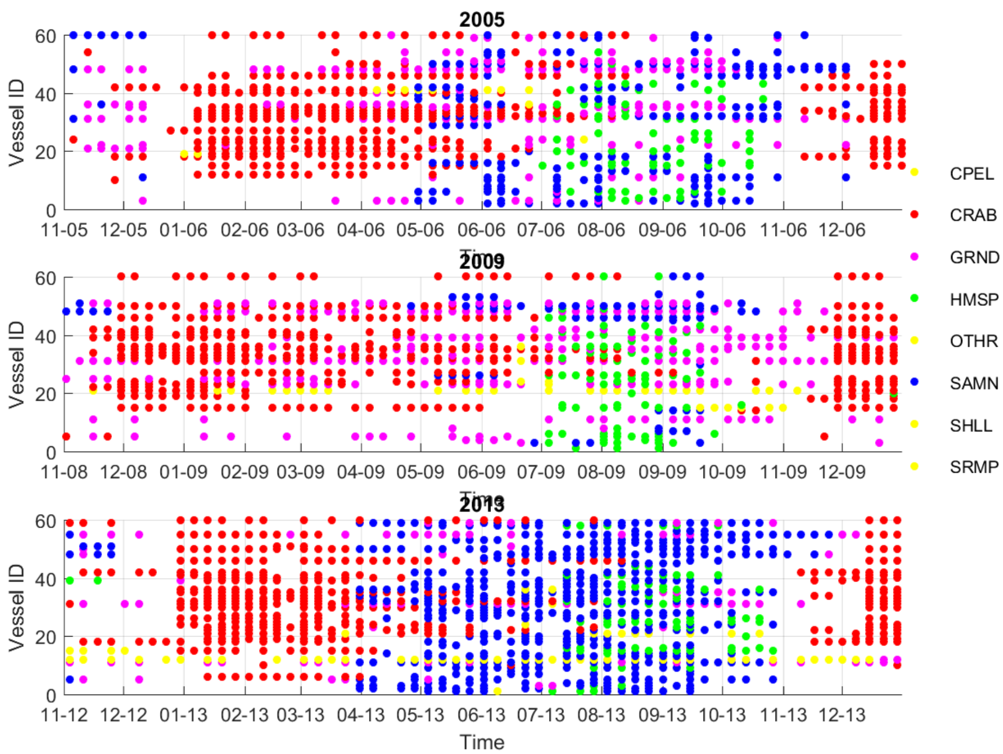

FIGURE 2.2: Weekly Fishery Participation Across all Fisheries.
Each plot depicts weekly fishery participation of the same 60 randomly selected troll salmon vessels. Each dot represents a fishery participation, where each fishery is represented by a different color. For comparison purposes CPEL, OTHR, SHLL, and SRMP have been aggregated into the OTHER category and colored in yellow.

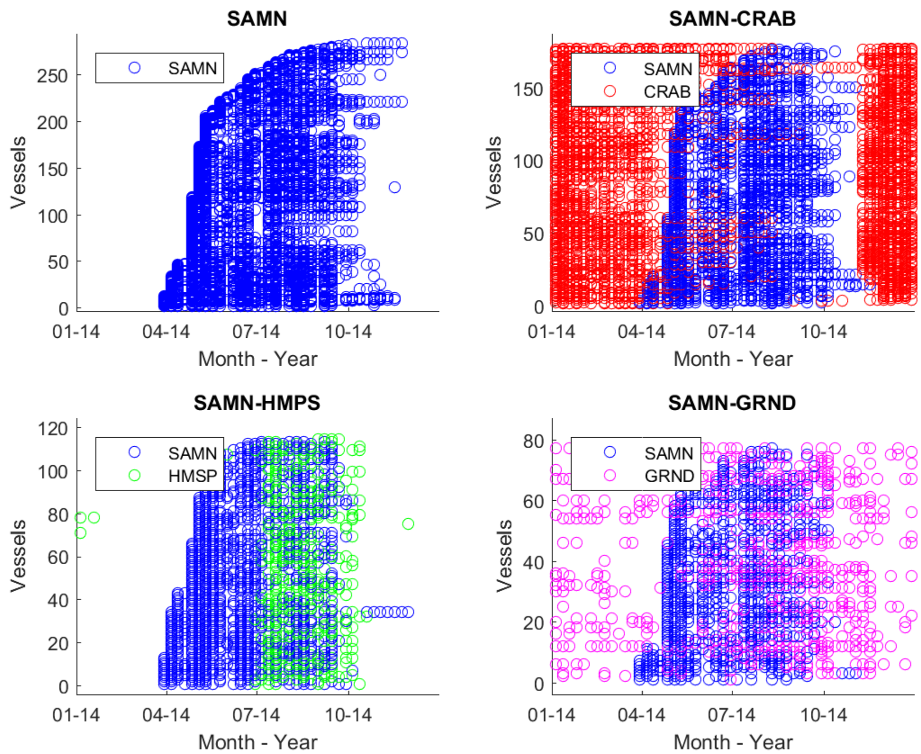

FIGURE 2.3: Switching Behavior Across Two Fisheries 2014.
Each plot depicts fishery participation of salmon troll vessels. Plot 1 (upper-left corner), shows participation behavior of vessels that participate exclusively in the salmon fishery. Plot 2 (upper-right corner) shows participation behavior of salmon troll vessels that also participate in the crab fishery, and so on. Vessels have been listed according to the earliest date they participate in the salmon fishery.

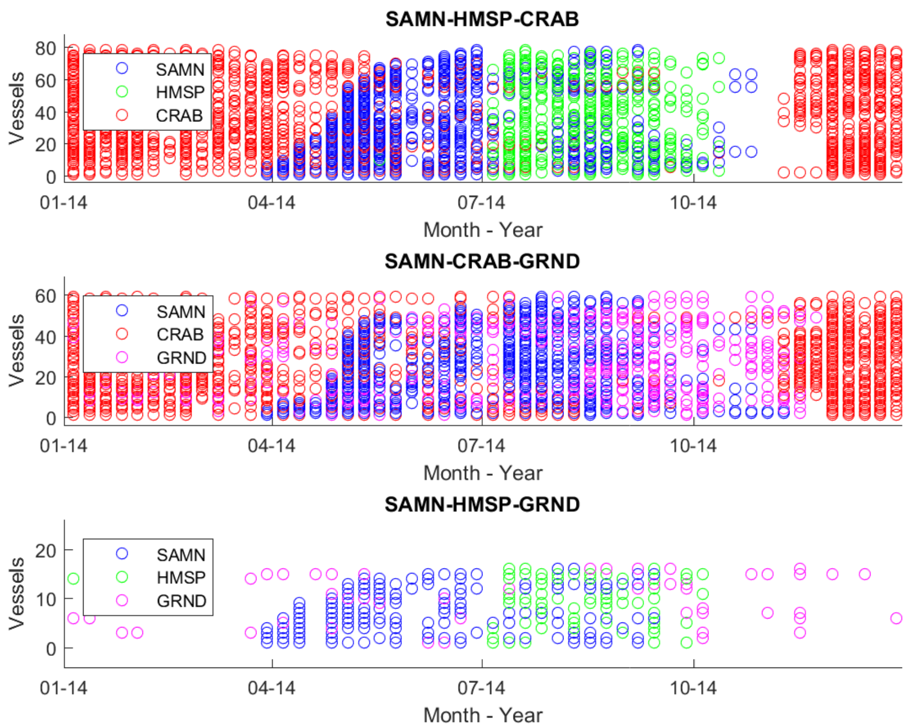

FIGURE 2.4: Switching Behavior Across Three Fisheries 2014.
Each plot depicts fishery participation of salmon troll vessels that participate in three fisheries. For example, plot 1 (upper row), depicts fishery participation of vessels that participate in the salmon, highly migratory, and the crab fishery. Vessels have been listed according to the earliest date they participate in the salmon fishery.

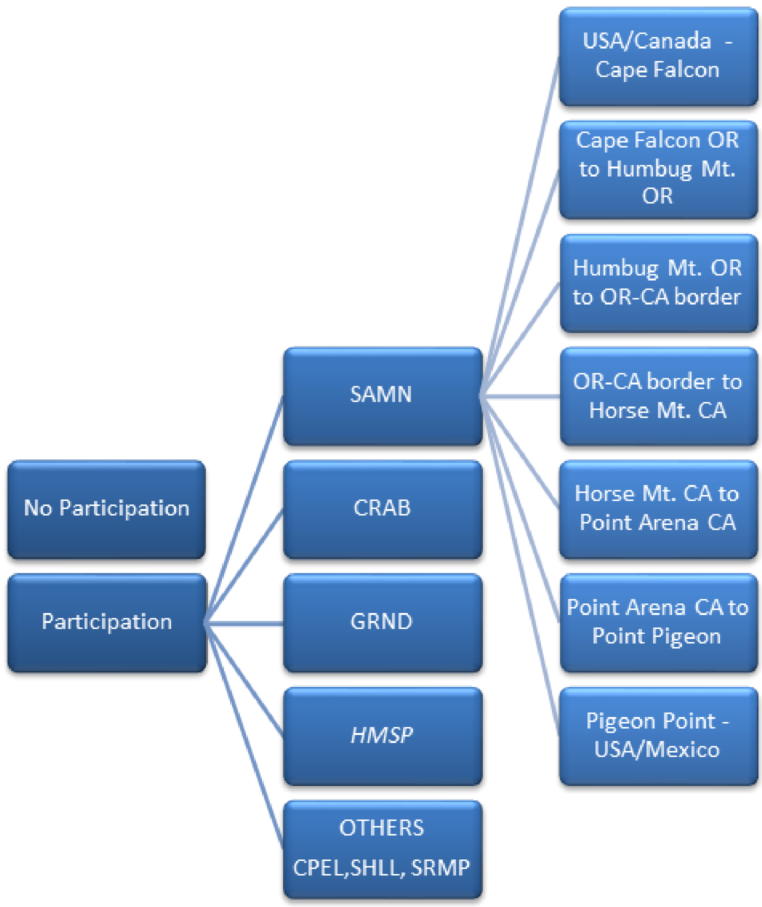

FIGURE 2.5: WC Salmon Fishermen Full Set of Alternatives

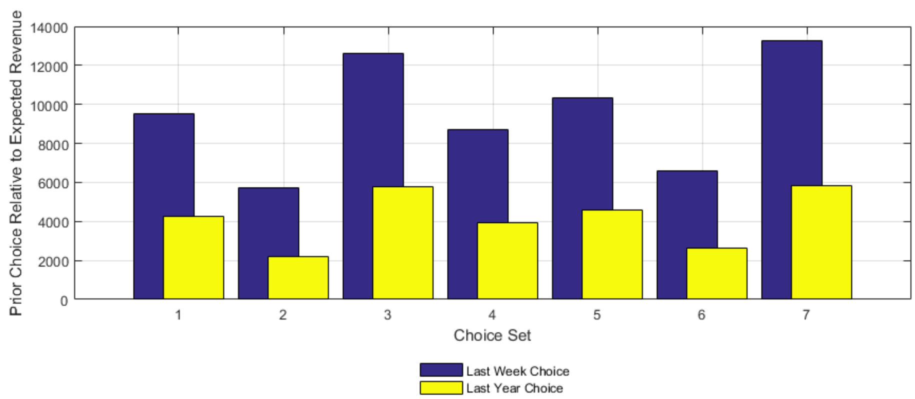

FIGURE 2.6: State Dependence Coefficient Comparison
Choice Sets: (1) Only Salmon, (2) Salmon/HMS (3) Salmon/Crab, (4) Salmon/Groundfish, (5) Salmon /HMS/Crab, (6) Salmon/HMS/Groundfish, and (7) Salmon/Crab/Groundfish.

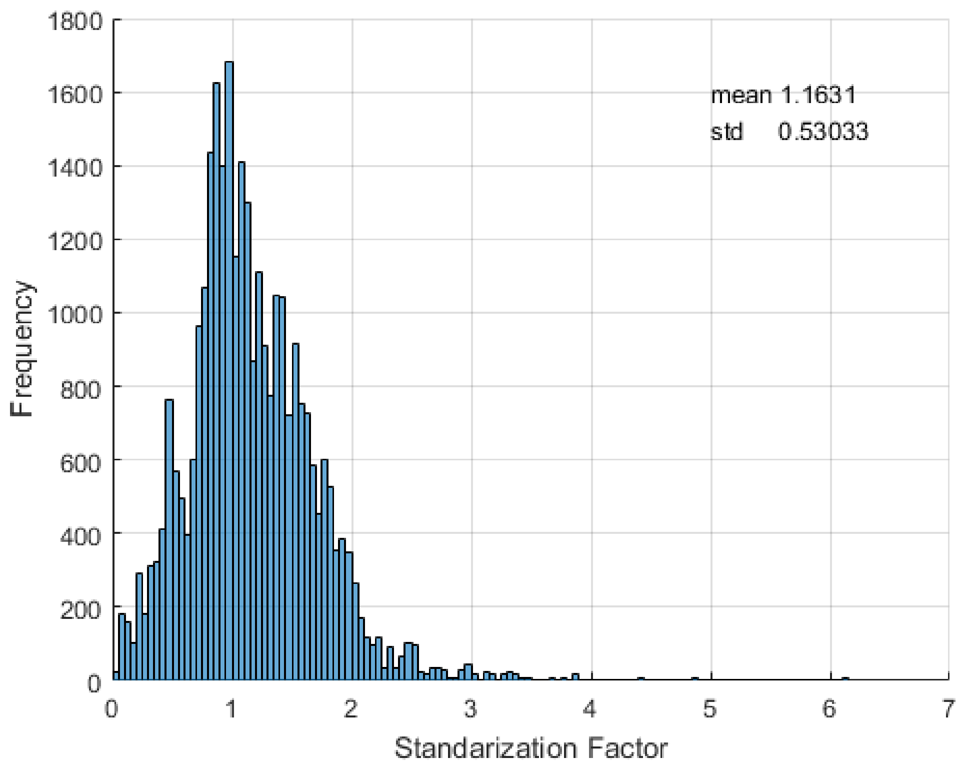

FIGURE 2.7: Distribution of Standardization Factor

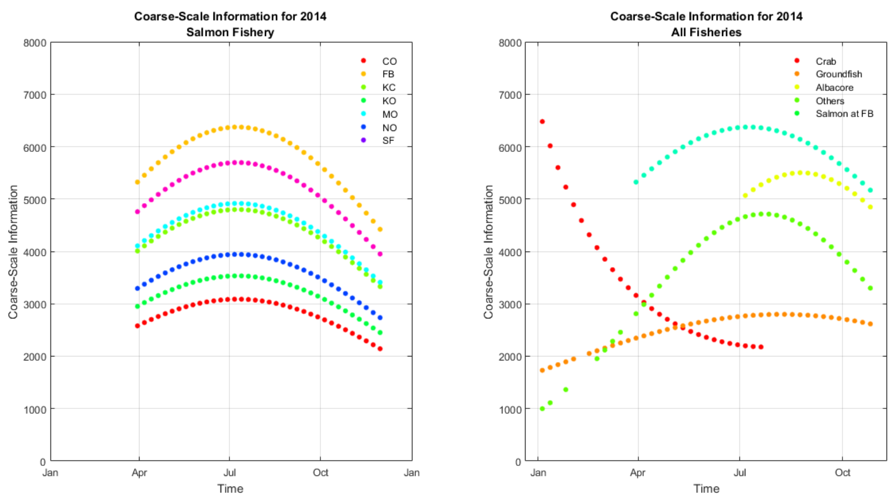

FIGURE 2.8: 2014 Coarse-Scale Revenue Information
Coarse-scale revenue information was calculated using coarse-scale estimates in Table 2.4.

FIGURE 2.9: Vessel Categorization
Each plot depicts vessels' characteristics as given by their length, tons capacity, and horsepower. Plot on the right shows same distribution as in plot in the left but vessels are colored coded according to their group. Groups were created with k-means clustering partitioning method. Each cluster has a centroid marked in black. The centroid for each cluster is the vessel to which the sum of distances from all other vessels in the cluster is minimized.

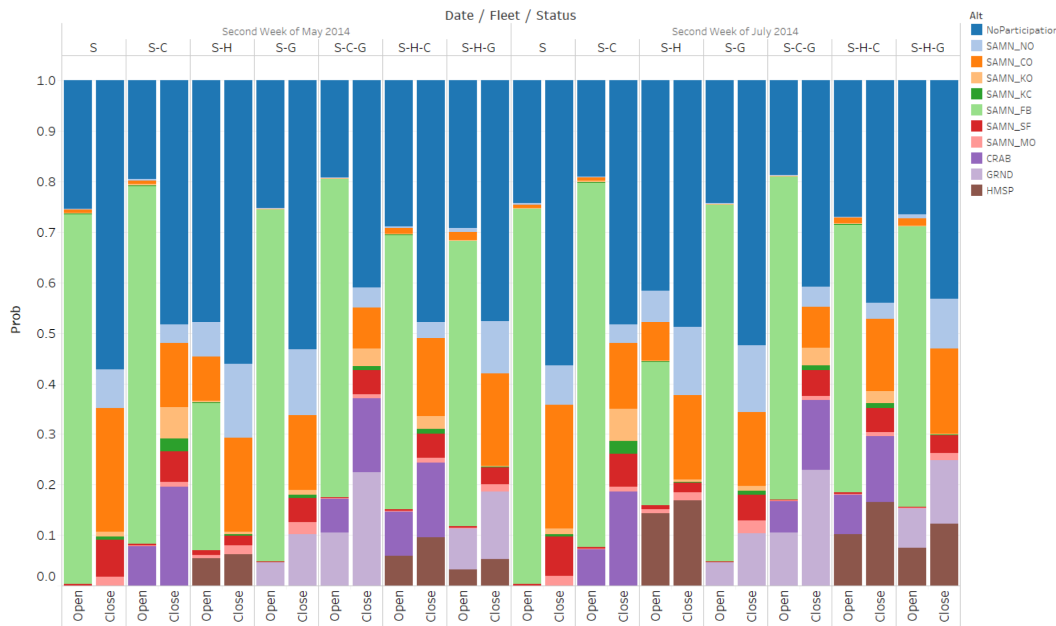

FIGURE 2.10: Choice Probabilities Under a Open and Closed Scenarios for a Salmon Management Areas

The plot displays, along the y-axis, choice probabilities for all fishery participation and location choice alternatives as well as the no participation alternative denoted by color coding. Choice probabilities by scenario (open/close), date, and fleet are listed along the x-axis. Fleets names are S: only salmon, S-C: salmon and crab, S-H: salmon and highly migratory species, S-G: salmon and groundfish, S-C-G: salmon, crab, and groundfish, S-H-C: salmon, highly migratory, and crab, and S-H-G: salmon, highly migratory, and groundfish.

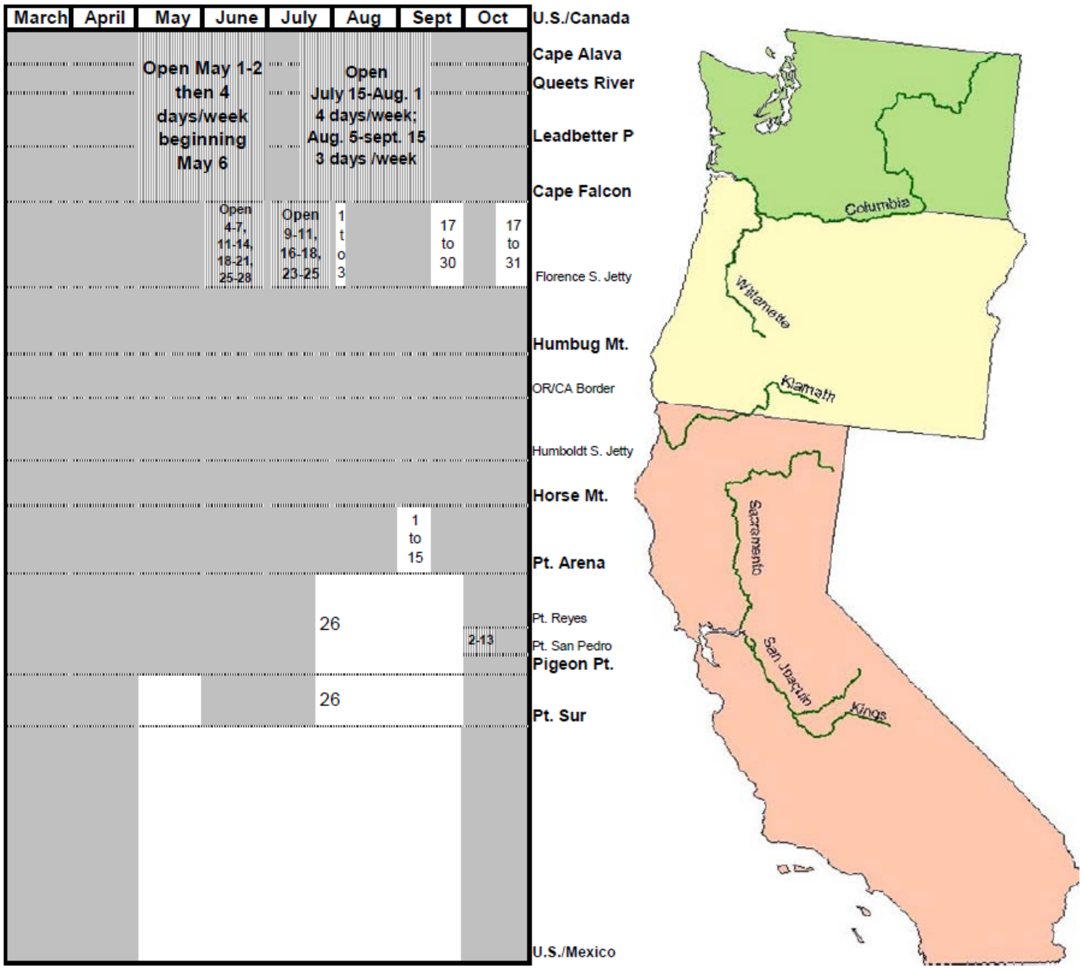

FIGURE 2.11: Commercial Salmon Fishery Season for 2006
Pacific Fishery Management Council adopted commercial salmon seasons for 2006. Dates are the first or last days of the month, dark areas correspond to area-temporal closures while white areas denote open areas. Adopted seasons are published every year in the Preseason Report III and prepared by the Salmon Technical Team (Council 2006)

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3 Ecological-Economic Model of a Mixed Stock Fisheries

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Abstract

Mixed-stock systems present a daunting problem when low and high abundance stocks are mixed and harvested together and when both the fisherman and the regulator are unable to assess harvest composition at catch. I developed a spatially explicit mixed-stock fishery model that integrates 1) spatial in-season dynamics of low and high abundance stocks 2) myopic fleet behavior, and 3) a single regulatory agency that establishes in-season area-temporal closures in order to achieve both conservation and fishery benefit objectives. I used model simulations to explore the effect that monitoring regimes at different spatial scales of mixed-stock harvest composition have on achieving weak stock escapement goals and economic benefits for the fishery. The model is motivated by current efforts in the West Coast Salmon fishery to monitor mixed-stock harvest composition using Genetic Stock Identification techniques and harvest data. Simulation results suggest that spatial monitoring of mixed-stock harvest composition allows for higher profits for the fleet, while meeting conservation goals, only when it takes place at a fine spatial scale. In particular, the greatest fishery benefits are obtained when sampling and monitoring takes place at the spatial scale at which fishermen make fishing location choices.

[1] With Gil Sylvia and Dan Holland. This study was supported and monitored by National Oceanic and Atmospheric Administration (NOAA) under LMRCSC AB Grant 16-04.

3.1 Introduction

Many terrestrial and marine species share the same habitat and exploitation grounds. With marine species in particular, harvest selectivity of mixed species is imperfect due to several factors, such as non-discriminatory fishing gear (Boyce 1996; Androkovich and Stollery 1994), costly avoidance (Singh 2015), high spatial correlation among the target and the non-target species (Sampson 1994; Abbott 2009; Ono et al. 2013), or the imperfect observation of catch. Mixed-stock fisheries, which occur when more than one re-productively isolated sub-population are aggregated in fishing grounds and are harvested simultaneously (Satterthwaite, Mohr, et al. 2014; Satterthwaite, Ciancio, et al. 2015), are ecosystems that are characterized by the presence of the same issues as mixed species species fisheries but may have the additional complication of an inability to differentiate stocks even when they brought on board. Management of mixed-stocks fisheries must take into account that stocks of different productivity may require different harvest strategies. A daunting problem occurs when low productive stocks (weak) are mixed and caught together with high productivity stocks (healthy) (Ono et al. 2013; Dougherty et al. 2013). While management that seeks to maximize fishery benefits may lead to the depletion of the weak stock, the management for the protection of weak stocks may lead to the forgone fishing opportunities (Sampson 1994; Hilborn et al. 2004). The management challenge for mixed-stock fisheries is one of avoiding harvest of weak stocks while allowing for harvest opportunities in the fishery. A key solution to this problem lies in the managers' and harvesters' ability to monitor the spatial and temporal ocean distribution and co-occurrence of individual stocks in such a way that fisheries can discriminate between different stocks [2].

Ocean salmon fisheries have been used as a prime example of a mixed-stock fishery (Paulik et al. 1967; Hilborn 1976; Kope 1992). The fishery is composed of

[2]Alternative solutions to the management of mixed-stock fisheries relies in the ability to improve gear selectivity or changes in fishing behavior, such as tow speed time of day.

multiple stocks originating from different river systems that are aggregated in the ocean and consequently are harvested simultaneously. In the West Coast ocean troll salmon fishery, current management practices aim to allow for fishing opportunities while achieving escapement for all stocks, especially weak stocks. As a result, the salmon commercial fishery is frequently limited due to stocks of concern. This weak stock management approach is often accomplished via spatial-temporal closures attempting to maximize overall harvest opportunities without exceeding the acceptable harvest level on weak stocks (Satterthwaite, Mohr, et al. 2014; Bellinger et al. 2015). For instance, in 2008 all Chinook salmon fisheries south of Cape Falcon, Oregon, were closed due to low projected spawning escapement of Sacramento River fall Chinook and low stock abundance forecast for Klamath River Fall Chinook. The closure led to a declaration of a fishery disaster by the Department of Commerce, resulting in federal payments to fishing communities totaling more than $ 225 million dollars (NOAA 2008). More recently, in 2017, management areas between Florence South Jetty, Oregon, and Horse Mountain, California, were closed to the commercial salmon troll fisheries (Commerce 2017) due to concerns on the same stocks. The closure was predicted to result in a loss of $5.5-$8.9 millions in income, $12.8-$19.6 millions in sales, and 200-330 jobs (Richerson et al. 2018).

Recent advances in Genetic Stock Identification (hereafter GSI) have enabled detention of genetic differences among stocks by assigning sampled fish to their most likely stock, or stock complex, of origin (Miller et al. 2010). GSI advances combined with fine-scale area-temporal effort information have made it possible to estimate harvest stock mixture composition. This information allows scientists to map ocean distribution of salmon stocks by combining genetic information of individual stock with its catch location (Bellinger et al. 2015; Satterthwaite, Mohr, et al. 2014; Hess et al. 2014). Fine-scale information on stock distributions is intended to enable fishery managers to advance catch monitoring and design fisheries that both reduce catch of stocks of concern while allowing catch of healthy stocks.

The goal of this work is to evaluate the impacts of fine-scale fishery area-temporal closures on achieving biological outcomes (escapement goals) and economic benefits of the fleets that participate in a mixed-stock fishery. To achieve this goal, I developed a stylized fishery model that accounts for both the mixed-stock nature of the fishery and stocks' spatial interactions. The model integrates the economic behavior of the fleet and accounts for an in-season weak stock management strategy in the form of area-temporal closures employed by a fishery regulator as a result of near-real time stock composition monitoring via GSI.

To explore the benefits of fine-scale fishery regulation, I use simulation and compare results of three different spatial scale regulation scenarios; further, I evaluate effort distribution, harvest, escapement, and revenue under each scenario. Each simulation scenario characterizes a different spatial scale at which the regulatory agency monitors spatial distribution of individual stocks via GSI. The baseline scenario represents coarse-scale management areas while other scenarios represent a partition of the coarse-scale management areas into smaller management units. Simulation results suggest that near-real time monitoring with implementation of fine-scale area-temporal closures can be used to achieve both conservation and fishery benefit objectives. Further, the greatest fishery benefit is obtained when monitoring takes place at the spatial level of actual fishing location choices made by fishermen. Sensitivity analysis of the model shows that the more diverse the migration patterns of stocks of concerns, the less likely the manager is to re-direct the fleet to avoid harvest of weak stocks.

The mixed-stock system developed in this paper builds on the mixed-species fishery literature studying the avoidance of non-target species (Clark 1990; Androkovich and Stollery 1994; Boyce 1996; Bisack and Sutinen 2006). This work furthers the fisheries economics literature by characterizing an ecological system where harvest composition is unknown to both the harvester and the manager. The model explicitly accounts for the spatial interaction and dynamics among stocks for an in-season settings. Spatial dynamics of individual stocks operate at two different scales, a dispersal process across space and the degree of mix among weak and healthy stocks. While I have used a mixed-stock system to highlight the benefits of fine-scale spatial monitoring for in-season management via area-temporal closure, the model can accommodate alternative management scenarios for the avoidance of weak stocks, such as taxes or ITQs.

In the next section, I describe general characteristics of the West Coast Salmon fishery and a brief description of the GSI monitoring that has been in operation since 2007 and that gives grounds for this work. Section three presents a literature review on mixed-species and mixed-stock systems found in the literature. A special attention is given to the literature that includes spatial correlation among the target and non-target species. Section four describes the stylized ecological model that characterizes a mixed-stock system regulated via area-temporal closures. Section five describes the simulation scenarios to evaluate the role of fine-scale management. Results and sensitivity analysis are shown in section six. Conclusion and final considerations for model improvement are described in section seven.

3.2 Background

3.2.1 The West Coast Salmon Fishery

Chinook salmon (*Oncorhynchus tshawytscha*) occur naturally along the West Coast of the U.S., from California to Alaska, and support fisheries of great economic and cultural importance. West Coast salmon troll commercial fisheries target mixed-stock aggregations of natural and hatchery salmon species off the coasts of Washington, Oregon, and California [3]. The anadromous life cycle of Pacific salmon results in

[3]Hatchery stocks rely on artificial production, on the other hand natural stocks have at least some component of the stock that rely on natural production. Both hatchery production and natural spawning hatchery fish may contribute to abundance and spawning escapement estimates (Council 2014).

juveniles spending up to two years in freshwater, followed by two to four years at sea before returning to their natal river to spawn. The unique genetic structure in salmon is derived from fidelity to their natal stream and the timing of their breeding readiness (Satterthwaite, Ciancio, et al. 2015). During ocean migration, Chinook salmon form mixed-stock aggregations that are often subject to fishing pressures. On the West Coast, Chinook salmon fisheries south of Cape Falcon, Oregon, target mixed-stock salmon originated from California Central Valley, California Coast, Northern California and Southern Oregon Coast, Oregon Coast, and Columbia River.

West Coast salmon management measures are intended to prevent over-fishing and to apportion the ocean harvest equitably among treaty Indian, U.S. and Canada treaty requirements, non-treaty commercial, and recreational fisheries (Council 2014). To prevent over-fishing, total harvest is constrained to be consistent with requirements for stock specific conservation objectives [4] and specified ESA [5] consultation or recovery standards (Council 2014). To achieve conservation objectives the Pacific Fishery Management Council (PFMC) sets commercial troll and recreational fishing seasons based on a combination of factors, including projected abundance per individual stock, expected encounters, and expected stock composition of harvest.

South of Cape Falcon, a typical fishing season starts the first week of May and ends late September of each year. At each management area, fishing area-temporal closures are set to allow fishing opportunities while achieving escapement goals for all stocks, especially stocks of concern, such as the Sacramento River Fall Chinook (SRFC) and the Klamath River Fall Chinook (KRFC). Forecast of escapement levels below conservation objectives [6] for both the KRFC and the SRFC have led to closures

[4]Pacific Fishery Management Council conservation objectives are generally expressed in terms of spawning escapement estimated to be optimum for producing MSY over the long-term. The escapement objective is usually specified as the number or a range for the desired number of adult spawners (Council 2014).

[5]Current ESA listed Chinook (*Oncorhynchus tshawytscha*) includes: Upper Columbia spring, Sacramento River winter-run (endangered), Snake River spring and summer, Snake River fall, Upper Willamette spring, Lower Columbia, Puget Sound, and California coastal (threatened).

[6]Conservation objectives are 122,000 and 40,700 natural and hatchery adult spawners in any one

of fisheries south of Cape Falcon to the Mexico/US Border. The management of the salmon fishery is difficult because of the need to address a variety of complex issues, such as meeting escapements goals for all stocks and the lack of knowledge of in-seasonal stock specific spatial distributions. Determining relative stock contribution to harvest on an in-season basis is an essential task for management of the West Coast salmon Chinook fisheries to achieve conservation objectives while allowing for fishing opportunities throughout the season.

3.2.2 West Coast Genetic Stock Identification Program

Concerns over identification, stock specific timing, and abundance of Chinooks stocks have prompted GSI sampling program in the salmon commercial fisheries in California, Oregon and Washington [7]. In these programs, GSI sampling has been complemented with electronic data-logging systems coupled with Global Positioning Systems (GPS) to generate high resolution of distribution of individual stocks on in-season basis; a detailed description of the sampling program and logistics are described elsewhere (Bellinger et al. 2015; CROOS 2007). GSI when coupled with high resolution fishery catch and effort data can be used to calculate stock specific catch per unit effort (SSCPUE) and individual stock degree of concentration on the mixed-stock harvest. This information allows for the assessment of stock specific ocean distribution and impact of harvest on individual stocks. Figure 3.1 shows stock specific CPUE information, as derived from West Coast Salmon GSI Collaboration sampling program (WCGSI), for selected stocks across management areas south of Cape Falcon and aggregated at a monthly basis; this plot has been reproduced from Bellinger et al. 2015.

Harvest's impact on specific stock can be generated at different spatial and temporal scales according to the level at which GSI samples are aggregated. According

year for the SRFC and KRFC respectively.

[7] The two major sample programs are the West Coast Salmon GSI Collaboration and The Collaborative Research on Oregon Ocean Salmon project (ProjectCROOS) http://projectcroos.com/.

to the Collaborative Research on Oregon Ocean Salmon (project CROOS) reports, GSI and effort data can be used to monitor composition of the mixed-stock Chinook salmon fishery with a rapid turnout (24-48 hours after sampling) allowing for near-real time monitoring of stocks being impacted by fishery harvest. One of the primary goals of the program is for managers to make use of this information to redirect fishery effort toward abundant stocks (CROOS 2007). The spatial scale of in-season adjustments depend on the spatial level at which GSI sampling takes place.

Taking the case of mixed-stock salmon fishery and the the West Coast salmon GSI sampling programs to monitor impacts of harvest on individual stocks, I developed a general model mixed-stock model regulated via in-season area-temporal closures. The stylized model accounts for the mixed-stock nature of the Chinook salmon fishery where low abundance stocks, such as KRFC and SRFC, are aggregated in a single pool with healthy stocks. In the model, aggregated stocks are harvested by a single fleet. Management of the fishery is executed by a single manager entity who seeks to meet escapement goals for low abundance stocks (i.e. weak stocks management approach). In this model, the manager utilizes area-temporal closures to achieve conservation and fishery opportunity goals. Near-real time information on distribution of individual stocks is used by the manager to establish area-temporal closures and re-direct effort to harvest healthy stocks while avoiding weak stocks.

3.3 Literature Review

The incidental catch of species with low reproductive and/or abundance, also known as bycatch, has been largely studied in the fisheries economics literature. The bycatch problem in the mixed-species fisheries can be understood as the general case where fishing activities affect target and non-target species. The incidental catch of weak stocks in the mixed-stock fisheries can be seen as a particular case of bycatch where the target and the non-target fish are only genetically differentiated. A crucial difference between the general case of bycatch in the mixed-species system and avoidance of weak stocks in the mixed-stock fisheries is the inability to distinguish catch composition in the mixed-stock fisheries. The purpose of this section is to present a short overview of the methodologies and insights derived from the mixed-species literature studying the bycatch problem.

For the purpose of this literature review, I have divided the fisheries economics papers on bycatch into two types of literature. The first contains the set of papers that focus on the optimal management of bycatch where usually open access outcomes are compared with Individual Transferable Quotas (ITQs), optimal taxation, or common-pool quota scenarios (Androkovich and Stollery 1994; Boyce 1996; Herrera 2005). The second set of papers follow the same tradition as the first but accounts for spatial correlation of the target and the bycatch species (Sampson 1994; Bisack and Sutinen 2006; Abbott 2009; Ono et al. 2013). Finally, I will provide a short overview of non-economics literature that studies the management of mixed-stock fisheries.

3.3.1 Mixed-Species Bioeconomic Model

The general model of mixed-species fisheries build on the one species bioeconomic model in the literature (Clark 1990; Flaaten 2011). In particular, assume that the fishery targets a species x_1 with the unintended consequence of harvesting other species, $x_2, x_3, ...$ where each species follows its own dynamics defined as:

$$\frac{dx_i}{dt} = G_i(x_i) - q_i x_i E \quad \forall i = 1, ..., n \tag{3.1}$$

where $G_i(x_i)$ defines the growth function for species x_i, q_i is the species i catchability coefficient, and E defines the effort variable [8].

Equation 3.1 characterizes a mixed-species fishery given the fact that a single effort variable E is common to all species dynamics (Clark 1990). The single level of

[8] Note that in this setting species are not ecologically inter-dependent, such as prey-predator system, so that each G_i depends only on species x_i. Ecologically interdependent systems have been studied elsewhere (Flaaten 1991; Hoagland and Jin 1997).

effort provides a mixed-species harvest composition such that $h = \sum_{i=1}^{n} q_i x_i E$. Under this setting, fisherman behavior is driven by choosing level of effort that maximize profits derived from the total harvest composition. In particular, the fishermen behavior problem is defined as:

$$\max_{E} \sum_{i=1}^{n} (p_i q_i x_i - c) E \tag{3.2}$$

where c denotes the cost per unit of effort. Clark 1990 shows that in open access bioeconomic equilibrium species i can be fished to extinction if, and only if, fishing mortality is larger than the species' intrinsic growth. That is, when species i has a low ratio of intrinsic growth with respect to its catchability coefficient. Preventing depletion of vulnerable species can be accomplished by any measure that reduces catchability of species i such as: changing fishing gear, closures of hot spots, or avoidance of areas that contain high concentration of weak species. This mixed-species system has served as a framework to study the bycatch problem, a theme described in the following subsection.

3.3.2 Muti-Species Fisheries and the Bycatch Problem

The literature focusing on the optimal management of bycatch builds on the work of Androkovich and Stollery 1994, Boyce 1996, and Herrera 2005. Before comparing results from these papers, I will briefly describe the institutional settings used in each study and its characterization based on the mixed-species framework described above. For the purpose of consistency across papers, I will denote species x_1 as the target species while the species x_2 will denote the non-target species. All models consider species x_1 and species x_2 to be ecologically independent.

Androkovich and Stollery 1994 study the bycatch problem using a dynamic, discrete time, two species, and two fisheries system where harvest of either of the two species is incurred in the catch of the other, creating a mutual externality across fisheries. In particular, Fishery One (F_1) targets species x_1 with an incidental catch of species x_2 while Fishery Two (F_2) catch is composed of target species x_2 and bycatch species x_1. This work is inspired by the North Atlantic fishery where cod and haddock are species targeted individually but the other species result in an incidental catch of the targeted species.

Uncertainty in the system is introduced by augmenting a stochastic element in the catch composition of each fishery so that harvesters experience different realization of bycatch rate from i.i.d. probability distribution in each period. In particular, harvest in fishery j, at time t, is given by $h_{jt} = \sum_i q_{it} x_{it} e_{jt} \theta_{ijt}$, where θ_{ijt} are species specific uncorrelated random variables. The profit function is an extension of mixed-species revenue equation 3.2 that includes a random component in harvest composition.

The authors parameterized their model with 1969 data from Nova Scotia cod and haddock fisheries and used stochastic dynamic programming methods to solve the expected present value of net benefits arising from the combined fisheries while considering three different scenarios. Scenario one presents a coordinated tax system where the regulator is able to set specific taxes on the landing of each species irrespective of origin. Scenario two presents an uncoordinated tax in which each fishery is managed in isolation with taxes on the target species but not on the bycatch species. The last scenario studies a dual-quota scheme where catch quota is set on the target catch of each species.

While Androkovich and Stollery 1994 work is dynamic, Boyce 1996 paper developed a one period stylized model of bycatch. In this model, Fishery One (F_1) targets species x_1 with a bycatch of species x_2 while species x_2 may target species by Fishery Two (F_2) or it may be a species not targeted by any commercial fishery. The model also allows for the bycatch species x_2 to have commercial, non-commercial, or existence value [9]. As in the traditional mixed-species general framework, harvest of species x_1 by Fishery One is defined as $h_{11} = q_1 x_1 E_1$, however bycacth of species x_2 is treated as a function solely of the harvest rate of the target species ($h_{21} = b(h_1)$, which is assumed to be a positive function and increasing in catch of the target species). Season

[9] Existence value to society.

profits to vessel j in Fishery One and Fishery Two are denoted by:

$$\begin{aligned} \pi_{j1} &= T_1\{p_1 h_{11j} + \delta b(h_{11j}) - c_1 E_1\} \\ \pi_{j2} &= T_2\{p_2 q_2 x_2 E_2 - c_2 E_2\} \end{aligned} \tag{3.3}$$

where T_n denotes the season length in fishery $n \in \{1,2\}$, p_1 denotes price of species 1, delta is a parameter with values $\delta \in \{1,0,-1\}$ to characterize cases where the bycatch species x_2 has commercial value, non-commercial value, or existence value respectively. The author uses this model to compare open access and ITQ equilibrium under the different values δ.

Herrera 2005 presents a model that builds on the Androkovich and Stollery 1994 stochastic mixed-species model. The model considers two species, x_1 and x_2, with dynamics represented by the general case in equation 3.1. In this model, Fishery One targets species x_1 with x_2 as bycatch and Fishery Two catches only species x_2. Harvest of a vessel in Fishery One, at time t, is composed of both species and is denoted by $H_t = h_{1t} q_{11} x_{1t} E_{1t} + \theta_{1t} q_{12} x_{2t} E_{1t}$ where θ_{1t} is a random variable with an i.i.d distribution.

Contrasting with Androkovich and Stollery 1994 work, in Herrera 2005 the bycatch species x_2 can be sold by Fishery One, such that profits for Fishery One are denoted by $\pi_{1t} = p_1 h_{1t} + (1-\gamma) p_2 h_{2t} - c_{1t} E_{1t}$ where $1-\gamma$ is a discount price factor. The introduction of the discount price factor of the bycatch species in Fishery One allows for a vessel to have an incentive to discard the target species x_1 in favor of the bycatch species x_2 (highgrading) whenever the price of bycatch is larger than the target species. The discount factor also allows for an incentive to discard the bycatch species whenever the target species price is greater than the discounted bycatch price.

The model in Herrera 2005 is used to explore the dynamic and strategic interaction between a social planner and the two groups of harvesters [10]. The model is

[10] Dynamic and strategic behavior in the sense that a social planner maximizes the present value of stream of discounted net benefits by choosing season length and number of vessels while accounting for the optimal behavior of vessels. Optimal behavior of vessels is found by solving for the level of

evaluated by comparing outcomes between the unconstrained optimization and the optimization with three bycatch controls: taxes, trip limits, and value-based quotas.

In general, the authors of these three papers found that bycatch controls outperform open access outcomes under certain circumstances. Androkovich and Stollery 1994 results suggest that tax prescription easily dominates the quota instrument. Furthermore, they also find that independent taxation requires higher tax rates to control the stock externality than the optimal coordinate taxation. Their results showed that the quota system performed worse than the unregulated open access scenario under a high level of stochasticity. Boyce 1996 demonstrates that a competitive quota market can maximize social welfare but only if there are competitive markets for the quota of both species. In particular, the bycatch quota needs to be tradable among the two fisheries to guarantee this result. Additionally, the ITQs cannot achieve the social optimum if there are external benefits from preserving the bycatch species (i.e. bycatch species has no commercial value but it has an existence value).

Evidence in favor of taxes to control bycatch is also found in Herrera 2005. In particular, the author shows that taxes dominate, from the efficiency (net present value) standpoint, trip-based quotas (such as trip limits) and value-based quotas. Price instruments are able to eliminate discarding on all trips by taxing away the difference between the ex-vessel price of the target and non-target species. Furthermore, the efficiency of trip limits and value added quotas are adversely affected by variance in the bycatch process.

3.3.3 The Bycatch Problem: Spatial Considerations

While the literature in the previous subsection recognized that the bycatch problem derives from the spatial coexistence of multiple species, none of the papers accounts for the spatial correlation between the target and the non-targets species

effort and discarding that maximizes profits under four regulatory control scenarios: no constraint on bycatch, tax on bycatch, trip limits, and value-added quota.

in their analysis. In this section, I review fisheries economics literature that extend the general mixed-species fisheries framework and account for the spatial interaction of species to study the incidental catch of non-target species. In particular, I review Sampson 1994, Bisack and Sutinen 2006, Abbott 2009, Ono et al. 2013 and highlight insights from this literature that are relevant to the problem of avoidance of weak stocks in the mixed-stocks fisheries.

Sampson 1994 develops a single period model for fishing location choices for a mixed-species fishery composed of two species, x_1 and x_2, whose density vary with distance from port. In this model, mixed-species harvest is defined as $h = \sum_{i=1}^{n} q_i x_i E(d)$ and revenue is defined as $\sum_{i=1}^{n} (p_i q_i x_i - c)E(d)$. This modeling approach assumes that fishermens' level of effort is a function of the distance from port d. Distance from port also determine the spatial distribution of each species and the harvest composition. In this model, fisherman follows a myopic behavior and selects the distance from home port that maximize profit in a single period. The model is used to determine fishing tactics and to explore the conditions that generate deliberate discarding when one of the species harvested is constrained by trip limits.

Bisack and Sutinen 2006 augmented the mixed-species fishery framework, equation 3.1 and 3.2, to develop a one season model that incorporate spatial and temporal patterns of abundance and harvest rate. For instance, the model introduces a temporal stratification, denoted by s, and a spatial stratification given by area-port combination from which the vessel operates, denoted by j. Thus, x_{isj} denotes species i abundance at season s and location j. In this model, Harvest of species i at season s and location j is a function of number of string hauled per trip, z_{sj}, species size x_{isj}, ex-vessel prices p_{isj}, and number of fishing trips by vessel E_{sj} ; thus $h_{isj} = (z_{sj}, x_{isj}, p_{isj}, E_{sj})$. Accounting for spatial and temporal dimension of the system, the total annual catch of species i is $H_i = \sum_s \sum_j N_{sj} h_{isj}$; that is the sum of the catch across all vessels, denoted by N_{sj} [11] and all season-port combinations.

As in the general mixed-species fishery model, equation 3.2, fisherman behavior is driven by choosing the level of effort at each season-port combination that maximize profits across all season-area combinations such that:

$$\max_{E_{sj}} \sum_s \sum_j \sum_i (p_i h_{isj} - c_{sj}) E_{sj} \tag{3.4}$$

The authors use their model to estimate the efficiency and distributional differences between Individual Transferable Quotas (ITQs) and area-temporal closures in reducing the incidental take of harbor porpoise in the New England sink gillnet fishery. Area-temporal closures are represented in the model by eliminating area-port combinations from equation 3.4 so that fishermen maximize profits across smaller number of sj combinations. Under the transferable quota scenario the above maximization problem includes a constraint where the sum of the harbor porpoise species across all areas and seasons must be less than or equal to a given harvest level, that is $\sum_s \sum_j h_{2sj} \leq \bar{Q}$.

The mixed-species model is used to study a common-pool quota system in a simple static and deterministic framework in Abbott 2009. The model assumes two species, target species x_1 and bycatch species x_2, with harvest level denoted h_1 and h_2 respectively. In this model, total allowable catch (TACs) for both species are established at the beginning of the season and the fishing season closes when one of the TACs binds. As in Boyce 1996, the harvest of bycatch species is defined as a function of harvest of target species, such that $h_2 = b(h_1)$ [12]; in particular, the function is defined as $h_2 = b(h_1)^{\alpha}$ for $b > 0$ and $\alpha > 1$. Relevant to this literature review, the parameter α captures the spatial correlation of species density, a larger

[11] Vessels are consider homogeneous as in the rest of the reviewed literature (Boyce 1996; Herrera 2005; Abbott 2009; Ono et al. 2013).

[12] The function $h_2(h_1)$ satisfies the following assumptions $h_2(0) = 0$, $h_2' > 0$, and $h_2'' > 0$, indicating that bycatch avoidance generates a cost in the form of reduced harvest of species 1 and that these costs are increasing in the degree of intended avoidance.

parameter value of α is associated with high spatial correlation between the target and the bycatch species.

Individual fisherman profit is defined as $\pi(h_1) = ph_1 - ch_2(h_1)$. p denotes the prices of target species x_1 and c denotes unit cost due to potential yield and product losses because of diversion of resources toward sorting and discard of bycatch [13]. An additional feature of this model is the inclusion of the regulator decision rule which enforces quotas Q_1 and Q_2 by manipulating season length. The authors derived an analytical solution to a finite repeated game where a fisherman chooses the level of harvest of target species that maximizes profits accounting for the behavior of all other fishermen as well as the decision rule of the regulator.

The effect that spatial overlap among two species, productive x_1 and unproductive species x_2, has on fishery outcomes is studied in Ono et al. 2013. The authors model two stocks distributed across a linear array of cells. Contrast to the general mixed-species dynamics model, equation 3.1, population dynamics of both species is driven by growth, recruitment, fishing, and movement. After growth, recruitment, and fishing, each species disperse across cells according to a diffusive movement model. The movement between any two cells are driven by a habitat sustainability index (which measures species habitat preferences) and the distance between cells. Vessels maximize expected profits on each consecutive trip by choosing to fish in the location with the highest expected profit. The authors use this model and a simulation approach to study how spatial mixing across species affect the performance of the fishery under a competitive total allowable catch scenario (TAC in x_1 and x_2 with discarding), TAC and MPAs (TAC with some area closures), TAC with discard ban, and Individual Vessel Quota (IVQs).

The literature that accounts for spatial interaction between the target and non-target species provides insight on mixed-species fisheries outcomes. For instance, when

[13] Bycatch does not have commercial value as in the case of Boyce 1996 and Androkovich and Stollery 1994.

the fishery is regulated with trip limits on the bycatch species, Sampson 1994 suggest fishermen cannot avoid bycatch unless they forgo fishing opportunities. Additionally, the author also suggests that a high degree of correlation leads to high incidental catch and discarding. A similar result is found in fisheries that are regulated with a common pool quota. Abbott 2009 demonstrate that the equilibrium will generally be characterized by excessive discards, shortened seasons, and forgone target species harvest. This result is derived by incentives generated by the common-pool quota system that causes fishermen to ignore the effect of their behavior on the equilibrium season length. Abbott 2009 also finds that a high spatial correlation between the target and non-target species leads to more conservative harvest behavior and increased rents.

The positive effect between the degree of spatial correlation and profitability is also supported in Ono et al. 2013. The authors find this positive effect holds in long run equilibrium for fisheries under a common-pool quota system when discarding is not allowed. This positive effect takes place because of two mechanisms. First, in the short run, high correlation reduces the catch of productive stocks because of harvest constraints in low productive stocks. Second, in the long run, the biomass of productive stock increases and cost per unit of catch decreases. As supported in the non-spatial literature, Ono et al. 2013 also suggest that under TAC, without the discard ban, the risk of depleting the weak stock increases; further, this risk is high when the overlap among species increases.

To correct for risk of depletion and discarding, Bisack and Sutinen 2006 argue that area-temporal closures are inefficient because they consistently reduce industry profits. ITQs on the bycatch species is more efficient than closures; it leads to higher profits despite lower landings of the target species. Ono et al. 2013 also suggest that profitability of the mixed-species fishery can be increased with Individual Vessel Quotas, even at high degree of correlation among species. Furthermore, TAC (with discard ban and set at MSY) has the largest increase in profits regardless of the spatial overlap. In general this literature suggests that the overlap of target and non-targets species, under any management regime, affect both species biomass and economic outcomes on a mixed-stock fishery.

3.3.4 Mixed-Stock Fishery Review

Mixed-stocks fisheries have been commonly studied in the non-economics fisheries literature. This literature addresses the problem of obtaining the maximum equilibrium yield of a mixed-stocks system targeted by a common fishery; the Pacific salmon stocks in particular have been used as a case study (Paulik et al. 1967; Hilborn 1976; Kope 1992). This literature generates harvest rules for mixed-stocks fisheries without explicit economic content and often solely based on biological parameters. Paulik et al. 1967 demonstrates that the maximum sustainable yield from mixed-stocks fisheries involve elimination of less productive stocks, as supported in the fisheries economics literature (Clark 1990). Similarly, Hilborn 1976 demonstrates that optimal harvest rates depend on the relative abundance of stocks. The author also concludes that mixed-stocks fisheries should be harvested more heavily when the composition of the stocks differs from the one to one ratio. Kope 1992 agrees with Paulik et al. 1967 and Hilborn 1976 and shows that optimal harvest rates that produce healthy runs of natural spawners create a substantial surplus of hatchery spawners (high productivity stocks).

3.3.5 Literature Review Conclusions

The fisheries economics literature demonstrates that the incidental catch of non-target species presents multidimensional challenges given technological limitations, costly avoidance, stochasticity of the stocks, and the limited choice of policy instruments available to managers to induce fishermen to alter their behavior. Papers studied in this literature review build on the mixed-species system framework described in equations 3.1 and 3.2. The literature suggests that low productivity (weak) species may be driven to extinction whereas the high productivity (healthy) species continue to support the fishery in bioeconomic equilibrium. This result becomes more severe when weak and healthy species have a high degree of spatial correlation. The mixed-species literature also suggests that policy instruments can influence fishermen catch composition and thereby the quantity of bycatch. Mechanisms to manage bycatch includes area-temporal closures (Bisack and Sutinen 2006; Ono et al. 2013), common pool quotas (Abbott 2009; Androkovich and Stollery 1994; Herrera 2005), trip limits (Sampson 1994; Herrera 2005), taxes (Androkovich and Stollery 1994; Herrera 2005), and ITQs (Boyce 1996; Bisack and Sutinen 2006).

Results from the mixed-species literature provide insight on the problem of bycatch in a mixed-stock fishery, where the low and high abundance stocks are harvested together. For instance one would argue that low productivity stocks (weak) may be depleted in bioeconomic equilibrium when weak stock co-occur with high productivity stocks (healthy). The mixed-species literature also suggests that avoidance of harvest of weak stocks cannot occur unless we forgo fishing opportunities for healthy stocks, especially in case of high spatial correlation among stocks.

The mixed-species literature also provides insights on the modeling mixed-stock fisheries. However, one needs to recognize that mixed-species and mixed-stock fisheries have a fundamental difference. For instance, harvest composition is unknown to both the fishermen and the regulator on a mixed-stock system, on the other hand, in a mixed-species system the harvest composition is defined as the aggregation of known quantities of the target and non-target species, as in equation 3.2. Additionally, a question that still arises is: Do incentive mechanisms proposed in the mixed-species literature also apply to the mixed-stocks fisheries where catch composition is hard to assess at harvest?

Finally, while the spatial consideration has been taken into account when modeling mixed-species systems, little has been done to explicitly account for the dynamic spatial interaction among species. In particular, there has not been a study that characterizes in-season spatial dynamics of highly migratory species, such as salmon. Spatially explicit systems need to consider the fact that weak and healthy species, or stocks, may or may not be mixed at a particular time and location within a season and that the degree of concentration of individual stocks changes over time. When the spatial correlation among species (or stocks) is difficult to assess and management decisions are made in a dynamic and stochastic environment, such as in the case of the mixed-stocks fisheries, bycatch management alternatives may require different approaches than those described in this literature review.

3.4 Mixed-stock Fishery Model

3.4.1 The Ecological Model

The stylized mixed-stock fishery model consists of I stocks spatially linked via their distribution across a single space. For simplicity, I assume that the space is represented by a rectangle shape that can be divided into J contiguous units of equal size. I also assume that the model represents a single season of size $t = T$. s_{ijt} represents stock i abundance (for $i \in \{1, ..., I\}$) measured in number of fish at location j (for $j \in \{1, ..., J\}$) at discrete time t (for $t \in \{1, ..., T\}$) [14]. The spatial distribution of stock i at time t across locations is captured by the row vector $S_{it} = (s_{i1t}, ..., s_{iJt})$; thus, total stock i size at time t is given by $s_{it} = \sum_{j=1}^{J} s_{ijt}$. Figure 2 depicts the spatial representation of the stylized mixed-stock fishery. The mixed-stock nature of the system is given by the fact that at each location j the total biomass is composed of the aggregation of all stocks. Thus, the total abundance at location j is given by

$$S_{jt} = \sum_{i=1}^{I} s_{ijt} \tag{3.5}$$

At each location j there are two spatial scales operating. The first is the dispersal process, of stock i, from locations j to any of the adjacent locations denoted as j'. The second is the degree of concentration of each stock at location j. The degree of concentration is based on individual stock abundance and overall stocks abundance.

[14] A similar representation as in Bisack and Sutinen 2006.

The dispersal process [15] of stock i from location j to adjacent location j' is driven by the migration pattern that the stock follows from $t = 1$ to $t = T$ in order to complete its ecological process [16]. This migration process drives individual stocks i spatial distribution during the fishing season. This spatial process is represented by

$$s_{ijt+1} = s_{ijt} + \delta_{ij} s_{ijt} + \sum_{\forall j'} \delta_{ij'} s_{ij't} \tag{3.6}$$

where δ_{ij} represents the constant rate of outgoing stock i from location j to adjacent locations ($-1 < \delta_{ij} \leq 0$). On the other hand, $\delta_{ij'}$ represents the constant rate of incoming stock i from locations adjacent to j ($0 \leq \delta_{ij'} < 1$) [17]. The difference between the last two terms in equation 3.6 captures the net migration of stock i from location j to its adjacent locations.

The second spatial process taking place in this mixed-stock system is given by relative stocks abundances at each location j. This spatial process is characterized by the degree of concentration of stock i at location j. The degree of concentration of stock i is defined by its relative abundance with respect to the total mixed-stock biomass at same location. The degree of concentration, represented by θ_{ijt}, of stock i can be represented as

$$\theta_{ijt} = \frac{s_{ijt}}{\sum_{i=1}^{I} s_{ijt}} \tag{3.7}$$

Note that the degree of concentration for stock i is defined per each location j at each time t. It is important to recognize that the degree of concentration is driven by individual stock i abundance, overall stocks abundance at location j (i.e. $\sum_{i=1}^{I} s_{ijt}$), and the migration pattern as defined in equation 3.6.

[15] This dispersal process is similar to the one presented in Ono et al. 2013 with the difference that the dispersal is driven by migration pattern rather than by habitat affinity. Further, this dispersal process represents exclusively in-season spatial dynamics and not between season population dynamics.

[16] For example, adult salmon stocks in the West Coast are known to migrate from marine environment to their river of origin in order to spawn.

[17] One can interpret δ_{ij} and $\delta_{ij'}$ as the transition probabilities of stock i from, and to, location j. For the case of the Chinook salmon, estimated parameters for δ_{ij} and $\delta_{ij'}$ that characterize inter-annual marine distribution can be obtained from Coded Wire Tag data.

Figure 3.3 depicts a simulated spatial distribution of 3 stocks at five different time steps, and Figure 3.4 shows the degree of concentration of each stock. At time $t = 1$ each stock is randomly distributed across space. Each stock migration pattern, as given by equation 3.6 and parameter values in Table 3.1, dictates its spatial behavior during a single period of $t = 20$. The migration pattern of an individual stock is dictated by the location of its place of origin located on the right side of the diagram [18]. For illustrative purposes, stock 1 follows a southward migration behavior, stock 2 follows a northward migration behavior, while stock 3 follows a eastward migration pattern.

3.4.2 The Economic Model

Harvesters, as a single fleet, exert non-selective effort $E_t = (e_{1t}, ..., e_{Jt})$ across all fishing grounds J [19], at time t, with catchability coefficient (q). Catchability coefficient is assumed to be constant across locations and time steps. Effort e_{jt} is measured as the number of vessels harvesting at location j, at time t, which must be non-negative and bounded by the total number of vessels on the fleet (i.e. $0 \geq e_{ij} \leq \bar{E}$). At every location j, harvest is linear in effort and stock as in the standard Schaefer model, that is

$$h_{jt} = qe_{jt}S_{jt} \tag{3.8}$$

where S_{jt} denotes the mixed-stock biomass at location j as defined in equation 3.5. Note that the spatial harvest h_{jt} is a function of abundance of aggregated stocks at location j. This harvest representation is the same as the mixed-species system described in the literature review with the addition of spatial and temporal dimension, as in Bisack and Sutinen 2006, and with a constant catchability coefficient.

[18] In the salmon fishery for example, stocks return to their natal river of origin to spawn.

[19] Note that fishing grounds correspond to the same locations at which individual stocks dynamics take place. In particular, each location j serves as the data generating scale at which each stock's abundance and harvest are measured in the mixed-stock system.

Harvest stock composition is unknown to the harvester and the market, thus harvest mixed-stock biomass sells in perfectly competitive markets with unique price p, constant across time steps. The revenue associated with effort e_{jt} is

$$\pi_{jt} = (pqS_{jt} - c)e_{jt} \tag{3.9}$$

This equation is a spatial version of the revenue function introduced in the mixed-species literature, equation 3.2. Constant catchability coefficient, q, and cost per unit of effort, c, across locations and time indicate that vessels are homogeneous in harvest capacity; a convenient and common assumption in the mixed-species literature (Abbott 2009; Bisack and Sutinen 2006; Boyce 1996; Herrera 2005; Ono et al. 2013) [20] [21]. At time t, the revenue of the fishery is the sum across all locations, associated with effort vector $E_t = (e_{1t}, ..., e_{Jt})$, that is

$$\Pi_t = \sum_{j=1}^{J}(pqS_{jt} - c)e_{jt} \tag{3.10}$$

In this model, at each time step, the fleet chooses the level of effort $E_t = (e_{1t}, ..., e_{Jt})$ in proportion to relative utility scores. The utility score for each fishing location j is determined by the expected revenue from that location relative to all other locations and expressed in terms of landings per unit of effort. Thus, equation 3.9 is restated as expected revenue at location j at time t as

$$\pi_{jt} = pCPUE_{j,t-1}u_{jt} - c \tag{3.11}$$

where $CPUE_{j,t-1}$ denotes landings per unit of effort at location j at previous time step, $t - 1$. Given the spatial dynamics of individual stocks, the current $CPUE$ at all locations J are unknown to the harvester, however, previous $CPUE$ serves as a proxy for current $CPUE$. The term u_{jt} is a location specific random variable that

[20] This simplified assumption is intended to characterize a stylized version of the fleet, however a complex version of vessel heterogeneity (fishing capacity, spatial cost, and fishing portafolio) can be accommodated to characterize a more complex harvest system.

[21] This assumption is also applicable to the troll-based salmon fisheries

accounts for the imperfect information on current $CPUE$; a stochastic term similar to Androkovich and Stollery 1994 and Herrera 2005.

Utility scores are calculated by first normalizing expected revenues denoted n_{jt} [22], then taking exponentiation and finally calculating relative exponentiated-normalized expected revenues. That is, utility score pr_{jt} for location j at time t is defined as

$$pr_{jt} = \frac{e^{\beta n_{jt}}}{\sum\limits_{j=1}^{J} e^{\beta n_{jt}}} \tag{3.12}$$

pr_{jt}, represents the probability of choices for location j, note that $0 \geq pr_{jt} \leq 1$ and that $\sum\limits_{j=1}^{J} pr_{jt} = 1$. β is a weight of expected revenues; as β is increase, the model concentrates fishing effort more heavily in the most profitable areas. For simulation purposes, I have assumed that $\beta = 1$ [23]. Probabilities are used to distribute effort across all fishing locations. If location j is closed, I set probability of choosing location j to zero and re-scaled the other probabilities so that the condition $\sum\limits_{j=1}^{J} pr_{jt} = 1$ holds and used the re-scaled probabilities to distribute effort across open locations.

3.4.3 Integrated Ecological-Economics Model

Equation 3.6 represents the net migration of stock i, at location j, and captures transitions of individual stocks across time steps in the absence of fishing mortality. Accounting for harvest at each location, spatial distribution of stock i evolves according to

$$s_{ijt+1} = s_{ijt}(1 - qE_{jt}) + \delta_{ij} s_{ijt}(1 - qE_{jt}) + \sum_{\forall j'} \delta_{ij'} s_{ij't}(1 - qE_{j't}) \tag{3.13}$$

This equation is a modified version of equation 3.6 where harvest takes place before stocks dispersal.

[22] Normalized expected revenues for each location j at time t is calculated by dividing location specific expected revenue π_{jt} by the maximum expected revenue across all locations (i.e. $\max(\pi_{1t}, \pi_{2t}, ...\pi_{Jt})$).

[23] Random Utility Models are used to estimate empirically β.

In this integrated ecological-economic model, harvest at location j at time t has two potential effects on the mixed-stock system. First, it changes the overall stocks abundance at each location j as well as the overall abundance (i.e $\sum_{j=1}^{J} s_{ijt}$) at each time step t. Second, it changes the stock composition at all adjacent locations to j for further period; thus, affecting the spatial distribution of individual stocks throughout the season.

3.4.4 Weak Stock - Near Real Time Management

The multi-stock fishery system described above is managed by a single entity who seeks to allow for fishing opportunities for the fleet while achieving escapement targets per stocks of concern, similar to a quota system for non target species in Androkovich and Stollery 1994, Boyce 1996, and Abbott 2009. Management of the fishery occurs as follows: at the beginning of the season, the fishery manager sets conservation goals defined as escapement targets and measured by number of fish [24]. Escapement goals for stock i at time t can be stated as

$$\bar{s}_i \leq \sum_{j=i}^{J} s_{ij1} - \sum_{t=1}^{t} \sum_{j=1}^{J} h_{ijt} \tag{3.14}$$

where the first term in the right hand side denotes stock i abundance at the beginning of the season and distributed across all locations. The second term denotes the overall harvest of stock i across all location j for all time periods prior to t. Equation 3.14 states that original abundance minus total harvest up to t, across all location, has to be greater or equal to a escapement goal $\bar{s}_t$. Note that equation 3.14 assumes the manager knows initial abundance of stock i, $\sum_{j=i}^{J} s_{ij1}$ [25]. Escapement goal $\bar{s}_i$ is defined outside of the system while escapement level for each stock, at each time step t, is defined within the multi-stock fishery system as defined in equation 3.13.

[24] In the West Coast salmon fishery for example, the Pacific Coast Salmon Fishery Management Plan states conservation objectives per individual and measured by number of fish (Council 2014).

[25] Alternatively, one can consider the case where the initial stock is only approximated. For instance, each year, the Pacific Fishery Management Council provides with salmon stocks abundance forecast, per individual stock, in the Preseason Report I.

The model assumes the manager knows overall initial abundance per stock (exogenous information) but does not know the initial spatial distribution; that is $\sum_{j=i}^{J} s_{ij1}$ is known but individual stock abundances, s_{ij1}, are unknown. At each time step, the manager monitors total harvest, degree of concentration of individual stocks at each location, impact of harvest on individual stocks, and escapement levels of stocks of concern. Total harvest at time t, $H_t = q \sum_j \sum_i e_{jt} s_{ijt}$, is monitored by recording landings of all vessels across all locations.

Degree of concentration of weak stocks, θ_{ilt}, is monitored via retention or non-retention catch; l indicates the spatial dimensions, the management area, at which sampling takes place. Catch information and Genetic Stock Identification analysis is used to perform a mixed-stock analysis and calculates individual stocks degree of concentration at every time step at the management area level l. The spatial scale of management areas is set by the regulator according to the spatial level of intended area closures and the monitoring capacity of the agency. A key feature of this model is the spatial scale of fishing location choices j is different than the management area scale set by the regulator, l. Estimated degree of concentrations are used by the manager to estimate impacts of harvest on individual stocks as well as escapement levels of stocks of concerns.

To achieve conservation objectives, the manager employs area-temporal closures. The degree of concentration of individual stocks at previous period θ_{ilt-1} provides information on the stock distribution at current period with a degree of uncertainty. That is, $\hat{\theta}_{ilt} = \theta_{ilt-1} v_{ilt}$, where the random variable v_{ilt} accounts for such uncertainty [26] and the discrepancy of the two values due to stocks' dispersal process [27]. Based on $\hat{\theta}_{ilt}$, the manager may choose to close management area l at time t if $\hat{\theta}_{ilt} \geq \bar{\theta}_i$,

[26] GSI and mixed-stock analysis provides probabilistic information on mixed-stocks composition (Bellinger et al. 2015).

[27] The structure of dispersal process as well as the parameters of it, equation 3.13, are unknown to both the harvester and the regulator. Thus, v_{ilt} accounts for the inability of the regulator to perfectly forecast degree of concentration of stock i at each location using past information.

where $\bar{\theta}_i$ denotes maximum degree of concentration at which harvest is allowed. This management approach can be considered as near-real time management for weak stocks because information on degree of concentration of weak stocks is based on recent lagged information. Under this weak stock management scenario, the season either ends when the final step is reached (i.e. $t = T$) or whenever the escapement goal for a weak stock is reached as denoted in equation 3.14.

3.5 Simulation Scenarios

To evaluate the benefits of fine-scale, near-real time, weak stock management of a mixed-stock fishery, I simulated three different management scenarios using the model described above. In the first scenario, called coarse-scale, the entire fishing grounds is divided into seven management areas [28]. Each management area is limited only by latitude coordinates. On the second scenario, called fine-scale, each management area in the coarse-scale scenario is split into two units. The division of each management area takes place at longitude coordinates creating a total of 14 management areas. The third scenario, called finest-scale, splits each of the management areas in the fine-scale scenario into four units, so that the total number of management areas are 56. In this last scenario, management areas set by the regulator match fishing location choices made by the fishermen. Figure 3.9 displays a graphic representation of the number of management areas for each scenario.

Monitoring of harvest's impacts on individual stocks and regulatory tools (closures) take place at the management area spatial scale l. However, for all three scenarios, the finest spatial scale scenario ($j = 56$ locations) serves as the underlying data generating process for fish dynamics and fishermen location choices, equations 3.13 and 3.12 respectively. That is, stocks migration patterns, as described in equa-

[28] An scenario that is intended to represent current spatial scale management in the West Coast ocean salmon troll fishery.

tion 3.6, generate the dispersion process at the 56 locations in all three cases. Because spatial harvest at each location j is embedded in the dispersion process, equation 3.13, fishing location choices are also defined at the j spatial units.

Only at the finest-scale management scenario the regulatory agency is able to carryout at-sea data collection and sampling [29] at every fishing location at which the fleets operate. This exceptional case is only possible if the regulatory agency is capable of sampling the catch of most of the vessels on the fleet (via retention fishery) and/or at-sea data collection (via non-retention sampling) for all fishing locations. The fine-scale and coarse-scale scenario, characterizes situations where the regulator has limited ability to sample all fishing location choices. In these two cases, the regulator aggregated samples from a management area l in order to provide information on harvest's impacts on individual stocks.

Table 3.1 displays parameter values used in the three simulation scenarios. Parameter values are constant across management scenarios. While the ecological-economics system is flexible to allow for a larger number of stocks, I have only considered three stocks for all simulations. A three stocks system is used to represent two weak stocks and one healthy stock. One can see the single healthy stock as the aggregation of several healthy stocks. Although three is a small number of stocks, the three stock system captures the complexity of managing a fishery where harvest is constrained by more than one weak stock and where each stock follows a different spatial distribution and migration pattern [30].

The final time step used in the simulations is T = 20, which is intended to represent the duration of the fishing season. If each time step is considered a week, the total fishing season adds up to 5 months of a calendar year [31]. As previously

[29] Sampling at finest spatial scale may take place via retention fishery or non-retention sampling (Bellinger et al. 2015).

[30] For instance, currently the commercial West Coast salmon fishery south of Cape Falcon is constrained by meeting escapement levels for the Sacramento River Fall Chinook and the Klamath River Fall Chinook.

[31] The salmon commercial season usually opens on the first week of May and closes at the end of

mentioned, T is intended to represent only the in-season dynamics of individual stocks when the aggregated mixed-stock biomass is subject to fishing mortality, it does not represent population dynamics of individual stocks. This model assumes that at T, individual stocks are aggregated at the edges of the quadrant; location where place of origin is located.

The initial abundance values for stock one and two are intended to represent low abundances for two weak stocks. These values, shown in Table 3.1, were chosen so that 60% of the initial abundance of each stock corresponds to their minimum escapement level. Thus, harvest impact on each weak stock must be lower than 40% of initial abundances [32].

Given parameter values in Table 1, stock one characterizes a south migrating stock while stock two characterizes a north migrating stock. Stock three characterizes an aggregate of healthy stocks which for convenience follows an indistinctly west to east migration pattern. Figure 3.3 depicts dispersal pattern in the absence of harvest for both weak stocks and the aggregate of healthy stocks. The figure shows that at $t = 20$ stock one aggregates in the lower right corner, stock two aggregates in the upper right corner, and stock three aggregates along the right side of the figure.

Values of economic parameters in Table 3.1 were chosen arbitrarily. Note that for simplicity, cost per unit of effort has been set to zero. A extension to this analysis is to allow cost to vary by vessel or by fleets. For instance, cost can bee associated to vessel's distance travel between home port and fishing locations (allowing for heterogeneous vessels) and assuming that vessels' home port are distributed along the right side of the spatial representation. A cost variable also can be included to account for the monitoring cost to evaluate the effect that different spatial scale monitoring programs have on the net benefit of the fishery.

September (although dates may vary by management areas and by year).

[32]Escapement goals for stock one and two have been chosen to represent actual escapement targets for the SRFC and KRFC Chinook salmon stocks. Values were obtained in the Conservation Objective tables in the Pacific Coast Salmon Fishery Management Plan (Council 2014).

The crucial difference among each of the three simulation scenarios is the spatial scale at which the regulatory agency operates. Each of the three cases represents a spatial scale at which the fishery manager carries out the monitoring of the degree of concentration and consequently establishing spatial closures. For all three cases, a management area is closed at time t if the degree of concentration of either of the weak stocks at previous time step, $t-1$, is above 0.1.; the value indicates that at least 10% of the previous harvest at management area l was composed of either stock one or two (i.e. $\bar{\theta}_{ilt-1} \leq 0.1$). This rule was chosen arbitrarily, however, a sensitive analysis of the closure rule is presented in the results section.

For each of the management scenarios, the simulation of the system works as follows: at the beginning of the season, $t = 1$, all management areas l are open and effort is distributed equally at each fishing location j. Effort differs across fishing locations after $t = 1$ when the regulatory agency closes some of the management areas when the fishery allocates effort according to the utility score.

At each time period, the regulator monitors the degree of concentration of weak stocks at each of the management areas l. Monitoring takes places via genetic stock identification and mixed-stock analysis of sample of catches. Sampling takes place via catches of the fleet or as non-retention catches by the regulatory agency. The model assumes that the regulator estimate degree of concentration of weak stocks at each management area l at all periods. Estimated degree of concentration of stocks i at management area l at time $t-1$ provides with imperfect information about the degree of concentration at time t; that is $\theta_{ilt-1} \approx \theta_{ilt}$. At each time period, the fleet used CPUE of location j at time $t-1$ to select fishing location choices according to utility score approach as described in equation 3.12.

At each time period, the simulation of the mixed-stock system starts with a spatial distribution dictated by individual stocks distribution s_{ijt}. If the degree of concentration for a weak stock i at a given management area l is above the threshold $\bar{\theta}_{ilt-1}$, the management area l is closed at time t. The simulation assumes that the fleet used $CPUE_{jt-1}$ and equation 3.12 to allocate effort across all open locations j. After harvest, the manager once again monitors degree of concentration for all stocks. Information on the degree of concentration of individual stocks, at the management area level, allows the manager to monitor the impact that harvest has on escapement levels on stocks of concerns. Degree of concentrations are used to assess impact of harvest on stocks of concern; if escapement levels do not satisfy escapement goal conditions, equation 3.14, the season ends. When the degree of concentration is above the threshold at a given management area l, the area is closed for the next period. After harvest, the spatial distribution of individual stocks evolves according to equation 3.13.

3.6 Results

Figures 3.6 through 3.13 show results for the three simulation scenarios described in the previous section. Figures 3.6, 3.7, and 3.8 depict the degree of concentration of individual stocks for all time steps for the coarse, fine, and finest-scale management scenarios respectively. The degree of concentration at each management area dictates area-temporal closures shown in Figure 3.9. Note from Figure 3.9 that under the coarse management scenario the fishery remains closed after the $t = 1$. However, this situation is reversed as the monitoring of the degree of concentration of weak stocks increases in spatial resolution. For example, when the number of management areas equal to 14 the fishery opens occasionally during the season. Furthermore, only under the finest-scale monitoring scenario the fishery is allowed to operate during the entire season at selective management areas. Spatial distribution of effort is depicted in Figure 3.10 which shows that effort is distributed across space throughout the season only for the finest-scale weak management approach.

Harvest and escapement levels per individual stock are shown in figures 3.11 and 3.12 respectively. Both figures depict that under any monitoring scenarios harvest of weak stocks is reduced so that escapement goals are achieved at the end of the season. The figures also show that while closures are effective for meeting conservation goals, only fine-scale closures allow for harvesting opportunities in the fishery. The other scenarios achieve conservation objectives, via closure of hot stops, while reducing fishing opportunities. As suggested by the literature, this result shows that fishermen cannot avoid harvest of weak stocks unless they forgo fishing opportunities (Clark 1990; Sampson 1994; Hilborn et al. 2004).

Fleet benefits from stock distribution monitoring at all simulation scenarios can be observed in Figure 3.13. The figure shows that due to early closure of the fishery, the coarse-scale monitoring truncates fishery benefits after $t = 1$. Fine-scale degree of concentration monitoring increases coarse-scale revenue by 147%. This increase is due to the fact that under fine-scale monitoring, the fishery partially operates during the season while the fishery remains closed after $t = 1$ under coarse-scale monitoring. The greatest benefit to the fleet occurs when the regulatory agency is able to track individual stock distribution at a finest spatial scale simulation scenario. That is, when sampling of catches occurs at all fishing locations of the fleet. Under this scenario, fishery revenue increases 312 % compared to coarse-scale earnings.

3.6.1 Sensitivity Analysis

3.6.1.1 Migration Patterns

Contrasts with the migration patterns shown in Figure 3.3, where weak stocks move in opposite directions, Figure 3.14 shows the spatial-temporal distribution of three stocks for a situation where both weak stocks, one and two, share the same migration patterns. Area-temporal closures for these migration patterns, for all simulated management scenarios, are shown in Figure 3.15. The figure, shows that under this migration setting, the fine-scale management scenario allows for the fishery to operate at several management areas throughout the season; this result contrasts with management area closures shown in Figure 3.9. Figures 3.9 and 3.15 show that when weak stocks follow different migration patterns, management area closures occur more frequently than when weak stocks migrate in the same direction. This result indicates that the more diverse the migration patterns of stocks of concern are, the less likely the manager is to direct harvest to avoid areas with high concentration of weak stocks.

Figure 3.16 displays cumulative revenue for the three management spatial scale scenarios when both weak stocks, one and two, follow the same migration pattern. Similar to Figure 3.13, Figure 3.16 shows that season revenues are higher for the fine and finest-scale management scenarios compared with the coarse-scale scenario. In particular, the figure shows that revenue increases for the fine and finest-scale management scenario, with respect to coarse-scale scenario, by 134% and 279% respectively. Figures 3.13 and 3.16 show that in absolute values, revenues are lower (at any management scale) when migration patterns among weak stocks are similar. For the fine-scale scenario, this result suggests that when weak stocks share migration patterns the fishery operates throughout the season, however, it does not generate as much revenue than when the fishery experiences continuous closures and weak stocks follow different migration patterns. Overall, Figure 3.16 shows season revenue decreases when weak stocks share the same migration patterns.

3.6.1.2 Degree of Concentration for Closure Rule

Area temporal closures in the mixed-stock fishery model are set by the degree of concentration of either of the weak stocks at the management area level l. Management area closures shown in Figure 3.9 are set when the degree of concentration of either of the two weak stocks, at the previous time step, is above 0.1. Figure 3.17 shows escapement levels for stock one and two for different degrees of concentration and for all three management scale scenarios. For instance, the plot on top row and left column shows the escapement level of stock 1 for the coarse-scale management scenario when closures are established for different degrees of concentration. The plot indicates that when closures are set for degree of concentrations below 0.175, stock 1 reaches escapement goals by the end of the season but the goals are not met for a closure rules of $\theta_{ilt} > 1.75$. On the other hand, the plot on top row and right column shows that at coarse-scale management scenario, stock 2 reaches escapement goals whenever a management area is closed for a degree of concentration below 0.125.

Figure 3.17 shows that the lower the abundance of a weak stock, the lower the degree of concentration closure rule needs to be set in order to guarantee that conservation goals are achieved by the end of the season. For all simulation scenarios in Figure 3.17, stock one makes 20% of total abundance while stock two makes 7% of total abundance. For any management spatial scale, the degree of concentration that warrant meeting escapement levels for stock one does not necessarily warrant meeting escapement goals for the less abundant stock two. For instance, at finest spatial scale management scenario, the manager can achieve conservation goals of stock one by setting closure rules to degree of concentration of 0.2. However, at $\theta = 0.2$ stock two reaches conservation goals at $t = 12$; driving a closure of the entire fishery. This result suggests that area-temporal closures need to be set by the least abundance stock.

Figure 3.17 also shows that the degree of concentration rule decreases as the spatial management scale increases. When managing at a coarse-scale, low degree of concentration is required in order to achieve conservation goals of weak stocks. For instance, plot on top row right column indicates that a closure rule of $\theta \leq 0.125$ allows that both weak stocks meet escapement goals. However, a closure rule can be as high as $\theta = 0.15$ under the finest-scale management regime to achieve conservation goals.

3.6.1.3 Fine Temporal Scale Monitoring

Suppose that monitoring of spatial distribution of weak stocks can also increase in its temporal dimension, such that information on the degree of concentration of individual stocks on mixed-stock harvest could allow the manager to establish area temporal closures at short time frames [33]. Simulation results shown in figures 3.7 to 3.13 assume that the manager monitors degree of concentration of individual stocks during 20 time steps; the total lenght of the fishing season. Figure 3.18 and Figure 3.19 depict escapement levels and revenues for the three spatial management scenarios when the manager is able to act at a finer temporal scale. In this finer temporal scale each time step has been divided into two units so that manager can act at 40 time steps rather than 20. Figure 3.18 shows that under the finer temporal management scenario, escapement levels for the healthy stock are lower than under a 20 time step framework (see Figure 3.12).

Under finer temporal management, fine spatial scale management increases season revenues by 118% compared to the 147% increase shown in Figure 3.13. The increase in revenues from coarse-scale to finest spatial scale management is 447%; an increase greater than the 312% increase when time steps equal 20. Figures 3.13 and 3.19 show that coarse spatial scale management performs slightly better under finer temporal management than under the $t = 20$ season length management scenario. However, fine spatial scale management provides the highest revenue under $t = 20$ scenario than under a finer temporal scenario. Both figures also show that the highest possible season revenues are obtained when the fishery is managed at finest spatial scale and finer temporal scale.

3.7 Conclusions

Results from simulation scenarios show that a manager's ability to deploy area-temporal closures, to change the fleet fishing location choice behavior towards targeting healthy stocks, allows achieving both conservation goals and fishery benefits. Management scenarios simulations were conducted by using an ecological-economic

[33]GSI sampling programs in the salmon fishery, such as PROJECT CROOS, state that monitoring of stock composition of harvest can be done within 24 to 48 hours after sampling (CROOS 2007).

model that characterizes a multi-stock fishery system. The system accounts for the in-season spatial dynamics of stocks that differ in migration patterns and abundance. The model also accounts for the behavior of the fishing fleet. In each simulation, the manager uses stochastic information on past individual stock distribution to implement area-temporal closures to avoid harvest of weak stocks and redirect effort towards healthy stocks. The mixed-stock model has been inspired by the West Coast salmon fishery where Genetic Stock Identification programs are used to monitor stocks' spatial distributions in near-real time.

Simulation of management scenario differ on the spatial scale at which monitoring of stocks' distribution takes place. The fine and finest management scenarios partition coarse-scale management areas into two and four management units respectively. The finest-scale management area scenario reflects the spatial scale at which the fleet make fishing location choices. Simulation results suggest that finest spatial scale sampling is needed to achieve greater fishery benefits while meeting conservation goals. Coarse-scale monitoring achieves conservation goals of weak stocks but restricts fishing opportunities for fleet as suggested by the literature (Clark 1990; Sampson 1994; Hilborn et al. 2004).

The results also suggest that if finest-scale management is required to allow for the greatest fishery benefits. However, finest-scale management requires monitoring of fishemen location choices. This result suggests that GSI sampling may need to be carried out carryout by fishermen via retention or not retention fisheries in order to avoid coarse-scale closures. The model assumes that a single regulatory agency uses information on spatial distribution of stocks to establish in-season area-temporal closures. An open question is: how the fishermen may make use of information they collect (on spatial distribution stocks) in order to change their fishing location choice behavior? One can extend the mixed-stock model to study a situation where fishermen carryout GSI sampling and use the information to avoid hot spots without the intervention of a regulatory agency.

Sensitivity analysis shows that management of a mixed-stock fishery is a complex task given the effects that migration patterns and stock abundances have on conservation and fishery benefit outcomes. Sensitivity analysis shows that manager's ability to redirect effort away from hot spots is reduced when weak stocks follow different migration patterns. Unsurprisingly, the results also show that the lower the abundance of a weak stock the more conservative closure rules need to be in order to guarantee achieving conservation goals.

The model can be used to carryout a sensitivity analysis in economics parameters and study how changes in prices, catchability coefficient, and/or cost affect fishermen behavior. Sensitivity analysis on stochastic parameters can be used to study how an increase in the the degree of uncertainty, via higher variances, affect fleet fishing location choice behavior and manager area closure.

The model is a stylized version of the multi-stock fishery with shortcomings noteworthy to highlight. While the model allows for the representation of several stocks, for simplicity and tractability, I have only used a system of three stocks with two weak stocks. The model has been constructed to capture only in-season dynamics of the fishery. This multi-stock fishery model departs from traditional bio-economic models that account for the population dynamics of stocks considered in the model. Stocks mortality is driven exclusively by fishing mortality and spatial dynamics are driven only by migration patterns; no other source of mortality or spatial distribution are included.

As an additional shortcoming, the economic section of the model also relies on a simplified version of a non-forward looking fleet. The model assumes a homogeneous fleet of vessels. The fleet, as a single unit, allocates vessels across fishing location. For simplicity, fleet cost of effort allocation has been set to zero and constant across all locations. Further, the model assumes that the fleet acts myopically when choosing fishing location ground; thus, the fleet does not account for the effect that vessels' current behavior may have on further time steps or implication on further seasons.

Uncertainty in the model has been included in a simple fashion. The model introduces both uncertainty on fishermen and manager information by adding a random parameter on catch function at each location and the degree of concentration parameter respectively. Nothing is said of the role of monitoring on reducing uncertainty. Note also, that this work does not address the structural uncertainty inherent to the migration patterns on individual stocks [34].

The model can be augmented and improved in several fronts. A natural extension of this model is to allow for heterogeneous fleets. Heterogeneity across vessels could be achieved by accounting for fishing ground preferences, which can be a function of the distance between fishing locations and vessels' home port locations. As suggested in the literature, distance from home port affect fleet's fishing location choices due to travel cost (Sampson 1994). Currently the model accounts for a single fleet but one can augment the model to include several fleets (each with different spatial preferences) or a vessel specific cost parameter that accounts for travel cost.

Additionally, the model can be augmented by including a cost parameter that accounts for the cost of monitoring. One can argue that fine and finest-scale monitoring incurs higher cost than a coarse-scale monitoring. The results suggest that higher fishery benefits are obtained at a finer-scale monitoring, however, finer-scale monitoring may imply higher sampling cost. One needs to compare the trade offs between the cost of finer spatial management and fishery revenues.

This work can also be improved by using actual data from a multi-stock fishery, such as the West Coast salmon troll fishery. Simulation results were based on parameter values chosen arbitrarily. One can estimate parameter values using The West Coast salmon fishery. For instance, the model can be simulated using several stocks where values of dispersion parameters of each stock, equation 3.6, represent migrations patterns of actual Chinook salmon stocks. The value of the cost per unit of

[34] Recent GSI developments seek to provide information to characterize patterns on the spatial-temporal movements of individual stocks (CROOS 2007).

effort can also be estimated using information from the salmon fleet. Project CROOS information can inform on the cost of monitoring at several spatial scales and this information can be used in simulation of spatial management scenarios.

Addressing the caveats mentioned above, could provide a tool to explore questions regarding the role of near-real time management of the West Coast salmon fishery in particular and mixed-stocks systems in general. However, for the purpose of this paper, the model provides evidence that fine spatial scale monitoring of mixed stocks allows for fishing opportunities without compromising escapement goals for weak stocks. This stylize model can serve as a stepping stone to build more complex models that shed light on the in-season management of systems where weak stocks commingle with healthy stocks and where harvest composition is hard to assess.

3.8 Tables

TABLE 3.1: Ecological and Economic Parameters Values Used in Simulations

Ecological Parameters		
Time Steps	T	20
Initial Aggregated Biomass	$\sum_{i=1}^{3}\sum_{j=1}^{J} s_{ijt=1}$	1000000
$Stock_1$	$0.2\sum_{i=1}^{3}\sum_{j=1}^{J} s_{ijt=1}$	200000
$Stock_2$	$0.07\sum_{i=1}^{3}\sum_{j=1}^{J} s_{ijt=1}$	70000
$Stock_3$	$0.73\sum_{i=1}^{3}\sum_{j=1}^{J} s_{ijt=1}$	730000
Escapement Goal $Stock_1$	$\hat{s}_{1\tau}$	120000
Escapement Goal $Stock_2$	$\hat{s}_{2\tau}$	42000
	Dispersion Parameters	
	Entry	Exit
$Stock_1$	$\begin{pmatrix} 0.1 & 0.04 & 0 \\ 0.02 & s_{1jt} & 0 \\ 0 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0 \\ 0 & s_{1jt} & 0.02 \\ 0 & 0.04 & 0.1 \end{pmatrix}$
$Stock_2$	$\begin{pmatrix} 0 & 0 & 0 \\ 0.02 & s_{2jt} & 0 \\ 0.1 & 0.04 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0.04 & 0.1 \\ 0 & s_{2jt} & 0.02 \\ 0 & 0 & 0 \end{pmatrix}$
$Stock_3$	$\begin{pmatrix} 0.01 & 0 & 0 \\ 0.02 & s_{3jt} & 0 \\ 0.01 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.01 \\ 0 & s_{3jt} & 0.02 \\ 0 & 0 & 0.01 \end{pmatrix}$
Economic Parameters		
Catchability Coefficient	q	0.003
Total Effort	$\sum_{j=1}^{J} e_{jt}$	1000 vessels
Price	p	\$10 per lbs
Cost	c	0

3.9 Figures

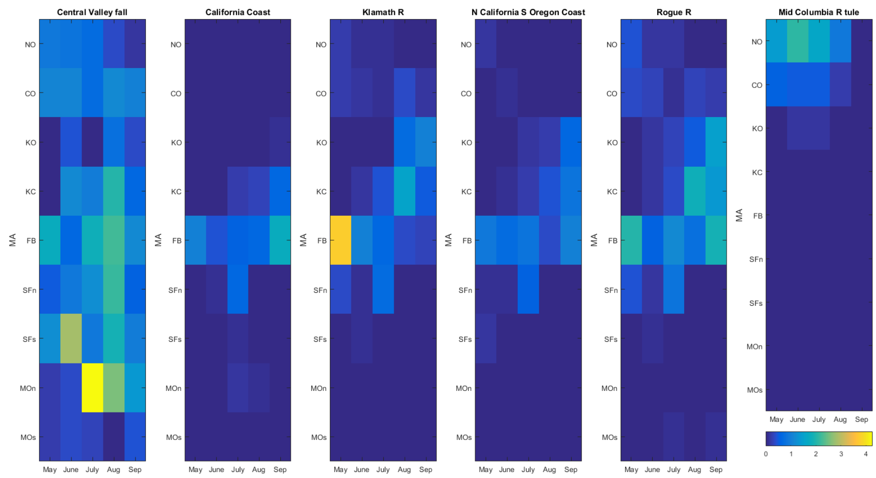

FIGURE 3.1: Stock Specific CPUE for Selected Stocks as Observed from GSI Data in 2010

Stock-specific catch per unit of effort represents the fraction of fish from each stock that a fishermen would, in average, encounter per vessel-day fishing effort; values are taken from Bellinger et al. (2015) (Bellinger et al. 2015). Management areas abbreviations are: NO, North Oregon Coast (Cape Falcon to Florence south jetty); CO, Central Oregon Coast (Florence South Jetty to Humbug Mountain); KO, Klamath Oregon (Humbug Mountain to CA/OR border); KC, Klamath Zone California (CA/OR border to Humboldt south jetty); FB, Fort Bragg (Horse Mountain to Point Arena); SF-n, San Francisco North (Point Arena to Point Reyes); SF-s, San Francisco South (Point Reyes to Pigeon Point); MO-n, Monterrey North (Pigeon Point to Point Sur); MO-s, Monterrey South (Point Sur to Mexican Border).

s_{11t} s_{21t}	...	...	...
...	s_{1jt} s_{2jt}	s_{1j+1t} s_{2j+1t}	...
...	...	...	s_{1Jt} s_{2Jt}

FIGURE 3.2: Spatial Representation of a Mixed-Stock System
Spatial representation of fishing ground for two stocks (i.e. $I = 2$) and J fishing locations.

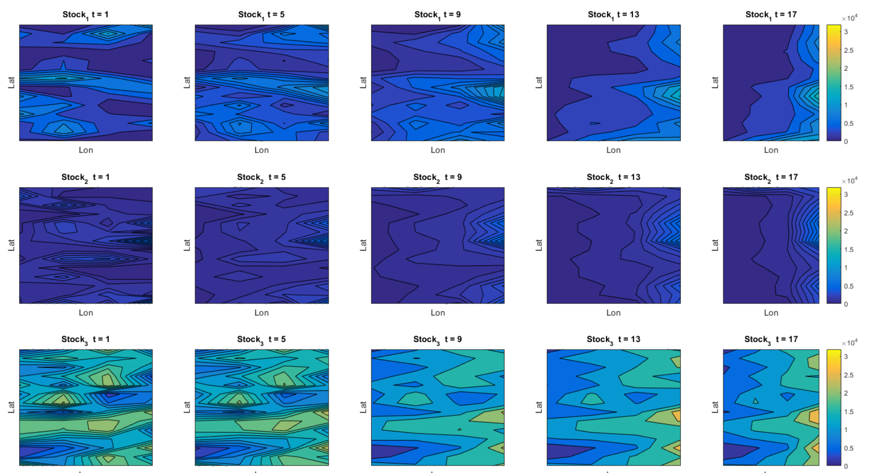

FIGURE 3.3: Simulation of Spatial Distribution of 3 Stocks
Each contour plot shows the number of fish along each longitude-latitude quadrant. The color bar denotes the intensity of number of fish; min = 0 and max = 4,000. Each column represents time step in simulation.

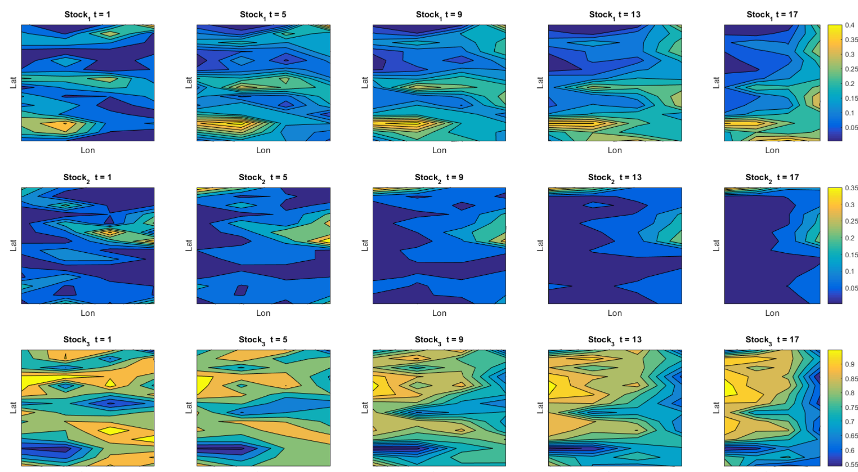

FIGURE 3.4: Degree of Concentration by Individual Stock
Each contour plot shows the degree of concentration of individual stocks along each longitude-latitude quadrant for 5 different time steps. Plots on top row, middle row, bottom row show degree of concentration of stock 1, 2 and 3 respectively.

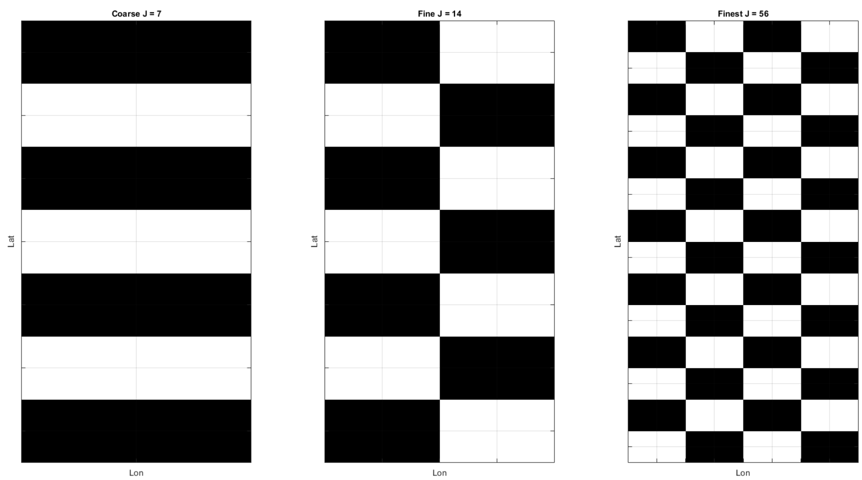

FIGURE 3.5: Representation of Spatial Scale Management Scenarios
Left figure depicts coarse-scale management scenario. Management areas are defined by latitude coordinates. Central figure depicts fine-scale management scenario where each management area in the coarse-scale scenario has been divide along longitude coordinate. Right figure portraysfinest-scale management scenario where each of the coarse-scale management units have been divided into eight management areas.

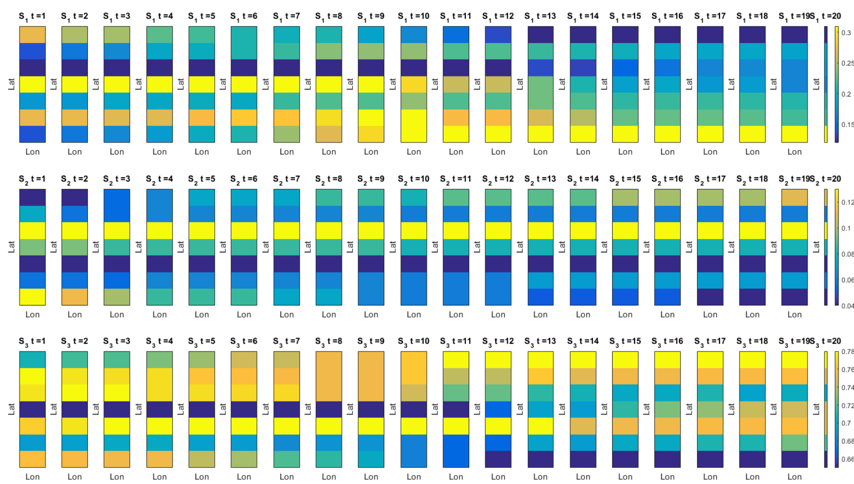

FIGURE 3.6: Individual Stock Degree of Concentration Coarse Scale Case
Each plot depicts stock specific degree of concentration estimated via GSI analysis at a coarse-scale management area level. The color bar represents degree of concentration, $0 \leq \theta \leq 1$; the closer θ is to 1 the higher the degree of concentration of stock i is in the management area. Degree of concentration for stock one, stock two and stock three are show in the first, middle, and last row respectively.

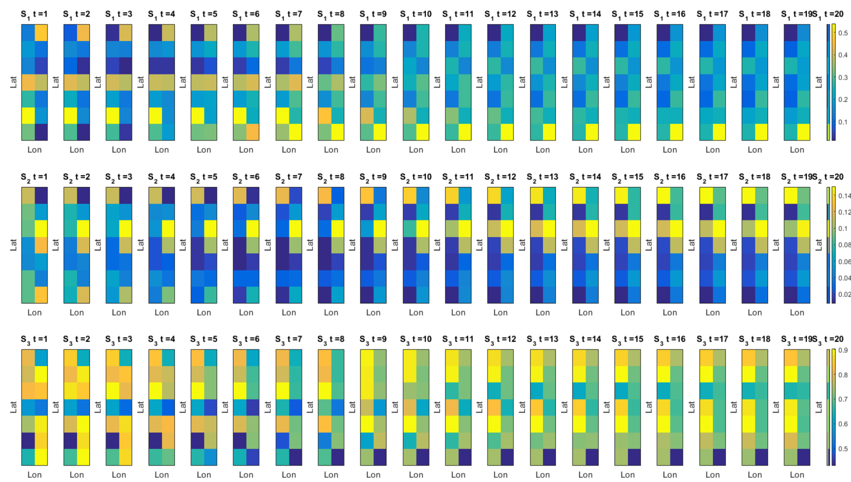

FIGURE 3.7: Individual Stock Degree of Concentration Fine Scale Case
Each plot depicts stock specific degree of concentration estimated via GSI analysis at a fine-scale management area level. The color bar represents degree of concentration, $0 \leq \theta \leq 1$; the closer θ is to 1 the higher the degree of concentration of stock i is in the management area. Degree of concentration for stock one, stock two and stock three are show in the first, middle, and last row respectively.

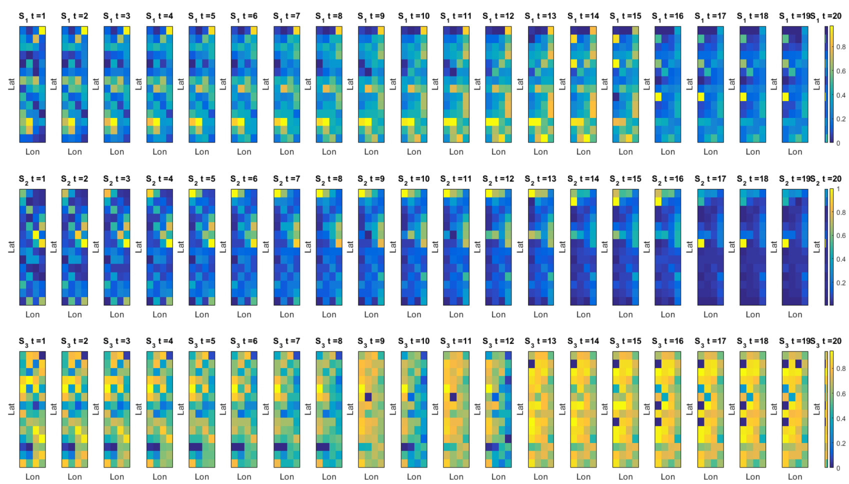

FIGURE 3.8: Individual Stock Degree of Concentration Finest Scale Case
Each plot depicts stock specific degree of concentration estimated via GSI analysis at the finest-scale management area level. The color bar represents degree of concentration, $0 \leq \theta \leq$; the closer θ is to 1 the higher the degree of concentration of stock i is in the management area. Degree of concentration for stock one, stock two and stock three are show in the first, middle, and last row respectively.

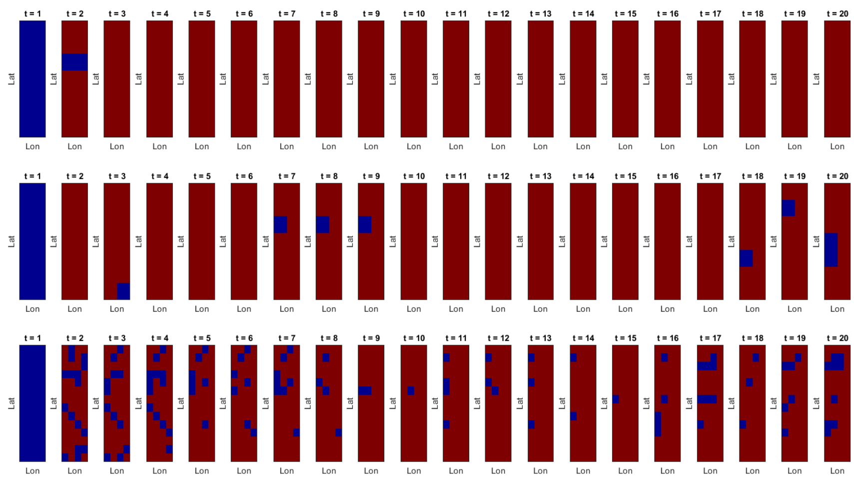

FIGURE 3.9: Area Closure for All Spatial Scale Managements Scenarios Management areas closed are red colored while open management areas are in blue. Top row shows closure under coarse-scale scenario, middle row shows fine-scale, and bottom row showsfinest-scale scenario.

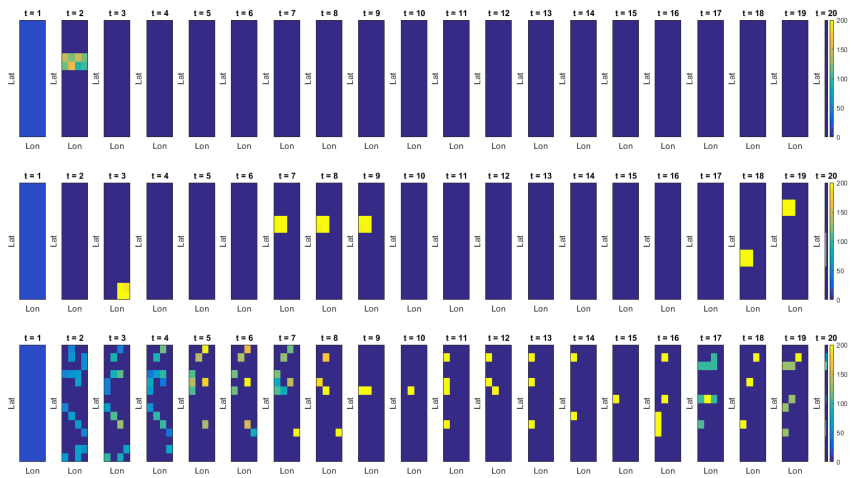

FIGURE 3.10: Spatial Distribution of Effort for All Spatial Management Scenarios
Each plot shows spatial distribution of effort at each management area. The first row shows spatial distribution of effort when regulations take placer at a coarse-scale. The middle row shows spatial distribution of effort at fine-scale while the bottom row shows spatial distribution of effort when regulations take place at the finest spatial scale.

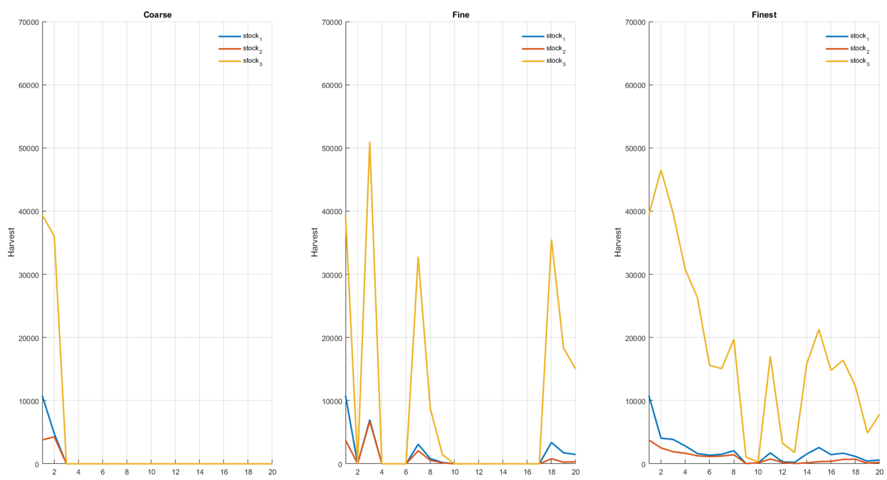

FIGURE 3.11: Harvest per Individual Stock for All Spatial Management Scenarios
Each line depicts harvest, aggregated across management areas, per individual stock at each time step. Each graph shows harvest level per stock per each management scenario.

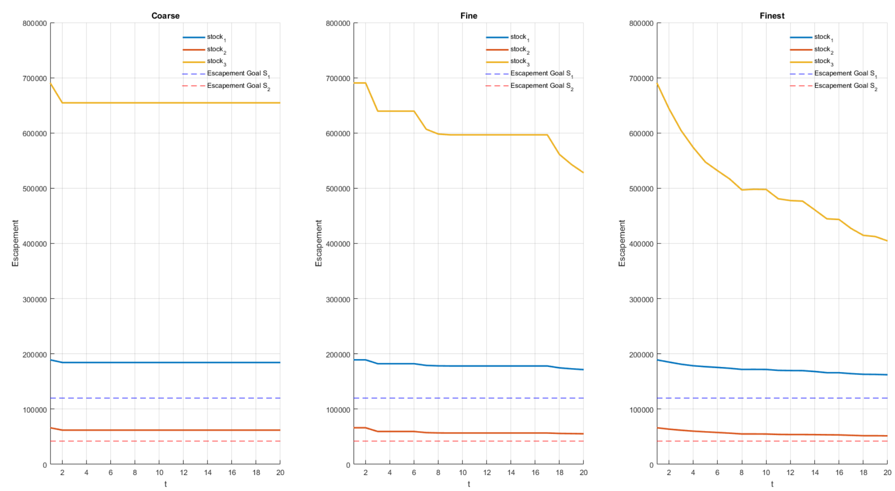

FIGURE 3.12: Individual Stock Escapement for All Spatial Management Scenarios Each line depicts escapement level per individual stock, measure in number of fish in the y-axis, at each time step. Each graph shows escapement level per individual stock per each management scenario.

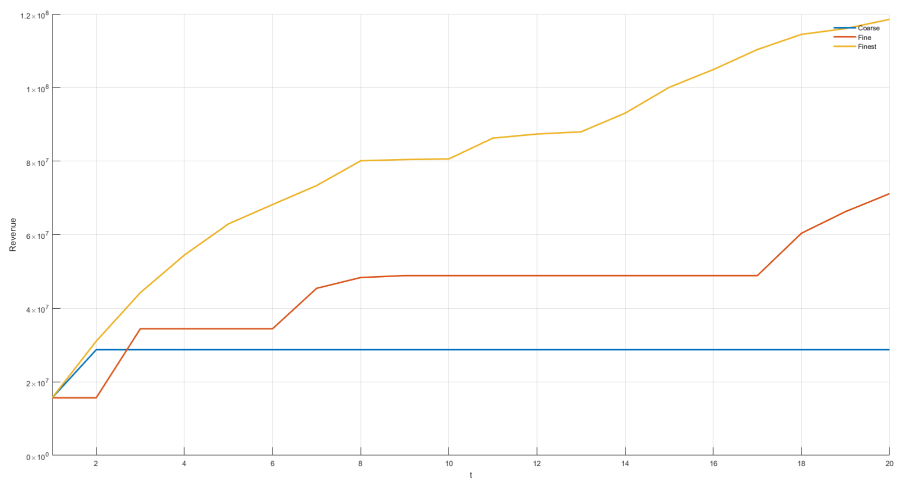

FIGURE 3.13: Fishery Revenue for All Spatial Management Scenarios
Each line depicts total revenue at each time step for a particular spatial management scenario. x-axis denote time step while y-axis denote revenue in dollars

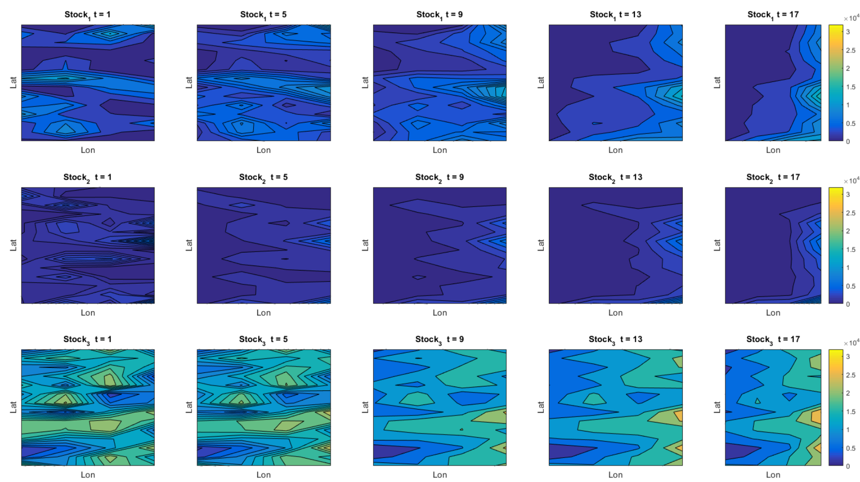

FIGURE 3.14: Spatial-Temporal Distribution of 3 Stocks When Weak Stocks Share Migration Patterns
Stocks one and two share the same migration pattern, towards Southeast of the diagram. Each plot shows distribution of individual stocks. Top, middle, and bottom rows show distribution of stock one, two, and three respectively.

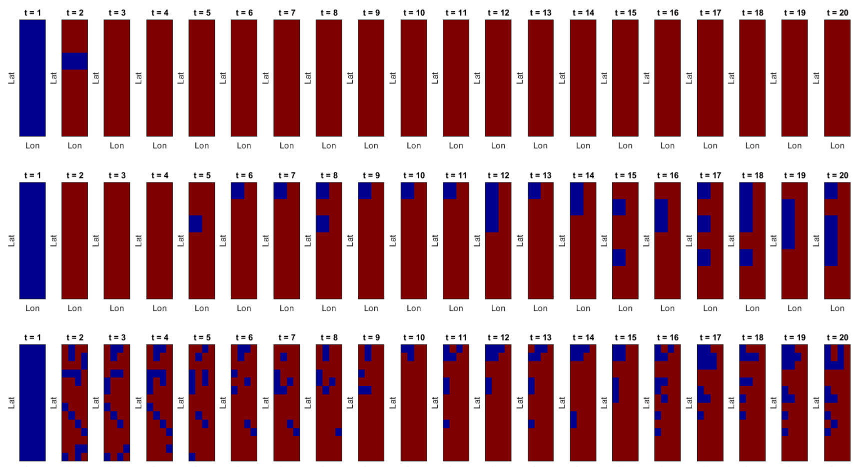

FIGURE 3.15: Area Closure When Weak Stocks Follow Same Migration Pattern Management areas closed are red colored while open management areas are in blue. Top row shows closure under coarse-scale scenario, middle row shows fine-scale, and bottom row showsfinest-scale scenario.

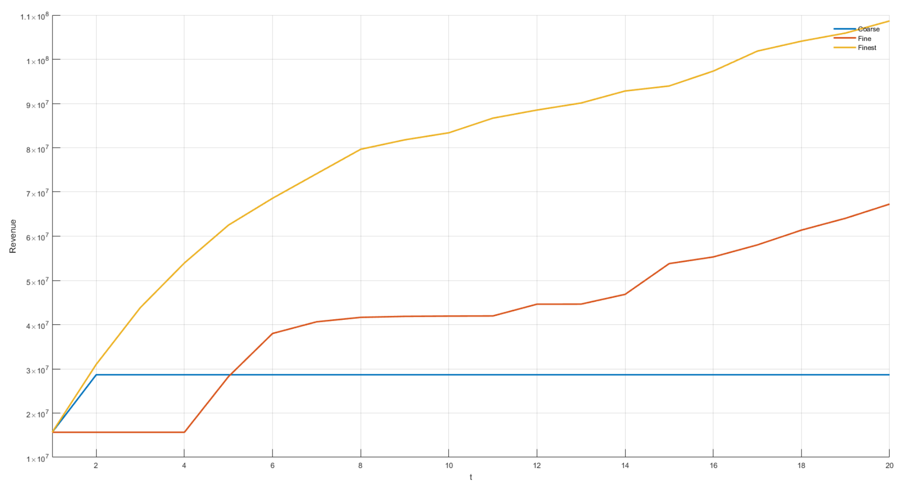

FIGURE 3.16: Fishery Revenue When Weak Stocks Follow Same Migration Pattern Cumulative fishery revenue for coarse, fine and finest spatial scale scenario for a situation where weak stocks follow same migration patterns.

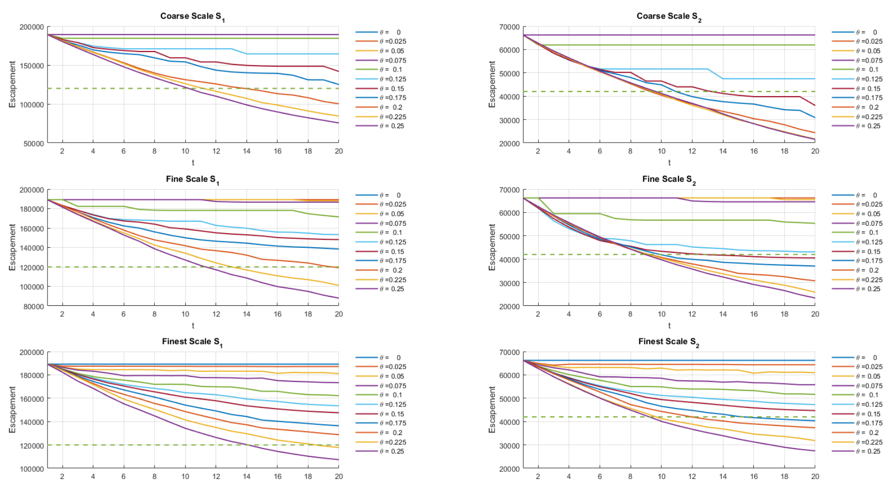

FIGURE 3.17: Escapement Level of Weak Stocks for Different Degree of Concentration Closure Rules

Each plot show escapement level for different degree of concentration closure rule. For instance, top left plot shows escapement level of stock one under a coarse-scale management scenario. Each line shows escapement for a given closure rules. Dotted lines shows stock-specific escapement goals.

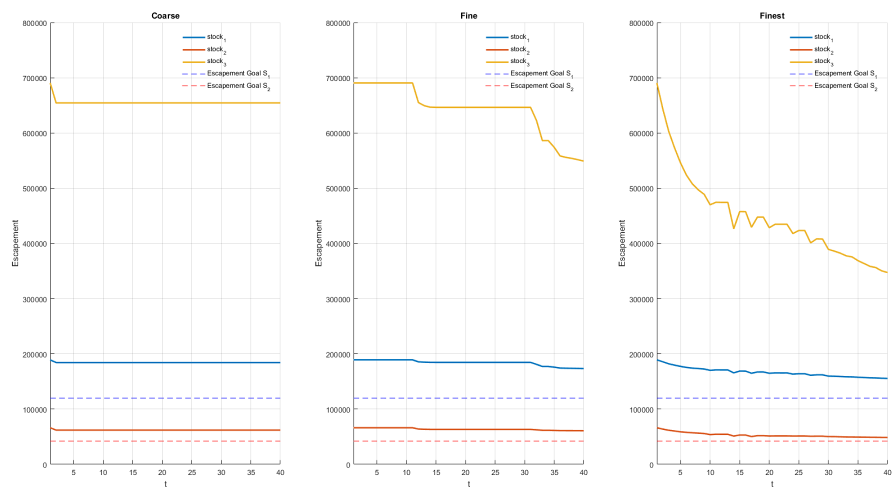

FIGURE 3.18: Escapement Level for Fine Temporal Scale Monitoring
Each plot depicts escapement level of individual stocks as well as escapement level for weak stocks. Note that time steps are double of the original time steps, indicating a fine temporal scale monitoring regimen.

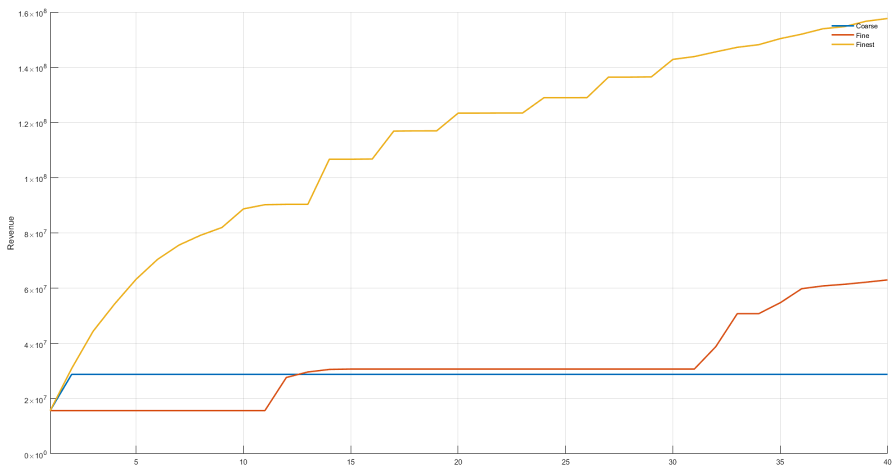

FIGURE 3.19: Revenue for Fine Temporal Scale Monitoring
Each line depicts cumulative revenue per spatial scale scenario when the temporal scale regime takes place at a fine scale.

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4 General Conclusions

The harvest of weak stocks in a mixed-stock fishery presents complex management problems. In order to study some of those complexities, I structured my research around the case study of the West Coast Chinook salmon fishery. The fishery is presently managed using coarse-scale area-temporal closures in attempts to provide some fishery opportunities without exceeding escapement goals of weak stocks. In recent years, new genetic identification techniques as well as near-real time information technologies have opened the possibility of managing the mixed-stock fishery at a finer spatial-temporal scales in order to avoid coarse-scale closures while achieving conservation goals. Given the complexities of mixed-stock fisheries, this dissertation had two goals. The first was to study how coarse-scale area temporal closures affect fishermen behavior. The second was to evaluate the potential economic and management benefits of finer-scale spatial-temporal management.

To achieve these goals, I developed an empirical model of fishermen behavior and a stylized model that characterize a multi-stock fishery. Chapter 2 describes the in-season behavior of the salmon fishery. The chapter shows that salmon fishermen participate as mixed fleets having different portfolios composed of salmon, crab, highly migratory, and/or groundfish fisheries. The participation behavior is not homogeneous across vessels with some vessels participating exclusively in the salmon fishery while others participating in two or more fisheries. Seasonal closures, and the portfolio of choices, significantly determine the switching behavior across fisheries. I characterize this fishery participation along with location choice behavior using a Random Utility Model where choice behavior is driven by expected revenues, history of past choice, and vessel characteristics. As described in the chapter, modeling fishery participation behavior is challenging given fishery alternatives vary in length of fishing trip, production capacity, and expected revenue information.

As discussed in Chapter 2, much of the spatial choice literature has ignored the effect that area-temporal closures have on fishery participation behavior. Many studies have treated spatial choice as a decision isolated from fishery participation choices, despite the fact that fishermen, such as salmon trollers, participate in more than one fishery on a seasonal basis. Results from Chapter 2 show that fishermen responses to spatial policies may affect fishermen participation across different fisheries. Results also suggest that analysts, as well as managers, need to account for the complex set of choices and behavior of fishermen when evaluating the effects of spatial policies.

The goal of Chapter 3 was to characterize a mixed-stock fishery using a stylized approach based on the characteristics of the West Coast salmon fishery including the spatial interaction of stocks, the spatial behavior of the harvesters, and the management goals and tools of a regulatory agency. I used the stylized model to represent a system where healthy stocks commingle with weak stocks preventing managing each stock as a distinct unit. The model also represents a management entity that sets opening and closing areas and bases this decision on projected abundance and expected stock mixture compositions by area. The model is simulated using three spatial regime scenarios, each differing in the spatial scale at which monitoring of mixture composition takes place. The results suggest that fine spatial closures reduce impacts to weak stocks, allows for longer seasons, and improves fishery benefits while meeting conservation objectives.

I cannot conclude this dissertation without discussing the limitations of my work. There are many complexities in the West Coast salmon fishery that were not addressed. In Chapter 2, attributes of the fishery and location choice includes expected revenues and history of past choices. Expected revenues are used as a proxy for expected profits. No information about detailed cost structure of the salmon vessels were included to account for the fishery participation choice. One can assume that the cost of participation across different fishery alternatives are relevant to fishermens decisions to switch across fisheries.

Cost parameters are also absent in Chapter 3. To help simplify modeling, a cost parameter was excluded implying that vessels' spatial choices are only influenced by revenue. However, as shown in the literature review in Chapter 3, cost parameters have been used because of their relevance in capturing the preferences for fishing grounds. A second relevant question not evaluated is how the cost of fine scale monitoring affects fishery benefit performance and conservation objectives. It is fair to assume that fine-scale and coarse-scale management will depend on the costs that are required to implement such programs. Future work should include different costs to understand the effects of costs including different categories of costs on industry, management, and policy.

This dissertation research can be improved upon on several fronts. Chapter 2 presents a static behavioral model of fishery participation and location choice. The model can be used to estimate choice probabilities of a single closure. However, a reasonable assumption is that fishermen make contemporaneous fishery participation and spatial decisions based on their expectation of future regulations and the behavior of the rest of the fleet. Thus, a further development of the static model described in Chapter 3 would be to broaden it into dynamic discrete choice model (DRUM) that describes optimal fishermen behavior throughout the season and accounts for the behavior of all fleets having alternative portfolio fishery options (a modeling approach similar to Huang and Smith 2014. The rich dataset used in Chapter 2 allows for the modeling of a robust profile of fishermen fishery participation choices within and between seasons. Moving away from a static model of single species management can advance fisheries economics towards more comprehensive ecosystem-based management policies.

Chapter 3 presented a stylized model that may be criticized for failing to account for many complexities of the West Coast salmon fishery. These complexities include the presence of many different salmon stocks (each with individual abundances and migration patterns), aggregation of natural and hatchery stocks, the role of Code Wire Tag (CTW) information to complement GSI stocks spatial distribution pattern information, and many more. The model only considers a single regulatory agency that fails to address scenarios of voluntary adoption of spatial constraints by the fishermen themselves. The model does not address structural uncertainty associated to salmon stock migration patterns and the role of GSI and CWT to address such uncertainty.

A logical next step in Chapter 3 would be to parametrize the mixed-stock fishery model based on actual data from the salmon fishery. Dispersion parameters could be estimated using Project CROOS and CWT stocks specific data. Cost and revenue information could be obtained from survey data and Project CROOS could provide the cost of monitoring data.

During the development of both Chapter 2 and Chapter 3, many have suggested that the mixed-stock fishery model and the fishery participation location choice model need to be integrated into a single framework. In Chapter 3, distribution of effort across location choices were modeled using a utility score approach, where the parameter of the utility score choice probability is assumed to be one. In Chapter 2 however, parameters of the choice probabilities are statistically estimated. Parameter values in Chapter 2 may resemble parameters of location choice probabilities in the coarse-scale scenario in Chapter 3. Thus, the fishery participation and location choice model in Chapter 2 can be integrated into the mixed-stock fishery model in Chapter 3 for the coarse-scale scenario only. Project CROOS fine-scale landing level data could be used to construct coarse-scale and refined-scale fishing location choices. Such data could also be used to estimate parameters of separate location choice models at a spatial scale that resembles monitoring scales in Chapter 3.

Although the fishery participation and location choice model and the mixed-stock model are estimated separately, a more complex model could be developed to characterize a model that accounts for a broader ecological structure of the multi-stock fishery and the complex behavior of fishermen that target multiple species. The fine-scale landing data provided by Project CROOS may provide the key link for integrating both models into a single ecosystem-based framework. This daunting task is the basis for my own future research agenda and provides a framework to move away from static models of single species management towards dynamic spatially explicit models evaluating policies consistent with ecosystem-based management approaches.

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