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A MANAGEMENT STRATEGY EVALUATION OF THE IMPACTS OF INTERSPECIFIC COMPETITION AND RECREATIONAL FISHERY DYNAMICS ON VERMILION SNAPPER (RHOMBOPLITES AURORUBENS) IN THE GULF OF MEXICO

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by

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ABSTRACT

In the Gulf of Mexico (GOM), Vermilion Snapper *(Rhomboplites auroruben)*, are believed to compete with Red Snapper directly for prey and habitat. The two species share similar diets and have significant spatial overlap in the Gulf. Red Snapper are thought to be the dominate competitor, forcing Vermilion Snapper to feed on less nutritious prey when local resources are depleted. In addition to ecological pressures, GOM Vermilion Snapper support substantial commercial and recreational fisheries. Over the past decade, recreational landings have steadily increased, reaching a historical high in 2018. One cause may be stricter regulations for similar target species such as Red Snapper and Gray Triggerfish. A better understanding of the impact of ecosystem and fishery dynamics is essential for successful, long-term management of the stock. In this study, I used management strategy evaluation to assess the effectiveness of current and alternative harvest control rules (HCR) for the stock when accounting for interspecific competition and increased recreational landings. I developed an operating model that simulates the underlying population and fishery dynamics of the Vermilion Snapper stock and includes an index of Red Snapper competition. The annual competition index values were the estimated annual abundance of Red Snapper relative to the total virgin or near-virgin abundances of Vermilion and Red Snapper combined. In the second chapter, I used a random utility model to estimate the probability of a recreational angler targeting Vermilion Snapper given past management for Red Snapper and Gray Triggerfish. I incorporated the predicted targeting probabilities into the operating model from chapter one and evaluated the outcomes of the simulation. In both simulations, catch limits were set using empirical or model-based approaches. I ran 100 trials for each scenario, projected over 50 years. I found that the GOM Vermilion Snapper stock is resilient to competition and increased recreational landings, and all HCR effectively managed the stock. This study provides a methodology to incorporate interspecific dynamics into a single-species assessment model.

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DEDICATION

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TABLE OF CONTENTS

ABSTRACT ii

ACKNOWLEDGMENTS iv

DEDICATION v

LIST OF TABLES ix

LIST OF ILLUSTRATIONS x

LIST OF ABBREVIATIONS xii

CHAPTER I – ECOLOGY, AND MANAGEMENT OF VERMILION SNAPPER IN THE GULF OF MEXICO 1

1.1 References 12

CHAPTER II - EVALUATING IMPLICATIONS OF INTERSPECIFIC COMPETITION FOR VERMILION SNAPPER MANAGEMENT IN THE GULF OF MEXICO 18

2.1 Introduction 18

2.2 Methods 24

2.2.1 Operating Model 24

2.2.1.1 Population Dynamics 24

2.2.1.2 Fishery Data 25

2.2.1.3 Indices of Abundance 27

2.2.1.4 Selectivity 28

2.2.1.5 Uncertainty 29
2.2.1.6 Competition Index 29
2.2.2 Assessment Model 30
2.2.2.1 Harvest Control Rules 31
2.2.2.2 Management Objectives 33
2.2.3 Performance Indices 34
2.2.4 Sensitivity Analyses 34
2.3 Results 35
2.4 Discussion 44
2.5 References 85
CHAPTER III – EVALUATING IMPACTS OF INCREASED RECREATIONAL TARGETING ON THE VERMILION SNAPPER STOCK IN THE GULF OF MEXICO 92
3.1 Introduction 92
3.2 Methods 98
3.2.1 MRIP Data 98
3.2.2 Random Utility Model 99
3.2.3 MSE 102
3.2.3.1 Operating Model 102
3.2.3.1.1 Population Dynamics 102

3.2.3.1.2 Fishery Data 103
3.2.3.1.3 Indices of Abundance 105
3.2.3.1.4 Selectivity 106
3.2.3.1.5 Uncertainty 107
3.2.3.1.6 Competition Index 107
3.2.3.2 Assessment Model 108
3.2.3.3 Harvest Control Rules 109
3.2.3.4 Management Objectives 111
3.2.3.5 Performance Indices 112
3.3 Results 112
3.3.1 RUM Analysis 113
3.3.2 Mixed logit model 114
3.3.3 Predicted recreational landings 114
3.3.4 MSE 116
3.4 Discussion 118
3.5 References 151

LIST OF TABLES

Table 2.1 Uncertainty and Error 52

Table 2.2 Harvest Control Rules 53

Table 2.3 Empirical Rules 54

Table 2.4 Number of Non-Converged Trials 55

Table 2.5 Terminal SPRs 56

Table 2.6 Empirical Rule Ranking 57

Table 2.7 Empirical Rule Ranking for Sensitivity Analyses 58

Table 3.1 Recreational Regulations 127

Table 3.2 Random Utility Models 128

Table 3.3 Future Management Regulations 129

Table 3.3 (continued) Future Management Regulations 130

Table 3.3 (continued) Future Management Regulations 131

Table 3.3 (continued) Future Management Regulations 132

Table 3.3 (continued) Future Management Regulations 133

Table 3.4 Harvest Control Rules 134

Table 3.5 Empirical Harvest Control Rules 135

Table 3.6 Number of Targeted Trips 136

Table 3.7 RUM Model Coefficient Estimates 137

Table 3.8 Number of Incomplete Trials 138

LIST OF ILLUSTRATIONS

Figure 2.1 MSE Simulation Process 59

Figure 2.2 Spawning Stock Biomass 60

Figure 2.3 Mean Catch 61

Figure 2.4 Simulated Indices of Abundance 62

Figure 2.5 Biomass Estimates 63

Figure 2.6 Mean Catches 64

Figure 2.7 Average Annual Variability 65

Figure 2.8 Terminal SPRs 66

Figure 2.9 Biomass Ratios 67

Figure 2.10 Fishing Mortality Ratios 68

Figure 2.11 Competition Index 69

Figure 2.12 Change in Mean Catch for ACL Rule 70

Figure 2.13 Change in Mean Catch for Quota Rule 71

Figure 2.14 Change in Mean Catch for eHCR1 Rule 72

Figure 2.15 Change in Mean Catch for eHCR2 Rule 73

Figure 2.16 Change in Mean Catch for eHCR3 Rule 74

Figure 2.17 Change in Mean Catch for eHCR4 Rule 75

Figure 2.18 Change in Mean Catch for eHCR5 Rule 76

Figure 2.19 Change in Mean AAV for ACL Rule 77

Figure 2.20 Change in Mean AAV for Quota Rule 78

Figure 2.21 Change in Mean AAV for eHCR1 Rule 79

Figure 2.22 Change in Mean AAV for eHCR2 Rule 80

Figure 2.23 Change in Mean AAV for eHCR3 Rule 81

Figure 2.24 Change in Mean AAV for eHCR4 Rule 82

Figure 2.25 Change in Mean AAV for eHCR5 Rule 83

Figure 2.26 Terminal SPRs for Sensitivity Analyses 84

Figure 3.1 MSE Simulation Process 139

Figure 3.2 Number of Trips 140

Figure 3.3 Predicted Relative Probability of Targeting 141

Figure 3.4 Predicted Recreational Landings 142

Figure 3.5 Predicted Recreational Catch Under 3 Regulation Scenarios 143

Figure 3.6 Eastern Commercial Catch 144

Figure 3.7 Western Commercial Catch 145

Figure 3.8 Recreational Catch 146

Figure 3.9 Average Annual Variation of Eastern Commercial Landings 147

Figure 3.10 Average Annual Variation of Recreational Landings 148

Figure 3.11 Terminal SPRs 149

Figure 3.12 Relative Targeting Probability 150

LIST OF ABBREVIATIONS

AAV	Average Annual Variability
ABC	Acceptable Biological Catch
ACL	Annual Catch Limit
AM	Assessment Model
BC	By-Catch
B_{MSY}	Biomass at Maximum Sustainable Yield
CE	Eastern Commercial
CPUE	Catch-per-Unit Effort
CW	Western Commercial
eHCR	Empirical Harvest Control Rule
F_{MSY}	Fishing Mortality at Maximum Sustainable Yield
GOM	Gulf of Mexico
GT	Gray Triggerfish
HCR	Harvest Control Rule
MRFSS	Marine Recreational Fisheries Statistics Survey
MRIP	Marine Recreational Information Program
MSCAA	Multispecies Statistical Catch-at-Age
MSE	Management Strategy Evaluation
MSP	Multispecies Production Model
MSST	Minimum Stock Size Threshold

MSVPA	Multispecies Virtual Population Analysis
MSY	Maximum Sustainable Yield
OFL	Overfishing Level
OM	Operating Model
REC	Recreational
RS	Red Snapper
RUM	Random Utility Model
SEDAR	South East Data Assessment and Review
SPR	Spawning Potential Ratio
SS	Stock Synthesis
SSASPM	State-Space Age-Structured Production Model
SSB	Spawning Stock Biomass
$SSB_{30\%SPR}$	Spawning Stock Biomass at 30% Spawning Potential Ratio
TAC	Total Allowable Catch
TL	Total Length
VPA	Virtual Population Analysis
VS	Vermilion Snapper

CHAPTER I – ECOLOGY, AND MANAGEMENT OF VERMILION SNAPPER IN THE GULF OF MEXICO

Vermilion Snapper (*Rhomboplites aurorubens*) are members of the Lutjanidae family and their range spans from Cape Hatteras, North Carolina to southeast Brazil, including in the Gulf of Mexico (GOM) and Caribbean Sea. They can live for over 15 years and the mean asymptotic length is estimated to be between 262 and 707 mm in the GOM (Allman 2007; Johnson et al. 2010) and 535 and 650 mm in the south Atlantic (Schirripa 1992; Potts et al. 1998). There is high uncertainty around the age-length relationship and they have highly variable growth rates in the Gulf of Mexico (Allman 2007; Johnson et al. 2010; Porch and Cass-Calay 2001) but generally grow quickly to reach their maximum lengths. Allman (2007) found that in the north central GOM, there are small-scale spatial variations in growth of Vermilion Snapper amongst depth strata, distance from shore, and sex. However, there are no Gulf-wide studies examining these patterns, so it is difficult to determine if this pattern persists across the GOM. Studies have shown that Vermilion Snapper become reproductively mature between one and two years old (Hood and Johnson 1999) and spawn multiple times between March and October (Hood and Johnson 1999). Their habitat of preference is on the shelf edge and live bottom reefs (Grimes et al. 1982) and they exhibit high site fidelity (Beaumariage 1966; Beaumariage and Whittach 1966; Grimes et al. 1982). Bortone et al. (1997) found that they are a dominate species of off-shore artificial-reef fish assemblages and tended to inhabit artificial reefs. Because of their high site fidelity and affinity for artificial reefs, Bortone et al. (1997) noted that they can be used as an indicator species of the presence of an artificial reef. High-relief structures provide suitable habitat for planktivorous fishes, which larger Vermilion Snapper can feed on (Dance et al. 2011).

A limited number of studies have been conducted on Vermilion Snapper diet habits in the GOM (Simons 1997; Weaver et al. 2002; Johnson et al. 2010; Davis 2015) . A study by Simons (1997) found the majority of individuals (76-100 mm) stomachs contained mega-benthic crustaceans and macro-benthic crustaceans. There were also small amounts of hypo-planktonic crustaceans and pelagic or midwater fish. This study was limited in both geographic and temporal scope, the species were collected from the Mobile Bay during the winter. However, based on the 16 individuals, Simons (1997) suggested Vermilion Snapper are non-selective carnivores that are not limited by vertical distribution or type of prey. Another study conducted in the GOM by Weaver et al. (2002) classified Vermilion Snapper (n = 72) as macroplanktivores that fed on amphipods, copepods, polychaetes, fish and fish larvae (including myctophids, prionotus, synodus), shrimps, *Lucifer faxoni*, pteropods, crab larvae, and squid. Stomach contents of smaller individuals (51 to 100 mm) analyzed by Darnell (1991) were dominated by crustaceans (88%), either shrimp or amphipods.

Off the coast of North and South Carolina, Vermilion Snapper were found to feed in the late afternoon and evening (Grimes et al. 1982). Individuals in this region tended to feed on planktonic or nektonic organisms; the most common prey taxa were amphipods, copepods, decapods, squid, and fishes, depending on the metric used to quantify stomach contents (Sedberry and Cuellar 1993). Sedberry and Cuellar (1993) found significant differences of prey frequencies between size classes. For example, while decapods were found in all size class stomachs, they were more frequent in smaller fishes (50 to 100 mm

SL). Increasing size classes showed decreasing amounts (relative number and volume) of small crustaceans and larger individuals tended to feed more on cumaceans than smaller (Sedberry and Cuellar 1993). In general, Vermilion Snapper shift their diet as they grow from many small copepods, to fewer, larger copepods, fishes, or decapods (Sedberry and Cuellar 1993). Vermilion Snapper are not the only species to experience this diet shift, the closely related Red Snapper exhibit similar behavior switching to more fish and squid as they grow above 60 mm SL (Szedlmayer and Lee 2004).

Vermilion Snapper are an integral component in the Gulf of Mexico food web because they provide a link between the lower trophic level benthos and the higher trophic level pelagic species. Vermilion Snapper consume large amounts of decapods, benthic organisms, pelagic schooling fish species such as *Sardinella aurita*, and squids (Grimes et al. 1982; Sedberry and Cuellar 1993), while also serving as prey for other reef species including Lionfish (Dahl and Patterson 2014), sharks, and other large reef fishes. Results from ecosystem models indicate that changes in fishing on prey or competitors can influence the biomass of Vermilion Snapper (Chagaris et al. 2015). For example, reduction of the bottom longline fishery effort had a positive impact on many reef grouper species, however, Vermilion Snapper biomass declined. Additionally, if there was an increase in the baitfish fishery effort, many of which serve as prey for Vermilion Snapper, Vermilion Snapper, Red Snapper, dolphins, and sea birds all experienced declines in biomass. Changes in either prey availability or interspecific competition can impact the Vermilion Snapper population, and if they have less competitive advantage than other species (Chagaris et al. 2015), the population may experience significant declines.

Commercial harvest of Gulf of Mexico Vermilion Snapper dates back to the early 1960's (Goodyear and Schirripa 1991). Commercial landings were relatively low in the early years of the fishery but between 1979 to 1990 annual harvests had tripled and the range of the fishery had expanded into the western Gulf (Goodyear and Schirripa 1991). The primary gear used is vertical hook and line but occasionally Vermilion Snapper are caught with long lines or traps. Commercial landings are reported in coastal logbooks in pounds whole weight. Because the contribution of landings from the long line and trap fisheries are very low relative to the hand-line fishery, only hand-line landings were included in the most recent stock assessment (SEDAR 45). Generally, there are higher landings in the eastern Gulf of Mexico compared to the western sector (SEDAR 45).

Historically, recreational landings were lower than commercial landings until 2018 when the recreational landing surpassed the commercial by almost 400,000 lbs ("Gulf of Mexico Historical Stock Landings and Annual Catch Limit Monitoring" 2020). Recreational landings are reported through several sampling programs, the Marine Recreational Information Program (MRIP), the Southeast Region Headboat Survey (SRHS), Texas Parks and Wildlife Department (TPWD) and the Louisiana Creel Survey. Recreational landings are counted from private boats as well as for-hire charter and headboats. The multiple sampling programs across the region and varying protocols among the programs can make the recreational landings difficult to accurately determine. Recently, an update to the protocol of how MRIP catches are calculated caused historical catches to be higher than previously thought. These changes can have implications for the potential fishing a stock can support. If the stock was not overfished under higher fishing levels than originally believed, the stock may be able to support increased fishing effort and catches.

In the United States, Vermilion Snapper are federally managed in the South Atlantic, Gulf of Mexico, and the U.S. Caribbean and Virgin Islands. In the South Atlantic, the commercial quota is divided into two six-month fishing seasons that can close early if the quotas are met before the end of the season. There are both size and trip limits, gear restrictions, and area closures to protect the stock. In the Gulf of Mexico, Vermilion Snapper are managed under Fishery Management Plan for the Reef Fish Resources of the Gulf of Mexico and have similar regulations as the South Atlantic with size and number regulations, gear restrictions, and early season closures can occur if the quotas are met. However, since 2012, the percentage of the total ACL that was actually caught has ranged between 66% and 94% ("Gulf of Mexico Historical Stock Landings and Annual Catch Limit Monitoring" 2020).

The initial regulations for Vermillion Snapper were implemented in 1990 which set the minimum size to 8 inches. Neither sufficient fishery nor biological data were available to conduct statistical assessments of the stock however, a catch-curve analysis was used to estimate total mortality. This estimate ranged from $Z = 0.26$ to $Z = 0.83$ because two growth models were used, one that represented a slow growth rate and on that represented a fast growth rate, with no compelling evidence to suggest one estimate was more accurate than the other. A limiting factor of the analysis was the lack of strong age and growth data. The ageing data available was based on scale-ageing and the resulting age-length relationships were conflicting and uninformative. The main conclusion from this effort was that more growth studies were needed to continue with stock assessment efforts.

A study conducted the following year found differences in growth rates between eastern and western portions of the Gulf and was able to estimate the stocks spawning potential as 36% of the virgin biomass (Schirripa 1992). Additionally, YPR analyses showed that increasing the minimum size limit from 8 inches to 10 inches would increase overall yield (Schirripa 1992). Four years later, an initial Virtual Population Analysis (VPA) was conducted for the stock that resulted in four estimates for fishing mortality. The three scenarios represented varying levels of fishing mortality and juvenile survivorship. Following the addition and refinement of data inputs, an updated VPA estimated a lower fishing mortality than the previous effort, however, the SPR of the stock was estimated to be below 20%, indicating the stock may be overfished. In response to this assessment, in 1997 the size limit was increased to 10 inches. In 2000, the first attempt at estimating a maximum sustainable yield (MSY) for Vermilion Snapper and the associated biomass and fishing mortality needed to achieve MSY (B_{MSY}, F_{MSY}) found that because of the high uncertainty in the stock-recruitment relationship, $F_{30\%spr}$ and $B_{30\%spr}$ were appropriate proxies for F_{MSY} and B_{MSY} (Schirripa and Legault 2000). While there was large uncertainties in the model results, one of the models showed high probability of the stock being overfished and undergoing overfishing (Schirripa and Legault 2000). The following year, two novel approaches were used, an age-structured VPA and a Pella-Tomlinson non-equilibrium production model to evaluate the stock status, however, there was little confidence in either approach (Porch and Cass-Calay 2001). Because of the high uncertainty of the age-growth relationship, the catch-at-age estimates converted from catch-at-length data were unreliable. Despite the uncertainty, the F estimates were similar to previous estimates and all of the model results showed either the stock was nearly fully exploited or already overfished (Porch and Cass-Calay 2001). In 2004, Amendment 23 established a rebuilding plan for Vermilion Snapper with a ten-year rebuilding timeline which included stricter and new regulations: size limit was further increased to 11 inches, a newly instated short season closure for the commercial fishery, and a 10 fish bag limit.

An updated assessment (SEDAR 2006) used a state-space age-structured production model (SSASPM) and found the stock was not overfished (SSB/SSB_{MSY} = 1.80, $SSB/SSB_{30\%SPR}$ = 1.76) nor undergoing overfishing (F/F_{MSY} = 0.65, $F/F_{30\%SPR}$ = 0.67). The accepted base model also suggested that the stock had never been overfished and overfishing had never occurred (SEDAR 2006)(Cass-Calay 2005). Likely reasons for the difference in stock status with the SSASPM model is because of the differences from the previously used Pella-Tomlinson model, which include allowing for fecundity-at-age relationships and the inclusion of age-composition data (Cass-Calay 2005). Another main difference in the two models was the starting years, the PT production model had a shorter timeseries of data available, so it started later in 1986 whereas the SSASPM assumed the stock was near virgin status in 1950 and tuned the historical population status estimates accordingly (Cass-Calay 2005). As a result of this assessment, the rebuilding plan was repealed, and the minimum size limit was reduced from 11 inches to the prior 10 inches. In 2011, an update for SEDAR 9 involved updating the data and changing the methodology for treating the shrimp bycatch index. A ‘super-year’ approach was utilized instead of the previous method of fitting the median every year. The super-year approach is different in that it allows the model to fit the median directly instead of assuming constant catch each year. This had impacts on the fishing morality (Linton et al. 2011). Again, the update showed that the stock was not overfished, nor undergoing overfishing.

The most recent stock assessments, SEDAR 45 and SEDAR 67, used the Stock Synthesis 3 (SS3) software. SS3 is a forward-projecting, integrated, statistical catch-at-age model that can be configured to varying levels of complexity. A moderately complex model was used for the Vermilion Snapper assessment which provided estimates of catch and associated age-compositions for three fishing fleets and one bycatch fleet, seven fishery-dependent CPUE indices of abundance, one effort index, and three fishery-independent indices of abundance. The model estimated stock-recruitment parameters for a Beverton-Holt relationship, selectivity function parameters for each fleet, abundance, biomass, spawning stock biomass, and harvest rates. The model started in 1950 when the stock was assumed to be near virgin conditions and included 15 age groups (0 to 14-plus). The results of these assessments showed the stock was not overfished nor undergoing overfishing and that the spawning stock biomass had leveled off and showed a possible increase in the last years (SEDAR 2016, 2020). From the assessment report, many research recommendations were suggested for further evaluating data inputs and possible reparameterizations. For example, because of limited age composition data and fast growth characteristics, it was suggested to explore the use of a length-based model instead of age-based. Additionally, reparameterization of the selectivity curves for fishery-independent surveys may improve model stability (SEDAR 2020). One major data concern was the limited information regarding discards from the fisheries, particularly the recreational fishery. Testing the impact of including discards and at what level they begin to impact the stock are valuable research efforts that would improve the assessment model. Additionally, the consequences of excluding certain indices of abundance from the assessment model have not been fully evaluated. To answer these concerns, simulation testing methods should be implemented that would provide valuable insight and lead to overall improvement of the Vermilion Snapper assessment.

One such simulation methodology is management strategy evaluation (MSE). Management strategy evaluation is a flexible framework that allows the user to test the robustness of a suite of alternative harvest control rules to uncertainties about the population dynamics, the data inputs, the enforcement of the regulation, or the structure of the assessment model and provides quantifiable indices of management objectives for the stock, fishery, and stakeholders. Since the IWC's first implementation MSE, the uses and complexities of MSE have expanded. MSE is a decision-making tool that has become the standard method to regularly assess fisheries and set harvest regulations globally (De Oliveira and Butterworth 2005; Punt 2006; Ono et al. 2018; Cunningham et al. 2019). De Oliveira and Butterworth (2005) used MSE to evaluate the effectiveness of environmental indices as indicators for recruitment for Anchovy, and Roel and De Oliveira (2007) investigated the risks for Western Horse Mackerel when there was implementation error or if there was high process uncertainty. In 2007, Australia introduced a harvest strategy policy for their federal fisheries that takes a precautionary approach to management by ensuring that all fisheries do not exceed a risk threshold, no matter the level of uncertainty (Smith et al. 2009). Harvest control rules for many fisheries including the southern school and gummy shark fishery (Punt et al. 2005), northern prawn fishery (Dichmont et al. 2006) and the data-poor spanner crab fishery (Dichmont and Brown 2010) were assessed using MSE. Dichmont et al. (2006) used an operating model that included spatial structure, implementation error, and time-varying fishing efficiency. In the Gulf of Alaska, A'mar et al. (2010) evaluated a management strategy for Walleye Pollock under varying levels of predator-prey interactions. MSE has also been used in multispecies fisheries to develop a management procedure that limited the risk of either species to collapse (De Oliveira and Butterworth 2004; De Moor et al. 2011) and minimized interannual variability in total allowable catches (De Moor et al. 2011). Along with testing present-day uncertainties, another utility of MSE is to test management strategies to predicted future conditions. A 'mar et al. (2009) evaluated management strategies for Walleye Pollock under projected environmental conditions as predicted by Intergovernmental Panel on Climate Change models.

MSE is not only used to quantify risk and set harvest strategies. More recent studies have used it to evaluate trade-offs in assessment techniques and models (Punt and Ralston 2007; Plagányi et al. 2018; Sagarese et al. 2019). Sagarese et al. (2019) used MSE to test the implications of using indicators or data-limited methods to determine harvest strategies. This study compares the outcomes of managing a stock using data-limited methods (assessment models or empirical harvest control rules) instead of data-rich methods which provides insight into the dangers or benefits of using less time and computationally intensive methods. Empirical harvest control rules can be effective in maintaining a stock at an acceptable level and are practical for fisheries where there is not ample data to support model-based harvest control rules (Plagányi et al. 2018). MSE can help scientist and managers understand which empirical control rules are more robust to uncertainties, what the risks and benefits of alternative ones are, and provide guidance for which one is the most appropriate for the stock in question.

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CHAPTER II - EVALUATING IMPLICATIONS OF INTERSPECIFIC COMPETITION FOR VERMILION SNAPPER MANAGEMENT IN THE GULF OF MEXICO

2.1 Introduction

Vermilion Snapper (*Rhomboplites aurorubens*) are a component of the multi-species snapper reef fish complex that supports one of the largest commercial and recreational finfish fisheries in the Gulf of Mexico (GOM). Vermilion Snapper are found on low profile, hard bottom habitats including natural and artificial reefs (SEDAR 2006) and feed mostly on benthic or reef associated amphipods, tunicates, shrimp, crabs, polychaetes, and small fish (Johnson et al. 2010). In the GOM, many snapper species (family Lutjanidae) occupy reef habitats with Vermilion Snapper and often compete directly with them for resources (Wells and Cowan 2007). As a result, the productivity of the Vermillion Snapper stock may be influenced by competitive interactions with congeneric species (Johnson et al. 2010). Vermilion and Red Snapper have similar habitat and feeding preferences in the GOM (Davis et al. 2015a). Davis et al. (2015) found that at sites where only one of the species was present, Vermilion and Red Snapper had high dietary overlap; however, at sites where both occurred, diet overlap was low. The low overlap at sites of co-occurrence suggests that resource partitioning is occurring, driven by competitive exclusion (Davis et al. 2015a). Johnson et al. (2010) and Davis et al. (2015) hypothesized that Red Snapper are more aggressive foragers than Vermilion. Red Snapper feed at higher rates and consume more prey than Vermilion Snapper (Davis et al. 2015a). Additionally, it is typical for predatory species with fast growth rates, such as Red Snapper, to swim farther from their reefs in search of high-quality prey (Davis et al. 2015a). In contrast, Vermilion Snapper stay closer and choose to feed on low-quality prey (Davis et al. 2015a). Consequently, if prey resources are reduced at a reef, Red Snapper are more likely to 1.) successfully acquire scarce prey in the area or 2.) be more willing to travel farther to forage. Vermilion Snapper exhibit high site fidelity (Grimes et al. 1982; Hood and Johnson 1999). As a result, at locations where Vermilion Snapper compete for resources, they may be forced to consume less desirable prey leading to reductions in the caloric content of the diet. Competitive interactions impact individual growth, development, and reproductive activity. I hypothesize that competitive interactions impact the Vermilion Snapper stock. Thus far, no research has been done yet to quantify this impact or understand the management implications it would have on the stock.

Currently, individual assessments and management decisions for Vermilion and Red Snapper (SEDAR 2016, 2018) do not account for behavioral competitive interactions between the species and the potential compensatory reactions that could have significant impacts on one or both of the populations in the future. Continuing the single-stock assessment approach, and ignoring competitive interactions, may have negative consequences for the precision of assessment efforts such as less accurate estimates of long-term abundance, and mis-specification of the stock dynamics and age-composition (Kinzey and Punt 2008). Red and Vermillion Snapper are assessed using a quantitative statistical catch-at-age assessment model approximately every five years and annual catch limits (ACL) are set by the Gulf of Mexico Fishery Management Council. The ACL for Vermilion Snapper was 3,420,000 lbs from 2012 to 2017 and was decreased to 3,211,120 lbs in 2018. The ACL for the Vermilion Snapper stock is allocated between the commercial and recreational sectors. The current recreational fishery bag limit is ten fish per person per day with a minimum size of 10 inches, and the season is all year but is subject to early closure if landings are projected to reach or exceed the catch limit (SEDAR 2016). The Red Snapper fishery has faced strict regulations in the recent past because overfishing has occurred and the stock exhibited drastically reduced biomass (Liu et al. 2017). The Red Snapper spawning stock biomass has been rebuilding since 2014 due to severely reduced recreational and commercial fishing seasons and bag limits (SEDAR 2018). The projected rebuilding period is expected to conclude in 2032. During rebuilding, Red Snapper biomass is expected to increase likely producing increased competition between Red and Vermilion Snapper. Accounting for this increased competition for food and habitat is critical for the determination of long-term management strategies that can be employed to promote sustainable harvest of Vermilion Snapper. Fishing pressure may compound the effects of depensatory processes caused by increased Red Snapper abundance, leaving the Vermilion Snapper stock vulnerable to overfishing if not properly assessed and regulated.

The desire to include interspecific interactions of stocks in other regions has led to the development and use of multispecies stock assessment models, such as multispecies production models (MSP), multispecies virtual population analysis (MSVPA) and multispecies statistical-catch-at-age models (MSCAA). Multispecies models incorporate sources of mortality such as predation or competition that may contribute substantially but are not normally specified in single-stock models (Curti et al. 2013). Multispecies models may also be used to detect shifts in community dynamics and identify dominant species in an ecosystem (Tsou and Collie 2001; Link and Garrison 2002). Some advantages of MSP models are that they are simpler and have fewer data requirements than MSVPA and MSCAA, and can provide biomass, predation mortality, and fishery reference point estimates needed for management. However, they do not account for age-structure in the population and fishery (selectivity, mortality, fecundity, etc.), and do not use the full range of data available for many stocks and fisheries. MSVPA is an effective method of estimating predation-induced mortality (Tsou and Collie 2001; Jurado-Molina et al. 2005); however, process error is not included in parameter estimates (Tsehaye et al. 2014). MSCAA models allow scientist to incorporate error in input data and quantify interspecies interactions through statistical estimation. This method is preferable over the MSVPA because it provides an estimation of parameter uncertainty and estimates of stock status for multiple species simultaneously, which can help managers make more informed management decisions (Curti et al. 2013).

Multispecies models have been used to assess effects of predation and competition of fish stocks in many regions, including the Northeast US (Gamble and Link 2009; Curti et al. 2013), Gulf of Alaska (Kirk et al. 2010), eastern Bering Sea (Jurado-Molina et al. 2005), the North Sea (Lewy and Vinther 2004), and Lake Michigan (Tsehaye et al. 2014). MSCAA models incorporate predation equations used in MSVPA (Lewy and Vinther 2004; Jurado-Molina et al. 2005; Curti et al. 2013; Tsehaye et al. 2014) into a single-species statistical catch-at-age model and estimate values of predation mortality (M2). M2 is derived by estimating a suitability coefficient that relates the abundance and selectivity of every predator-prey age combination (Jurado-Molina et al. 2005). An alternative method to estimate predation mortality and competition effects is to incorporate the Lotka-Volterra predation and competition models (Gamble and Link

2009). These models are used to relate the population abundances of two competing species through an interaction coefficient. Parameterizing any of these models requires sufficient stomach content data of predator species including size-at-age of prey in predator's stomachs. Notably, very few multispecies assessment models have been developed for the Gulf of Mexico, likely due to the sparsity or lack of stomach content data. For example, from the diet studies reported for Vermilion Snapper, prey items are only classified as low as order level and no length or weight measurements were recorded (Darnell 1991; Weaver et al. 2002). This level of taxonomic resolution is not useful for evaluating direct connections between predator and prey species. However, these studies support the need for inclusion of biological interactions into stock assessments - they show that competition and predation are influential sources of mortality and should be taken into account. It is critical to understand how predation and competition effect the population and consider how management regulations can account for them to effectively manage a stock.

A method that has become increasingly popular to test effectiveness and necessity of current and alternative management strategies for stocks in a single-species or multispecies context is management strategy evaluation (MSE) (Butterworth and Punt 1999). MSE involves simulating the population dynamics of a stock and the implementation of regulations, hereafter referred to as harvest control rules (HCR), to evaluate long-term success of a given management strategy. MSE serves as a framework for evaluating the impact of including multispecies interactions in an assessment and trade-offs associated with various management regulations when accounting for the interactions (Schweder et al. 1998; A'mar et al. 2010). A'mar et al. (2010) used MSE to evaluate the current management strategy for Walleye Pollock under scenarios of varying predator-prey functional relationships and future fishing mortalities on the predators. They found that the current management strategy, which did not account for predation, was able to maintain biomass above the reference level. In scenarios where predation was included in the operating model, the current management strategy remained effective, because it was biased conservatively. MSEs have three main components: an operating model (OM) is used to represent the population dynamics of a stock, the assessment model is used to represent the management strategy applied to the stock, and the performance indices are used to compare the performance of HCR under the given conditions. Operating models can represent a range of uncertainties within a system, for example stock-recruitment relationships (Maunder 2012; Plagányi et al. 2018) and spatial distribution (Fay et al. 2011; Jacobsen et al. 2019). The management strategy, which includes the HCR, stock assessment model, and management advice, evaluates the stock with regards to some reference limits or targets, and sets recommended catch limits for the following year(s). The feedback loop continues for a number of years and at the conclusion, the management strategies are evaluated on their robustness and performance under the modeled uncertainties. Performance indices are pre-established methods for assessing each management strategy's ability to achieve the goals of the fishery, stock, and stakeholders.

The objectives of this study are to use management strategy evaluation to understand how the inclusion of competitive interaction into assessment impacts management of the Gulf of Mexico Vermilion Snapper stock. In this work I 1) develop an operating model that includes interspecific competition between Vermilion and Red

Snapper, 2) compare the impact of including competition on stock status under current management, 3) test the robustness of alternative management strategies that can be used to accurately assess the Vermilion Snapper stock when accounting for interspecific competition, and 4) determine how the uncertainty in the true level of competition impacts our understanding of the stock from the assessment.

2.2 Methods

A simulation model was developed that included an operating and assessment model to test model-based and empirical HCR on the Vermilion Snapper stock (Figure 2.1). The operating model simulates the population's dynamics and generates data that are used in the assessment model. The suite of HCRs are used to test alternative management strategies for the stock and the efficacy of each HCR is evaluated with the performance indices. All model runs were conducted on the High-Performance Computer at the University of Southern Mississippi.

2.2.1 Operating Model

2.2.1.1 Population Dynamics

To model the population dynamics of Gulf of Mexico Vermilion Snapper, I constructed an age-structured operating model (OM) composed of 15 age classes, ages zero to 14+. The operating model was similar in structure to that employed in the most recent stock assessment, SEDAR 45, with the exception of the stock-recruitment relationship. The SEDAR 45 assessment model used a Beverton-Holt stock-recruitment relationship, however in the OM used in this work, no stock-recruitment relationship was modeled. Because of the lack of depletion in the stock, steepness was not well estimated and the predicted stock-recruit curve was not very informative. The magnitude of annual recruitment was generated using random selection of the observed deviations, (δ) from the mean historical recruitment, ($\hat{r}$) reported in SEDAR 45. Initial population conditions (i.e. numbers-at-age) were established from estimates derived from Stock Synthesis 3.24 and fit to data from 1950 to 2014. Life-history parameters for natural mortality, and the weight-at-length and length-at-age relationships were fixed in the OM.

The population dynamics were calculated using the following equations:

$$N_{y,a} = \begin{cases} \hat{r} * e^{\delta} & a = 0 \\ N_{y-1,a-1}e^{-M_{a-1}} - C_{y,a-1} & 0 < a < A \\ N_{y-1,a-1}e^{-M_{a-1}} - C_{y,a-1} + N_{y-1,a-2}e^{-M_{a-2}} - C_{y,a-2} & a = A \end{cases} \quad [1]$$

where a is age in years, A is the age of the plus group (individuals 14 years and older), and y is the year. The numbers at age a and year y ($N_{y,a}$) are determined by the number at age a-1 in the previous year ($N_{y-1,a-1}$), the natural mortality at age a-1 (M_{a-1}) and the catch-at-age in the previous year ($C_{y-1,a-1}$). Spawning biomass was calculated as the numbers-at-age multiplied by the fecundity-at-age derived from the SEDAR 45 assessment.

2.2.1.2 Fishery Data

Four simulated fishing fleets operate in the OM: the eastern Gulf and western Gulf commercial fleets, one Gulf-wide recreational fleet, and a by-catch fleet. In the initial five years of the simulation, prior to the first assessment and imposition of scenario-specific harvest control rules, sector-specific landings were randomly drawn from a normal distribution based on the mean and standard deviation of catches from the years 2009 to 2017 for the eastern commercial fleet (CE) and western commercial fleet (CW), 2010 to 2017 for the recreational fleet (REC), or 2011 to 2014 for the by-catch fleet (BC). These intervals were chosen for each fleet because they are assumed to represent current fishing practices (D. Goethel and M. Smith, National Marine Fisheries Science Center, personal communication). For example, because a reduction in effort and catch in the BC fleet occurred after 2010 compared to the historically higher levels, I assumed that this is representative of future effort (SEDAR 45). After the fifth year of the simulation, catch levels were determined by the harvest control rule and stock abundance estimates derived from the assessment. The projected total catch for the entire stock was calculated and the fleet-specific catch was determined by dividing the total catch by the mean historical catch proportion for each fleet. To maintain consistency with the formulation of the SEDAR assessment, catch was reported in biomass for the commercial fleets and numbers for the recreational fleet and the shrimp bycatch fishery. Harvest rate (H_y) for each fleet was calculated for eastern and western commercial fleets by

$$H_{a,y,f} = \left(\frac{C_{f,y}}{\sum(N_{a,y} * S_{f,a} * W_a)}\right) \qquad [2]$$

or

$$H_{y,f} = \left(\frac{C_{f,y}}{\sum(N_{a,y} * S_{f,a})}\right) \qquad [3]$$

for the recreational and by-catch fleets, where $S_{a,f}$ is the selectivity-at-age for fleet f, $C_{f,y}$ is the total catch in year y for fleet f, W_a is weight-at-age, and $N_{a,y}$ is the numbers-at-age. Catch-at-age was then calculated by

$$C_{a,y,f} = \left(H_{y,f} * N_{a,y} * S_{f,a} * W_a\right)e^{\varepsilon}, \qquad \varepsilon \sim N(0, \sigma^2) \qquad [4]$$

for the CE and CW fleets or

$$C_{a,y,f} = \left(H_{y,f} * N_{a,y} * S_{f,a}\right)e^{\varepsilon}, \qquad \varepsilon \sim N(0, \sigma^2) \qquad [5]$$

for the REC and BC fleets. Uncertainty in catch (σ^2) was incorporated to account for implementation error by sampling the true catch from a normal distribution with a mean of the fleet-specific catch and a standard deviation reflective of historical catch standard deviation.

Simulated age composition was generated for the commercial and recreational catches using a multinomial distribution. Age-composition data are frequently modelled with a multinomial distribution, with the underlying assumption that fish are sampled randomly from the population and ages that are sampled more frequently are estimated with greater precision (Hulson et al. 2011). Because sampling of age compositions is sporadic and inconsistent in the Vermillion Snapper fishery, an effective sample size of $n = 75$ was used every year. For simplicity, length composition data was not simulated.

2.2.1.3 Indices of Abundance

Indices of abundance were simulated for each fishing fleet, the SEAMAP Groundfish Survey (SEAMAP Operations Manual for Trawl and Plankton Surveys 2016), and the Reef Fish Video Survey (Campbell et al. 2014). Index values were calculated based on the biomass (or number) available to the fishery/survey and the catchability coefficient estimated from the assessment report. Catchability was fixed throughout the projection period in the OM. Index values were log-normally distributed with fleet- or survey-specific error. I converted the numbers-at-age to numbers-at-length using the age-length key derived from the SEDAR 45 assessment because the indices of abundance for the fishery-independent surveys are based on the numbers-at-length. Twelve length bins were used, starting at 1 cm up to 55 cm in 5 cm increments.

2.2.1.4 Selectivity

I used selectivity parameter estimates for each fishing fleet and survey from SEDAR 45. Age composition data is not available for the BC fleet, so a fixed selectivity was used with 100% vulnerability for age-1, 30% for age-2, 3% for age-3 and 0% for ages-4+ (SEDAR 45, 2016). For CE and CW, a logistic selectivity function was used, and a domed-shaped, double normal function was used for the REC fleet. Selectivity for both commercial fleets was modeled for the time period after 2007 when Red Snapper individual fishing quotas were implemented. The domed-shaped double normal selectivity function was also used for SEAMAP Groundfish Survey and Reef Fish Video Survey. The age-based logistic selectivity function is:

$$S_{f,a} = (1 + e^{-\ln(19)(L'_a - \beta_{1,f})/\beta_{2,f}})^{-1} \qquad [6]$$

where $\beta_{1,f}$ is the size-at-50%-selectivity, and $\beta_{2,f}$ is the difference between the size-at-95%-selectivity and that at 50%-selectivity. The length-based double normal selectivity function is defined as:

$$S_{f,l} = asc_{f,l}(1 - j_{1,f,l}) + j_{1,f,l}\left((1 - j_{2,f.l}) + j_{2,f.l}dsc_{f,l}\right) \qquad [7]$$

where the ascending (*asc*), joiner (j_1 and j_2), and descending (*dsc*) functions are:

$$asc_{f,l} = (1 + e^{-\beta_{5,f}})^{-1} + (1 - \left(1 + e^{-\beta_{5,f}}\right)^{-1})\frac{e^{\left(\frac{-(L'_l - \beta_{1,f})^2}{e^{\beta_{3,f}}}\right)} - t1_{min,f}}{1 - t1_{min,f}} \qquad [8]$$

$$dsc_{f,l} = 1 + \left(\left(1 + e^{-\beta_{6,f}}\right)^{-1} - 1\right)\frac{e^{\left(\frac{-(L'_l - peak_{2,f})^2}{e^{\beta_{4,f}}}\right)} - 1}{t2_{min,f} - 1} \qquad [9]$$

$$j_{1,f,l} = \left(1 + e^{\left(-20\frac{L'_l-\beta_{1,f}}{1+\left|L'_l-\beta_{1,f}\right|}\right)}\right)^{-1} \quad [10]$$

$$j_{2,f,l} = \left(1 + e^{\left(-20\frac{L'_l-peak_{2,f}}{1+\left|L'_l-peak_{2,f}\right|}\right)}\right)^{-1} \quad [11]$$

and $t1_{min}$ and $t2_{min}$ are defined as:

$$t1_{min,f} = e^{\left(-\frac{\left(L_{min}-\beta_{1,f}\right)^2}{e^{\beta_{3,f}}}\right)} \quad [12]$$

$$t2_{min,f} = e^{\left(-\frac{\left(L'_{max}-peak_{2,f}\right)^2}{e^{\beta_{4,f}}}\right)}. \quad [13]$$

2.2.1.5 Uncertainty

Uncertainty was incorporated into the OM in multiple components (Table 2.1). Process error was incorporated in the recruitment levels, to model natural annual variation. Implementation error was included in the projected catch to simulate years of the fleets catching more or less than their allotted limits. Observation error was incorporated with the indices of abundance.

2.2.1.6 Competition Index

An index of Red Snapper competition was created based on estimates of Red Snapper abundance from the most recent stock assessment. I assumed that ecosystem carrying capacity (K) was the sum of Vermilion Snapper virgin biomass and the mean Red Snapper biomass from 1940 to 1950. This period was chosen because it represents a period before heavy Red Snapper exploitation and coincides with the initial year of the

Vermilion Snapper assessment. Red Snapper biomass relative to *K* was used as the index for competition and was projected to 2116 based on estimates from an age-structured catch-at-age model, and fishing at a level to reach recovered biomass by 2032. In the OM, the number of Vermilion Snapper that died due to the Red Snapper competition was accounted for by the equation:

$$C_{a,y,rs} = \left(CI_y * N_{a,y} * S_{a,rs}\right) \qquad [14]$$

where the CI_y is the annual index value and selectivity is one for ages one plus. Consequently, the numbers-at-age killed by competition were removed from the population via the catches-at-age.

2.2.2 Assessment Model

I used a statistical-catch-at-age model, Stock Synthesis 3.24 (SS), as the assessment model in the simulation. The assessment model was parameterized the same as the most recent stock assessment, SEDAR 45, except for two differences. First, the stock-recruitment parameters were fixed in the model to the estimated values from SEDAR 45, to aid with convergence, and second, a second discard fleet was used as a proxy for Red Snapper competition-induced mortality. Previous studies have shown that a method for including sources of natural mortality into older versions of SS models (versions earlier than 3.3) is to incorporate an index to simulate a fishing fleet and allow SS to estimate the numbers killed (Sagarese et al. 2015). To reflect the current assessment cycle frequency, an assessment was run every five years. However, unlike the current cycle, all data were available up to the year before the assessment (e.g. if the assessment was run in 2019, data were available through 2018). The input data included the magnitude of catch for the commercial and recreational fleets (CE, CW, REC), magnitude of discard for the shrimp by-catch fleet and the Red Snapper fleet, CPUE indices for commercial, recreational, shrimp by-catch, and Red Snapper fleets, as well as for the SEAMAP Groundfish survey, and the Reef Fish Video Survey. Age composition data were included for the three commercial and recreational fleets. The assessment was run with new data and model convergence was checked. Once the model converged, the target B_{SPR} was checked and if it was not at least 30% (the limit reference point), the model was run iteratively changing the target SPR parameter until the target B_{SPR} was realized. After the assessment was run, management reference points were checked to determine catch limits and if a rebuilding plan should be implemented.

2.2.2.1 Harvest Control Rules

I evaluated and compared both model-based and empirical harvest control rules (HCR) as means for managing the Vermilion Snapper stock (Table 2.2). The model-based HCRs used an age-structured assessment model (Stock Synthesis) to evaluate the stock status and set catches. From the assessment model, values of overfishing level (OFL) and acceptable biological catch (ABC) were estimated. ABC was calculated as 75% of the OFL. The ABC was proportionally allocated between the three fishing fleets as follows: CE = 35%, CW = 17%, and REC = 48%. These fixed proportions pf were based on the mean proportions for the final five years of catch data (2010 to 2014). The empirical HCR did not use the assessment model. Instead, annual catches were determined by the indices of abundance and CPUE from the fisheries and surveys.

To align with the current management strategy, the base HCR was a constant conditional catch rule set at the current quota. After every assessment period, the status of the stock was evaluated and if it was not overfished, the quota for the next five years was not changed and fishing continued at similar to historical levels. The constant quota was set at 3,110,000 lbs (1,555 mt), which was the most recent target set in the Gulf of Mexico. However, if the stock was overfished, the quota was reduced until the next assessment based on the current National Marine Fisheries Service regulatory approach to determine rebuilding periods. Overfished status was defined as the spawning potential ratio (SPR) of the stock below 30% of unfished population levels. SPR30% was one of the three MSY proxies used in the previous assessment and it was deemed an acceptable MSY proxy (SEDAR 45). To calculate the reduced quota, the stock dynamics were projected with no fishing to determine the time taken to reach an SSB of 30%. If the time required to rebuild (T_{min}) was less than ten years, T_{target} was set to ten. If the time required was longer than ten years, the maximum time (T_{max}) allowed for rebuilding was calculated as T_{min} plus one generation time (seven years) (SEDAR 2018). Catch was calculated based on the level of fishing mortality required to rebuild the stock within the given period. Total catch was calculated and then allocated amongst the three fisheries based on the respective proportions. At the next assessment period, if the stock was still overfished but on track to rebuild by T_{target}, the catches from the previous assessment were kept. If the stock did not recover by the next assessment, catch was further reduced using the methods described above. If the stock was above SPR30%, the catch was no longer reduced and was set to the original quota.

Two alternative harvest control rules were evaluated, a constant conditional catch set to the annual catch limit and an empirical rule that was based on the indices of abundance. The constant conditional catch HCR was set to the annual catch limit, which was calculated as 75% of the OFL. If the stock was deemed overfished after an assessment, the ACL was reduced using the same methods described for the quota HCR. Otherwise, the total catch was set to the ACL and divided proportionally among each fleet. The empirical HCR was derived by modeling each of the indices from the previous *n* years (*n* = 5) using linear regression. Total allowable catch (TAC) was calculated by multiplying the slope of the fitted regression line (m_i) by the moving average of the previous 5 years' catch $\bar{C}_{y-5,y}$ and the respective weighting for each index (w_i):

$$TAC = \bar{C}_{y-5,y}(\sum_{i=1}^{I} w_i(1 + m_i)). \qquad [15]$$

The TAC was capped at the current quota (1,555 mt) for all scenarios. Different weightings of the indices were evaluated with sensitivity analyses (Table 2.3). In the first two scenarios, only fishery CPUE indices were considered when calculating the TAC. The third scenario considered only the survey and competition indices. The fourth scenario included all indices with approximately even weightings. Surveys were weighted slightly heavier, 0.15 compared to 0.14, to make the weighting equal 1 and because they are more reliable as an index of the population abundance than fishing CPUE indices. The fifth scenario uses only the Red Snapper index to determine catch for the following years.

2.2.2.2 Management Objectives

The current status of the Vermilion Snapper population is estimated to be above the target biomass level and therefore the management objectives for this project are to maintain the population above MSST, exploit the stock by allowing for greater catch when possible, and effectively implement rebuilding strategies if the biomass falls below the limit (MSST).

2.2.3 Performance Indices

In order to assess and compare the effectiveness of each harvest control rule in meeting the management objectives, I analyzed a suite of performance indices. To evaluate the impact of the management strategy scenario on the fishery, I calculated mean catch and average annual variability (AAV) of 100 trials of each management strategy scenario. To evaluate the impact of a management strategy on the stock, I calculated the terminal spawning potential ratio ($SPR_{terminal}$) where $SPR_{terminal}$ is the ratio of the SSB in year y to the virgin SSB, the probability of the stock being overfished ($B/B_{SPR30\%}$) at least once over n trials, and the probability of overfishing occurring ($F/F_{SPR30\%}$) at least once over n trials.

2.2.4 Sensitivity Analyses

To test the robustness of the harvest control rules, a suite of sensitivity analyses were run to evaluate the impact of uncertainty of the true Red Snapper competition level when assessing the stock. In the fixed scenarios, the “true” competition index was used in both the operating model and put into the assessment model. This was to simulate a scenario in which a perfect understanding of the magnitude and impact of Red Snapper competition on the Vermilion Snapper population. Because this is extremely unlikely, alternative scenarios were run with the Red Snapper “true” abundance index in the operating model having low (0.005), medium (0.01), or high (0.015) variability but the fixed abundance index was used in the assessment model. The same performance indices were used to compare the sensitivity runs for all management strategy scenarios.

2.3 Results

For each management strategy scenario, I compared model estimates for the stock and fishery to determine which strategies are more risk averse. To compare strategies, I report mean values for each performance index, and to enable evaluation, I show three randomly selected trials. This analysis is used to understand the variability among trials, within each management strategy scenario. Performance indices include the mean catch, average annual variability (AAV), terminal SPR, B-ratio ($B/B_{SPR30\%}$) and F-ratio ($F/F_{SPR30\%}$).

I ran 100 simulation trials for each scenario, however, convergence of the assessment model presented a challenge for some trials. After rerunning trials for a maximum of two times, a number of trials did not complete all 50 years (Table 2.4). The eHCR1 scenario had the greatest number of complete trials (79) and the ACL scenario had the fewest (67). Although the empirical management strategy scenarios did not depend on the SS3 assessment model to determine catch, every five years the assessment model was run to allow for comparison of some statistics with the other scenarios and non-convergence of the assessment model during the simulation resulted in incomplete trials. Thus, the empirical management strategies do not have 100 complete trials.

I first evaluated the base scenario which reflects the current assessment and management strategy. In these simulations, catch was set to the current quota level and Red Snapper competition was not included in the OM or AM. Over the 50-year projection period, the Vermilion Snapper population increased in abundance in the early years and then plateaued around 2030 at a high level for the remaining time period (Figure 2.2). The mean terminal SPR for the stock was at 63%, well above the limit reference point. Catches for the eastern commercial fleet and the recreational fleet were similar in magnitude to the recent historical levels (Figure 2.3). Western commercial fleet catch was lower than the high catches reported for 2013 and 2014, however, it was still within the range of historical catches since 2009. Under this management strategy scenario the probability (0.006) of the stock being overfished was low and overfishing never occurred. The indices of abundance show an upward trend for the commercial catches, with the CPUE values being greater than those observed in the earlier years. The recreational CPUE values are smaller than those observed in the earlier years and also exhibit less variability. The SEAMAP Groundfish and Reef Fish Video survey indices both generally increased (Figure 2.4). Without accounting for Red Snapper competition effects, the current management strategy is an effective one for managing the Vermilion Snapper stock.

I compared seven alternative management strategy scenarios, all of which included Red Snapper competition in the operating and assessment models: Quota, ACL, and five empirical rules (eHCR1, eHCR2, eHCR3, eHCR4, and eHCR5). For each of these strategies, the level of Red Snapper competition was assumed to be perfectly known and input into the assessment model with a very small standard error (0.01). The estimated mean biomass were similar for all scenarios. For each of the management strategies evaluated, the mean biomass trajectories exhibited an overall trend of decrease or stability in the long-term. All management strategy scenarios converged around a similar biomass level (20,000 mt) (Figure 2.5). Although the mean biomass trajectory is relatively flat for most scenarios, variability generally is large among trials in each scenario in each year (Figure 2.5).

Mean catch was lowest for all fleets with the Base and Quota strategies and greatest with the ACL strategy (Figure 2.6), because the ACL is larger than the current catch quota set for Vermilion Snapper. The mean catches were fairly similar among the five empirical management strategies (Figure 2.6). The best, in terms of allowing the greatest catch, of the five empirical scenarios is either eHCR4 or eHCR5. In the eHCR4 management strategy scenario, the catch is determined by all six indices (commercial and recreational CPUE, shrimp bycatch effort index, Red Snapper competition index, and the fishery-independent survey indices of abundance). In the fifth eHCR, catch is controlled only by the Red Snapper index of competition. For all scenarios, the commercial catches in the east were higher than in the west, which reflects the current commercial catch distributions.

Average annual variability of catch was most variable among management strategies for the commercial fleets and least variable for the recreational fleet (Figure 2.7). East and west commercial fleets displayed opposite trends between annual variability and management strategies. The AAV was higher for ACL, Base, and Quota management strategies for the eastern commercial fleet than it was for all empirical management strategies. Western commercial catches exhibited higher AAV for the empirical management strategies than for the ACL, Base, and Quota strategies. The AAV for recreational catches was fairly consistent among management strategies, with the empirical strategies resulting in slightly higher variability (Figure 2.7).

To understand the impact of each management strategy scenario on the stock, I evaluated and compared the terminal SPRs. Mean terminal SPRs were above the limit reference point level of 30% for all scenarios and each individual trial's terminal SPR trial was above the limit reference point (Figure 2.8). The mean terminal SPR for the five empirical HCRs and the Quota management strategy scenarios were at an SPR of 0.5 or above. The ACL strategy generally resulted in the smallest terminal SPR, with 75% of the data falling below the lowest 25% of the data from the other scenarios. Of the five empirical strategies, eHCR5 was the most variable for terminal SPR and had the lowest mean and median values (Table 2.5).

I compared stock and fishery status among management strategy scenarios by calculating $B/B_{SPR30\%}$ and $F/F_{SPR30\%}$. Values below one for $B/B_{SPR30\%}$ indicate the stock is overfished and $F/F_{SPR30\%}$ greater than one indicates that overfishing is occurring. The only management strategy that led to an overfished stock was the ACL strategy: the probability of the stock being overfished over the 50-year projection period was 2.2% (Figure 2.9). A total of 75 instances occurred where $B/B_{SPR30\%}$ fell below one. The stock was overfished for a minimum of one year and a maximum of sixteen years within a trial but for all trials except one, the stock was recovered by the end of the projection period.

Over the 50-year projection period, overfishing never occurred under any management strategy. The maximum fishing mortality threshold, using the limit reference point $F_{SPR30\%}$, ranged from 0.13 to 0.18. The mean F-ratio, calculated as the current harvest rate over the harvest rate at maximum fishing mortality threshold, did not go above one in any of the trials (Figure 2.10). The ACL management strategy scenario had the highest mean F-ratio, approximately 0.7 for the entirety of the projection period.

All management strategy scenarios showed a decline in the F-ratio in the last five to ten years.

Compared to the model-based control rules, the empirical control rules seemed to be just as effective, and in some cases more so, in preventing overfishing or overfished populations and maintaining high catches with reasonable variability. The mean catches for the empirical rules were lower than the ACL rule for all three fishing fleets, however, the medians differed by approximately 100 mt or less than 200 fish. The median average annual variation of the catch for the CE fleet was reduced by approximately 200 mt and increased by approximately 100 mt for the CW fleet compared to the model-based rules. The median AAV for the REC fleet was also higher for the empirical rules compared to the model-based rules but only by approximately 50 fish. When I compared just the empirical rules among each other to determine the most effective one, all were similarly effective. eHCR1 consistently had lower mean catches than the other 4 rules and eHCR4 and eHCR5 tended to have the highest mean catches. AAV was more variable among fleets. The REC fleet had a wider spread of AAV values, with eHCR2 having the largest range (268 to 429) and eHCR5 having the smallest (283 to 411). For the CE fleet, eHCR5 had the smallest range (145 to 383) and the eHCR3 had the largest (137 to 401). For the CW fleet, eHCR4 had the largest range (59.4 to 194), closely followed by eHCR5 (61.7 to 196), and eHCR2 and eHCR3 had the smallest ranges (58 to 184 and 59.2 to 185 respectively). Terminal SPR values did not vary much among eHCRs; eHCR1 and eHCR4 both had mean values of 0.52 and the other three (eHCR2, eHCR3, and eHCR5) had mean values of 0.50. Terminal SPR values for eHCR3 and eHCR5 had larger ranges (0.389 to 0.675 and 0.364 to 0.710 respectively). The lowest terminal SPR occurred under eHCR3 (0.389) but this was still above the limit reference point. Because each empirical rule performs differently for different fishing fleets and performance indices, I ranked each eHCR by PI and fleet on a scale of one to five, five being most effective at achieving the desired result and one being least effective at achieving the desired effect. The desired results were higher mean catch, a small range of AAV, a lower mean AAV, and a lower range of terminal SPR values. After I ranked the empirical control rules against each other for each performance index and fishing fleet, I added together each rank position. The one with the highest score was eHCR5 and the lowest score was eHCR3 (Table 2.6). Empirical rules one and two tied for second place and eCHR4 was third most effective. I did not include probability of overfishing and overfished because there was a 0.0 probability of that occurring under all empirical rules.

For all seven alternative management strategy scenarios, I evaluated the impact of varying levels of uncertainty in the knowledge of the true Red Snapper competition magnitude (Figure 9). Specifically, I evaluated differences in the mean values of catch, the variability in catch, mean terminal SPR, and fishery status among the scenarios given different levels of uncertainty. Overall, increasing the level of uncertainty in the knowledge of the true Red Snapper competition increases the variability within each category.

I compared the difference in mean catches between the fixed scenario and the low, medium, and high uncertainty scenarios for each management strategy scenario (Figure 2.11). Under the ACL HCR, CE catch showed a small increase under higher uncertainty, however, CW and REC catches both decreased with higher uncertainty (Figure 2.12). Under the Quota HCR, catches exhibited the opposite trend. CE catch decreased with high uncertainty while CW and REC catches increased (Figure 2.13). Under eHCR1, catches for all fleets decreased but medium uncertainty had the highest change in catch among the three uncertainty scenarios (Figure 2.14). With eHCR2, catch increased for high uncertainty in both the CE and REC fleets but was reduced for the CW fleet (Figure 2.15). Under eHCR3, catches decreased for all fleets under high uncertainty (Figure 2.16). With eHCR4, catches increased under increased uncertainty for all fleets (Figure 2.17) and with eHCR5, catch increased for all scenarios and fleets except for CE under high uncertainty (Figure 2.18). Under high uncertainty REC catch was notably higher. CE catch was increased even under scenarios of high uncertainty under the ACL, eHCR2, and eHCR4 HCRs. CW and REC catches were increased when uncertainty was high under the eHCR5 and Quota HCRs.

I compared the change in AAV between the fixed scenario and the different levels of uncertainty for each management strategy scenario. The change in AAV by HCR varied greatly among fleets, with large differences in the CE fleet and small differences in the REC fleet. Under the ACL HCR, any level of uncertainty decreased the AAV in the REC fleet catch (Figure 2.19). AAV for the CW catch increased as uncertainty levels increased and high levels of uncertainty increased the potential for change in AAV for CE catch. Trials with high uncertainty exhibited more extreme increases or decreases in AAV than the trials with low uncertainty. Under the Quota HCR, the CE catch showed that low levels of uncertainty increased the potential for decreases in AAV, but all levels had one instance of very high increased AAV (300 to over 1,000 times increase) (Figure 2.20). The CW catch had a wider interquartile range for all levels of uncertainty but the medians were all very close to zero which resulted in little change in AAV. REC catches experienced a reduction in AAV for low uncertainty scenarios and an increase in AAV for high uncertainty scenarios. Under the empirical HCRs, generally the medians were close to zero but exhibited a large range for change in AAV for CE and CW catches. However, no clear trends for increased uncertainty on AAV were obvious. Under eHCR4, the AAV for REC catches increased under higher uncertainty (Figure 2.24).

All HCRs were effective for minimizing change in AAV of REC catch under all levels of uncertainty. eHCR3, eHCR1, and ACL were able to reduce AAV of REC catch from the fixed scenario, even under high uncertainty (Figures 2.23, 2.21, 2.19). eHCR1, eHCR2, or eHCR3 minimized change in AAV of CE catch, even under high levels of uncertainty (Figures 2.21, 2.22, 2.23). Quota and ACL HCRs minimized change in AAV of CW under all levels of uncertainty.

I compared the terminal SPRs between the fixed scenario and the different levels of uncertainty for each management strategy scenario (Figure 2.26). Imposing high uncertainty consistently decreased terminal SPR for all HCRs. Low and medium uncertainty did not change the terminal SPRs much from the fixed scenarios except for a few scenarios. Under eHCR4, median terminal SPR for low and medium variability were also decreased from the fixed scenario median.

The only scenarios that led to an overfished stock were the ACL management strategies with all three levels of uncertainty. The probability of the stock being overfished was 1.9% for the mid-level uncertainty, 1.5% for the low uncertainty, and 0.7% for high uncertainty. A total of 30 trials resulted in overfished status at least once. The number of years the stock was overfished in a trial ranged from one to 21. The terminal $B/B_{SPR30\%}$ was less than one in four trials, two with high uncertainty, two with low uncertainty. Overfishing never occurred in the projection period. $F_{SPR30\%}$ ranged from 0.14 to 0.31.

I compared the five empirical rules using the same ranking system I used for the fixed scenarios. Each scenario was scored based on the ability to maximize or minimize performance indices - maximize mean catch, minimize mean AAV, and minimize the range of AAV and terminal SPR values where five was the best and one was the worst. Mean catch and AAV had three scores for each scenario because the three fishing fleets were scored separately. After scores were totaled for each objective, scenarios were ranked from one to five where five was the scenario with the largest score. When I compared the strategies against each other with the same level of Red Snapper uncertainty (low, medium or high), in the case of low uncertainty, eHCR5 performed the best and eHCR1 performed the worst (Table 2.7). When the uncertainty was increased to 0.01, eHCR2 performed the best and eHCR1 performed the worst again (Table 2.7). For the scenario with high uncertainty (0.1), eHCR2 performed the best and eHCR1 performed the worst. Empirical rule one was consistently a poor performer, ranking last in every scenario. Empirical rule two was the best performing management strategy for high and medium uncertainty and third best for low. Empirical rule four was second best for both low and high uncertainty, but for medium uncertainty eHCR3 was ranked second. Both eHCR2 and eHCR5 are governed by only one index, recreational CPUE or the Red Snapper competition index respectively and eHCR4 is governed by all seven indices.

2.4 Discussion

Management strategy evaluation was an effective framework for estimating the impact of Red Snapper competition on Vermilion Snapper population and testing alternative management strategies that are robust to the competition effects. The GOM Vermilion Snapper stock is resilient to interspecific competition from Red Snapper under current and alternative management strategies. To my knowledge, this is the first attempt to include interspecific dynamics into the Vermilion Snapper stock assessment model. Effective long-term management of the Vermilion Snapper stock is necessary for ensuring the resource can continue to support commercial and recreational fisheries in the Gulf of Mexico.

An index of relative abundance of Red Snapper was included into the operating model as another source of natural mortality. This allowed for the estimation of age-specific annual mortality of Vermilion Snapper caused by competition for resources such as food and habitat. The simple index used to represent competition-induced mortality caused by Red Snapper provides a way to incorporate interspecies dynamics into single-species assessments. In the Gulf of Mexico, there is limited data to understand the extent and impacts of competition. For example, information about the food habits of Red Snapper and Vermilion Snapper are generally low in taxonomic resolution and spatial and temporal breadth (Simons 1997; Ouzts and Szedlmayer 2003; Johnson et al. 2010; Davis et al. 2015a). Often prey items are identified to the order or class level and cannot provide the information necessary to estimate predation by Red Snapper on Vermilion Snapper, despite this phenomenon being reported within the literature (Mccawley et al. 2003; McCawley et al. 2006; Johnson et al. 2010). Therefore, I developed a methodology that uses information that is already known or estimated (i.e. another species' abundance) and incorporated that into the existing assessment model. Developing methods for incorporating competition or predation effects into single-species stock assessment models is crucial because ignoring interspecific interactions can have serious consequences on our stock perception (Trijoulet et al. 2019). Specifically, including predation effects in a multispecies model can lead to changes in biomass, productivity, and variance around spawning biomass estimates, compared to a single-species model (Kinzey and Punt 2008). Additionally, it can lead to bias in parameter estimates (Trijoulet et al. 2019) and overall mismanagement. The simple competition index I developed allows interspecific interactions to be included in a stock assessment model without using a multispecies or ecosystem model, which has much greater data requirements.

There was minimal impact to the Vermilion Snapper stock status when competition was incorporated into the model. The current harvest control rule was effective in preventing the stock from being overfished and overfishing from occurring. The simulations for the base scenario reflect the status quo assessment process and annual catch quota, while ignoring competition effects in both the operating model and assessment model. Under the current assessment process, the stock was above the limit reference points and the mean terminal SPR was over double the limit of 30%. The biomass trajectory showed an increase in the first ten years and after that it began to stabilize. When I applied the same assessment methods and HCR to the stock but included competition in both the operating model and the assessment model, the metrics I evaluated for the stock did not change greatly. The mean terminal SPR was slightly less than the base scenario, however it was still almost two times greater than the limit of

30%. The mean biomass trajectory over the 50-year projection was stable at approximately 21,000 mt, which is slightly greater than the stabilized biomass in the base scenario. While the mean trajectory was stable, inspection of individual trials for the Quota scenario indicated considerable variability, biomass among trials ranged from approximately 31,000 mt to 15,000 mt. The Base scenario showed similar magnitude in variability in biomass, ranging from approximately 10,000 mt and approximately 25,000 mt. When competition was included into the assessment model, historical Vermilion Snapper biomass was estimated to be higher than when it was not included. This is because if the landings and bycatch were the same in the past, and a new source of mortality was added, there must have been greater biomass to support the extra mortality. Based on the results from this study, if the current assessment and management protocols continued into the future, long-term, negative consequences for the stock are unlikely. It is encouraging to know that Vermilion Snapper stock is resilient and will be able to continue to support commercial and recreational fishing.

Seven alternative harvest control rules were tested and all were effective in managing the stock and preventing it from falling below limit reference points. Overfishing occurred in only 5% of the over 2,000 trials, and the stock never experienced overfishing. Based on the results of this study, an opportunity may exist to increase the annual catch limit for Vermilion Snapper with a low probability that the stock will be overfished. The most recent annual catch limit is set to 3,110,000 lbs or 1410 mt. In the simulations using the ACL HCR, ACL reached a maximum of 3,944,864 lbs, or 1789.36 mt and the mean ACL was 3,830,898 lbs or 1737.666 mt. Under this HCR, the stock was overfished only 2.2% of the time, which suggests that the limits could be increased for

Vermilion Snapper without harmful, long-term, impacts to the stock. In 2018, the ACL for Vermilion Snapper was exceeded by 84,000 lbs and recreational catch accounted for 57% of the total catch (“Gulf of Mexico Historical Stock Landings and Annual Catch Limit Monitoring” 2020). The ACL was not increased the following year but 85% of the ACL was caught (“Gulf of Mexico Historical Stock Landings and Annual Catch Limit Monitoring” 2020). The most recent years of landings data suggest that demand for Vermilion Snapper, particularly in the recreational fishery, has increased and to meet that demand, the ACL could be increased. Life-history traits of Vermilion Snapper such as early maturation (relative to other reef fish) can help maintain the population even under heavier fishing pressure.

The results of this study also indicate that empirical harvest control rules are effective for long-term management of the Vermilion Snapper stock. Empirical harvest control rules have been effectively implemented on many stocks (Punt et al. 2014; Plagányi et al. 2018) and provide an alternative to data-intensive and time-intensive statistical methods. Currently, the Vermilion Snapper stock assessment model is a statistical catch-at-age model that uses input data from multiple fishing fleets and fishery-independent surveys. The assessment process can take months to over a year to aggregate new data, incorporate it into the assessment model, update any necessary changes, perform modeling and sensitivity analyses, perform peer review, and write the report to provide recommendations for catch limits. After managers receive the catch recommendations, the process of setting new regulations is often delayed due to competing political and economic interests of the management panel, or the adequate inclusion of public comment (Shertzer and Prager 2007). Vermilion Snapper are typically assessed every five years and usually, when an assessment is conducted, the new data input into the model is lagged by a year more. This means that regulators are making decisions based on information that is not in real time. Long periods of time between assessments and lagged data can reduce recommended allowable catch limits and increase interannual variability of catches (Shertzer and Prager 2007; Li et al. 2016; Hutniczak et al. 2019). Some advantages of empirical harvest control rules are that they require less data, time, and effort for the assessment process; therefore they can be implemented more quickly while effectively achieving management objectives (Geromont and Butterworth 2015; Plagányi et al. 2018). For Vermilion Snapper, a stock that is not overfished, experiencing overfishing, or rebuilding, it may be worthwhile to increase the time between formal stock assessments and use an empirical rule that relies on less data in the interim. Increasing the time between formal assessments would use less resources, freeing up those for more at-risk or commercially and recreationally critical but still provide an updated catch recommendation.

Of the five empirical rules tested, the ones that performed the best were eHCR5 and eHCR2. Both of these rules relied on only one index, the competition index and the recreational CPUE index respectively. Because the two rules used a single index, they did not have to reconcile conflicting signals in stock abundance that may result in greater interannual variation of catch. Furthermore, conflicting signals in stock abundance may hide real population increases and not increase catch when possible. Even though these eHCRs met the management objectives, there are a few reasons they might not be optimal approaches. First, the recreational CPUE index alone is likely not reflective of the stock abundance and changes in CPUE can be caused by many factors including changes in angler efficiency and patterns of effort and targeting (Maunder et al. 2006). Second, the competition index does not contain information about the abundance of the Vermilion Snapper stock and operationalizing this approach would imply that the stock could be assessed using the relative abundance of another species. Likely, eHCR5 performed well because after the first few years of simulation, the index was stable at the rebuilt population level. In reality, the Red Snapper population may continue to increase or may experience heavy fishing pressure again and eventually decline. The competition index was based on the most recent stock assessment projection estimates (SEDAR 52) where the population reaches the target level by 2032. The different levels of uncertainty that were evaluated in the sensitivity runs are likely a more realistic approach, instead of the fixed scenario. Empirical rule one performed well in the scenarios where Red Snapper competition was known perfectly, however, it was extremely sensitive to any uncertainty in the competition index. Empirical rule one was ranked worst for all three levels of uncertainty in the sensitivity analyses. An alternative eHCR that performed fairly well in both the fixed and not-fixed scenarios was eHCR4. This eHCR rule depended on all seven indices and is the preferred option. This rule put a greater weight on the fishery independent surveys than it did the fishery-dependent CPUE indices.

Using the relative abundance of Red Snapper as a proxy for competition has some limitations. This index assumes that Red Snapper abundance and Vermilion Snapper mortality are directly related, when this relationship is likely more complicated. Other studies that have included interspecific competition typically use a biomass production model that incorporates the Lotka-Volterra competition model (Gaichas et al. 2012; Moffitt et al. 2016). The Lotka-Volterra model is based on the logistic population growth equation with additional competition coefficients. The competition coefficient (α) quantifies the effect an individual of one species has on the population growth of another species. The product of α and the population size of the second species gives the cumulative effect of the second population on the first species' population. Fitting the Lotka-Volterra model to estimates of population size for the two species allows for the estimation of α. This approach assumes that all individuals of a species have the same impact on the other population. However, it is more likely that competition for resources occurs more heavily at certain ages or stages of individuals than others. I did not use this method because I wanted to maintain age-structure in the operating model and assessment model. Another limitation was that I assumed that mortality was the same for ages 1+; however, future research could test alternative assumptions. Larval Vermilion Snapper recruit to reef habitats, while larval Red Snapper inhabit shell, mud, or sandy substrate habitats. Red Snapper move onto reefs at approximately 18 months where they begin feeding on reef-associated crabs, shrimp, and fishes (Szedlmayer and Lee 2004; Wells et al. 2008). Vermilion Snapper experience ontogenetic shifts in diet from benthic and planktivorous prey (copepods, nematodes, polychaetes) as juveniles (< 100 mm TL), to small, pelagic, crustaceans and cephalopods as adults (> 175 mm TL) (Grimes 1979). The potential for dietary overlap is greatest when Red Snapper are between the ages of two and four and Vermilion Snapper are between ages zero and two. While adult Vermilion and Red Snapper also have high dietary overlap, adult Red Snapper may travel farther to forage, so the impact of competition may be reduced on older Vermilion Snapper. So changing the selectivity function of the competition to a dome shaped function may be a more realistic representation of the competitive relationship.

In this study I incorporated a proxy for interspecific competition into the operating and assessment models for Vermilion Snapper. The utility of incorporating competition and predation effects into stock assessment models has been shown (Daan 1987; Shin et al. 2001; Jurado-Molina et al. 2005b; Gaichas et al. 2012) and excluding interspecific interactions can result in misinformed management. It is crucial that future research should develop a more representative index of competition. In order to do that, more stomach content data is needed for species. Additionally, Red Snapper is just one of the many competitors of Vermilion Snapper on the reefs. Another highly predatory species is the Lionfish. Lionfish pose a particular threat because they have no natural predators on the reefs and can change the dynamics of a reef quickly. Dahl and Patterson (2014) found that juvenile Vermilion Snapper were one of the most frequent species in Lionfish stomachs, so this could be a significant source of mortality to investigate. Expanding single-species stock assessments to incorporate multispecies or environmental (Sagarese et al. 2015) impacts is an ongoing effort in the Gulf and other regions of the US. To achieve this in the Gulf of Mexico, developing innovative methods is important because the data-limitations faced (few long-term monitoring data sets, lack of stomach content data, etc.) may not yet support the development of traditional multispecies models.

Table 2.1 *Uncertainty and Error*

Component	Based on	Values	Type
Recruitment	Deviates from historical estimates		Process
Catch	Fleet specific based on SE from SEDAR	0.05, 0.05, 0.15, 0.10	Implementation
Index of Abundance	Fleet/survey specific based on SEDAR	.369, .138, .2, .2, .2, .2	Observation

Components where uncertainty or error was included in the operating model.

Table 2.2 *Harvest Control Rules*

HCR	**Equation**
Quota	Quota = 1,555 mt
ACL	ACL = .75*OFL
Empirical Rule	$TAC = \bar{C}_{y-5,y} * \sum_{i=1}^{I} w_i * (1 + m_i)$

The three harvest control rules tested in the simulations and their equations.

Table 2.3 *Empirical Rules*

Scenarios	CE	CW	REC	BC	COMP	VIDEO	SEAMAP
eHCR1	0.33	0.33	0.34	0	0	0	0
eHCR2	0	0	1	0	0	0	0
eHCR3	0	0	0	0	0.34	0.33	0.33
eHCR4	0.14	0.14	0.14	0.14	0.14	0.15	0.15
eHCR5	0	0	0	0	1	0	0

The five empirical rules tested in the simulation and the weighting given to each index. Indices used included catch-per-unit-effort indices for the eastern commercial (CE), western commercial (CW), and recreational (REC) fisheries, an effort index for the shrimp by-catch fishery (BC), and indices of abundance for the competition index (COMP), reef fish video survey (VIDEO) and the SEAMAP groundfish survey (SEAMAP).

Table 2.4 *Number of Non-Converged Trials*

Scenario	Not Converged	n
eHCR1	21	79
eHCR2	22	78
eHCR5	22	78
Base	22	78
Quota	26	74
eHCR3	30	70
eHCR4	32	68
ACL	33	67

The number of trials that did not reach the end of the 50-year projection period and the number (n) of complete runs per scenario.

Table 2.5 *Terminal SPRs*

Scenario	Mean Terminal SPR	SD
ACL	0.43	0.067
eHCR5	0.50	0.062
eHCR3	0.50	0.053
eHCR2	0.50	0.057
eHCR1	0.52	0.044
eHCR4	0.52	0.057
Quota	0.58	0.054
Base	0.63	0.046

Mean terminal spawning potential ratio (SPR) and the standard deviation (SD) for each management strategy scenario.

Table 2.6 *Empirical Rule Ranking*

PI	eHCR1	eHCR2	eHCR3	eHCR4	eHCR5
Mean Catch	1,1,1	2,2,3	2,3,2	4,2,4	3,4,5
AAV (range)	4,2,4	2,3,2	1,4,3	3,1,1	5,2,5
AAV (median)	3,2,5	4,3,3	1,1,4	2,4,2	5,2,1
Terminal SPR Range	5	4	2	3	1
Total Score	28	28	23	26	33
Rank	2	2	4	3	1

Ranks of each empirical harvest control rule for performance indices. They were scored on their ability to achieve minimize or maximize each performance index (maximize mean catch, minimize AAV and AAV range, and minimize range for terminal SPR). For all PIs, 5 was the best score and total scores were summed and eHCRs were ranked. Catch and AAV were scored for each fishing fleet. eHCR5 performed the best under the performance indices.

Table 2.7 *Empirical Rule Ranking for Sensitivity Analyses*

	Low	Medium	High
eHCR1	4	5	5
eHCR2	3	1	1
eHCR3	3	2	4
eHCR4	2	4	2
eHCR5	1	3	3

Empirical harvest control rule rankings for each variability scenario (one is best performing, five is worst performing). eHCR5 performed the best when there was low variability and eHCR2 performed best under medium and high variability.

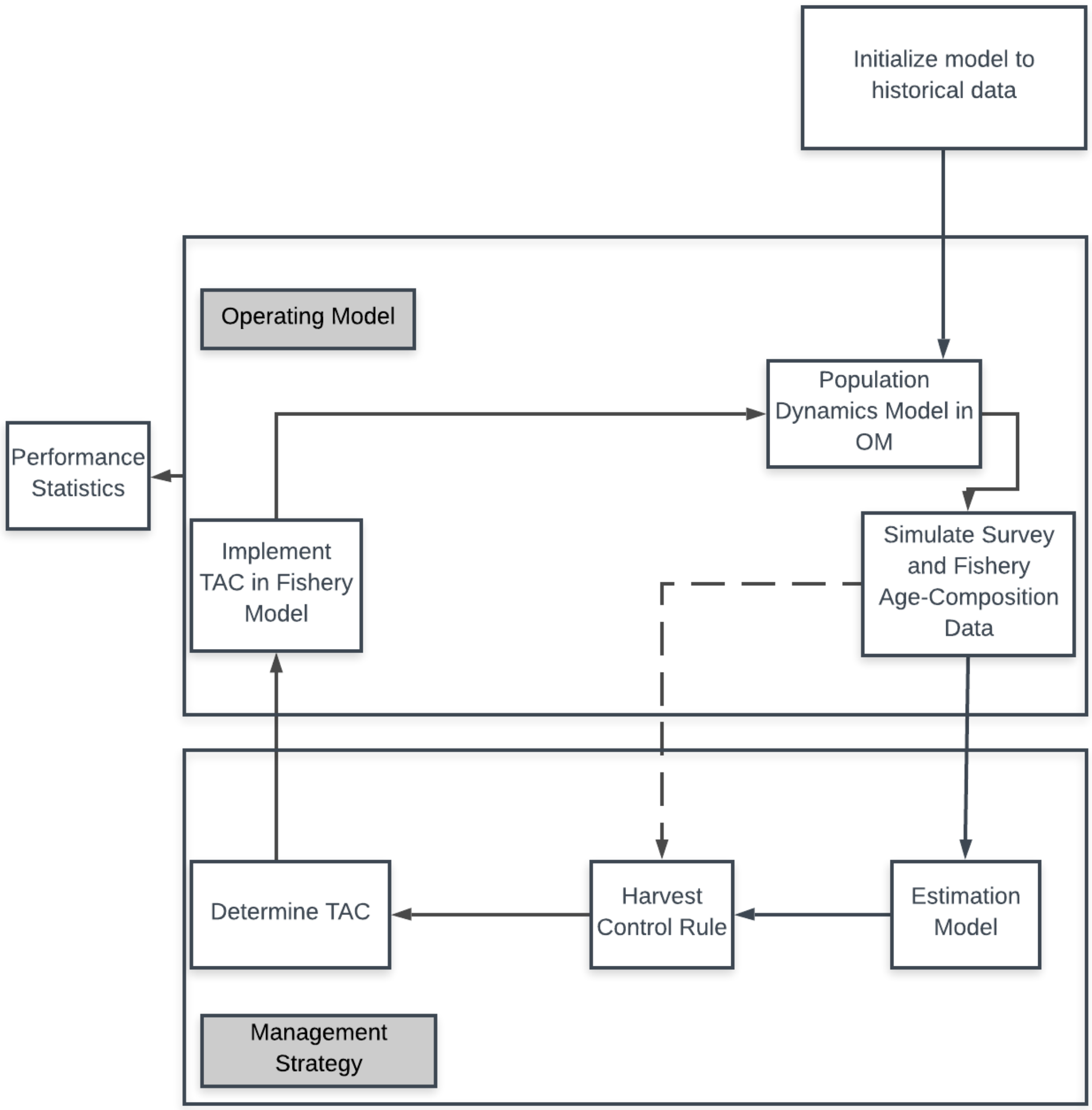

Figure 2.1 *MSE Simulation Process*

A representation of the MSE process. The operating model simulates the population and fishery dynamics. Data generated in the operating model are put into the management strategy component and the catch limits are determined using model-based or empirical harvest control rules. Performance indices are calculated at the end of the 50-year simulation period and are used to compare different management strategies.

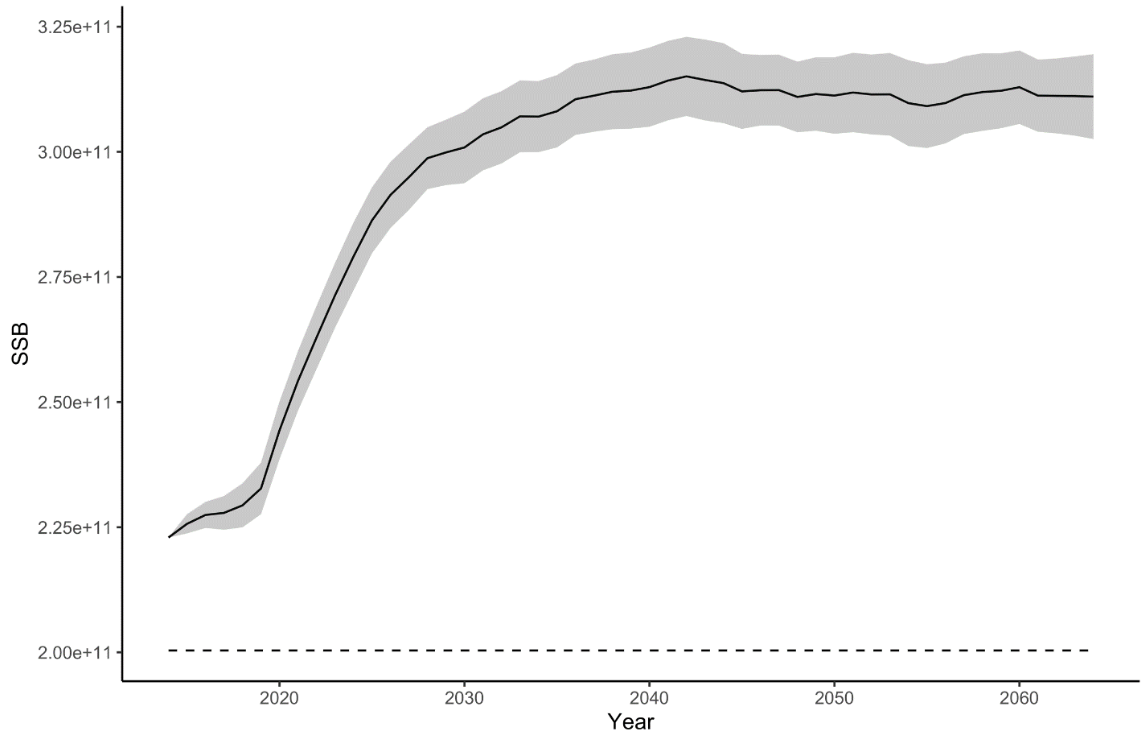

Figure 2.2 *Spawning Stock Biomass*

Mean spawning stock biomass under the base scenario (no Red Snapper competition) for the 50-year projection period. Grey area represents the 95% confidence interval and the dashed line represents the SSB at SPR 30%.

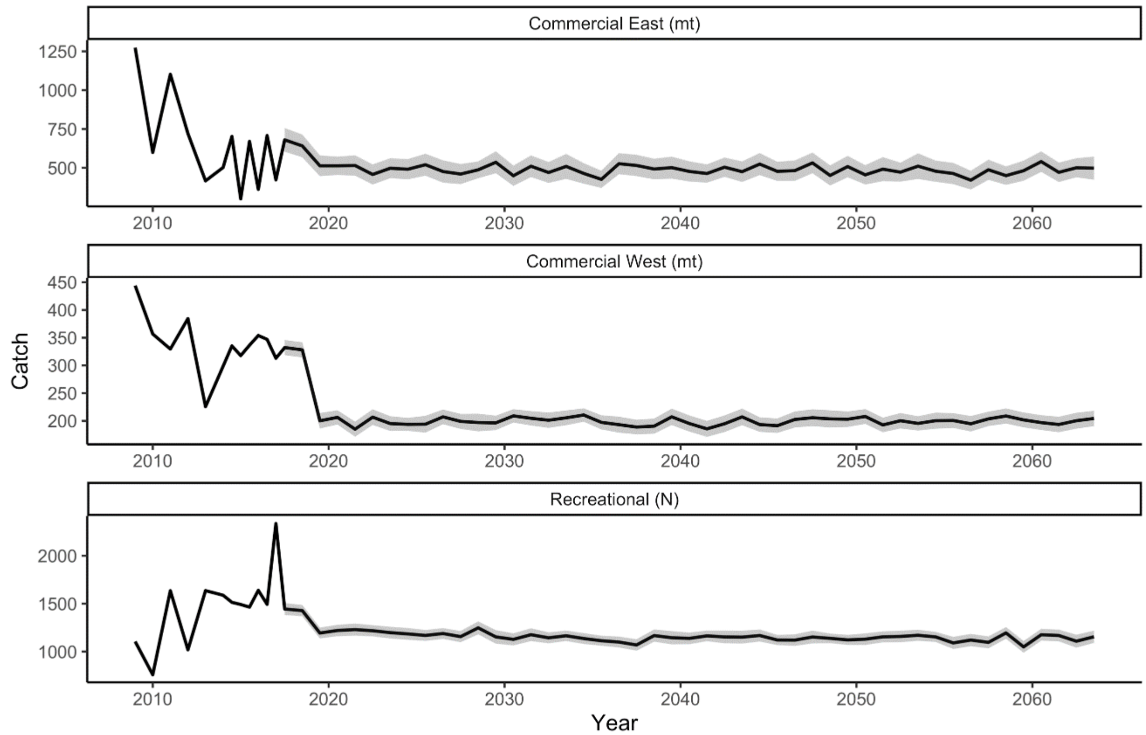

Figure 2.3 *Mean Catch*

The mean catches for all three fishing fleets and the 95% confidence intervals. Catch without the quantiles is from the pre-simulation period for comparison of simulated catch data to the real catch data. All simulated data had lower variability than the real data.

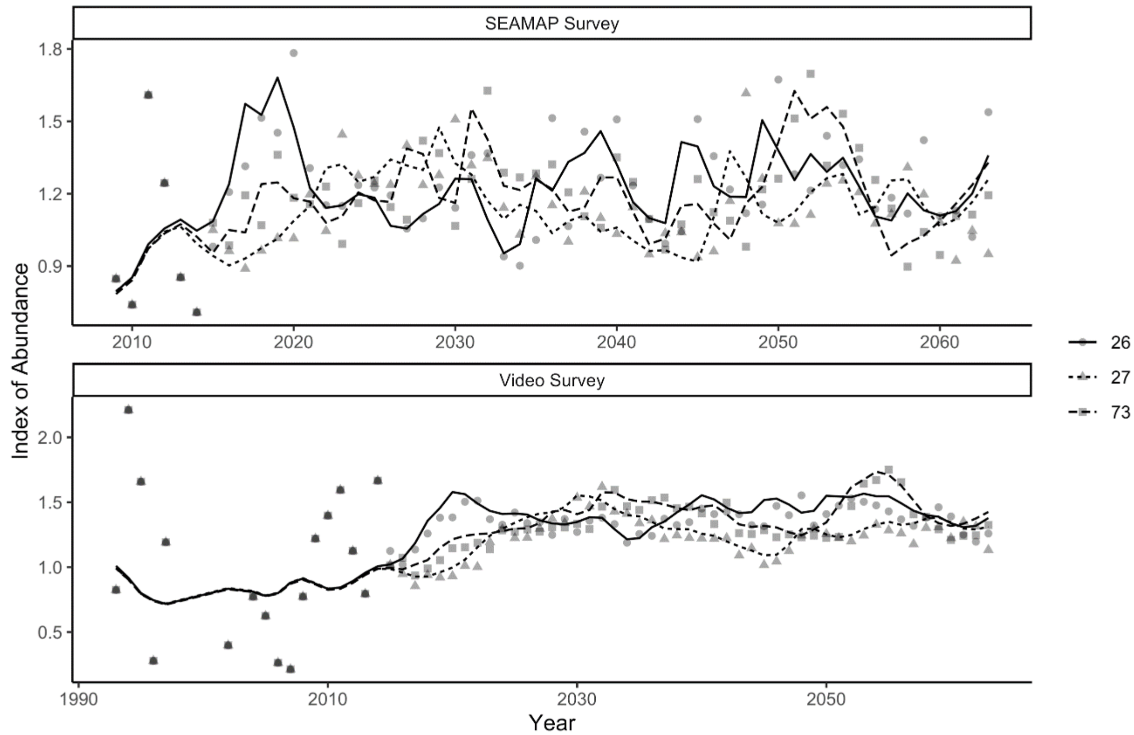

Figure 2.4 *Simulated Indices of Abundance*

Simulated observed and fitted indices of abundance from fishery independent surveys (SEAMAP groundfish and Reef Video) for three randomly selected trials (26, 27, and 73) from the Base scenario. Darker points represent the real observed data and the light grey dots represent the simulated data.

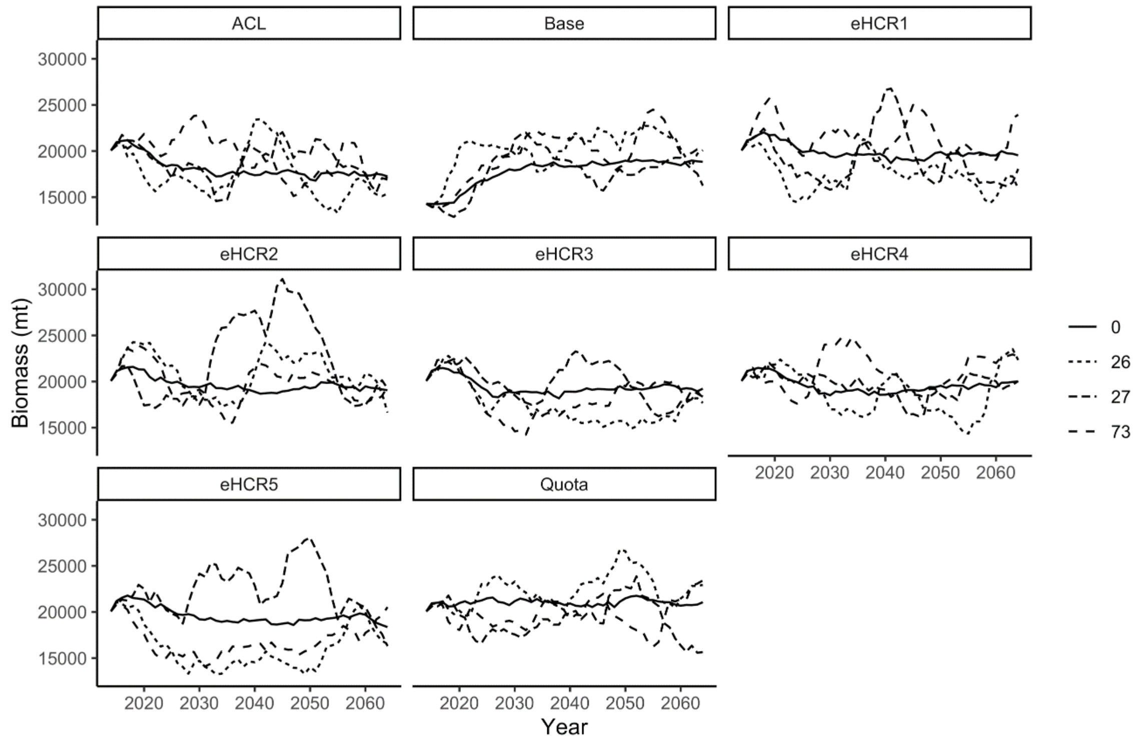

Figure 2.5 *Biomass Estimates*

Biomass trajectories for 3 randomly selected iterations (26, 27, and 73) and the mean biomass for each management strategy (solid line, 0).

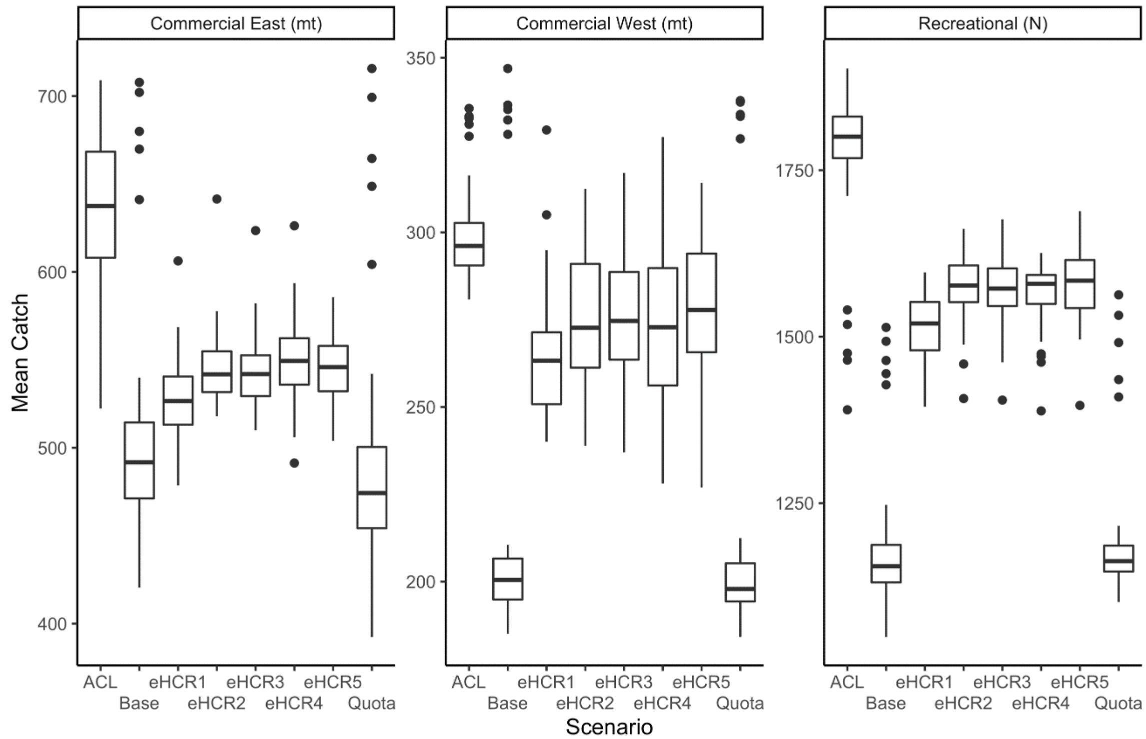

Figure 2.6 *Mean Catches*

Distribution of the mean catches for each management strategy per fleet. The commercial east and west fleets catch are reported in metric ton and the recreational fleet is in thousands of fish.

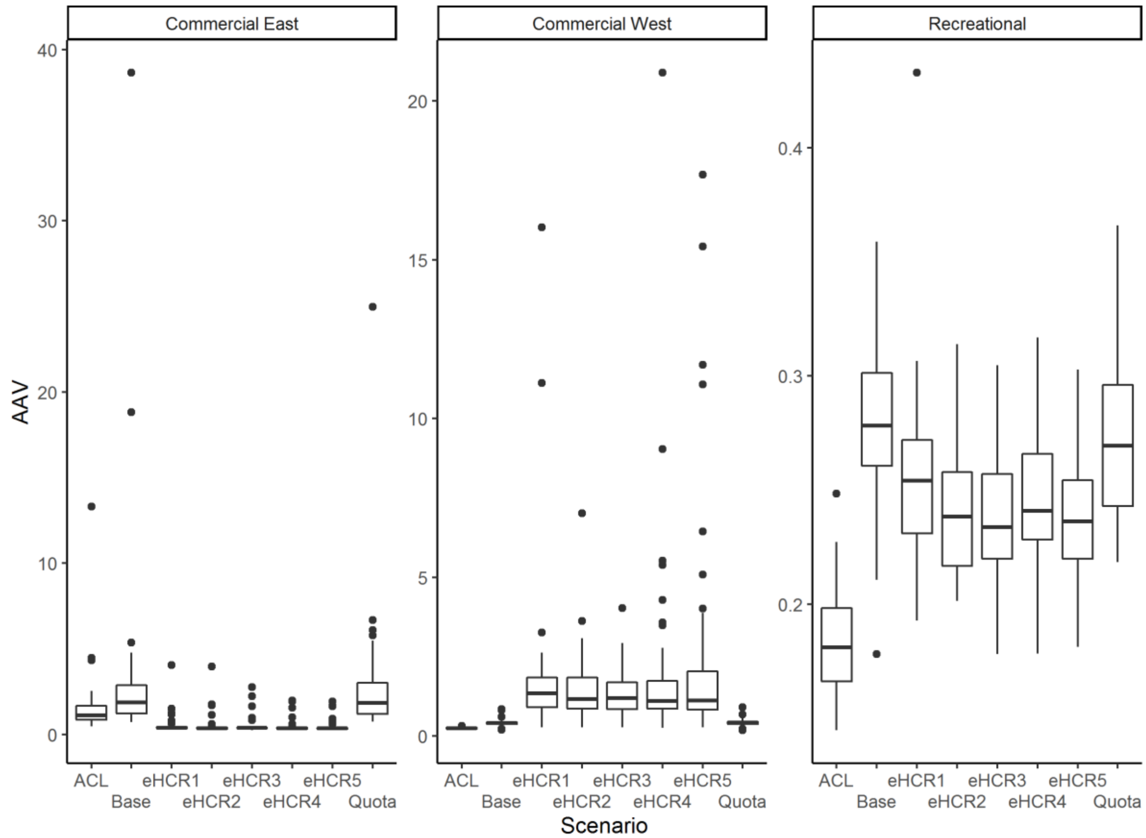

Figure 2.7 *Average Annual Variability*

Average annual variability (AAV) of catch for each management strategy and fishing fleet. Two data points were omitted from the figure because they were extreme outliers, one was from the base scenario and AAV = 79.5, and the other was from the Quota scenario and AAV = 323. Both points were for the eastern commercial fleet.

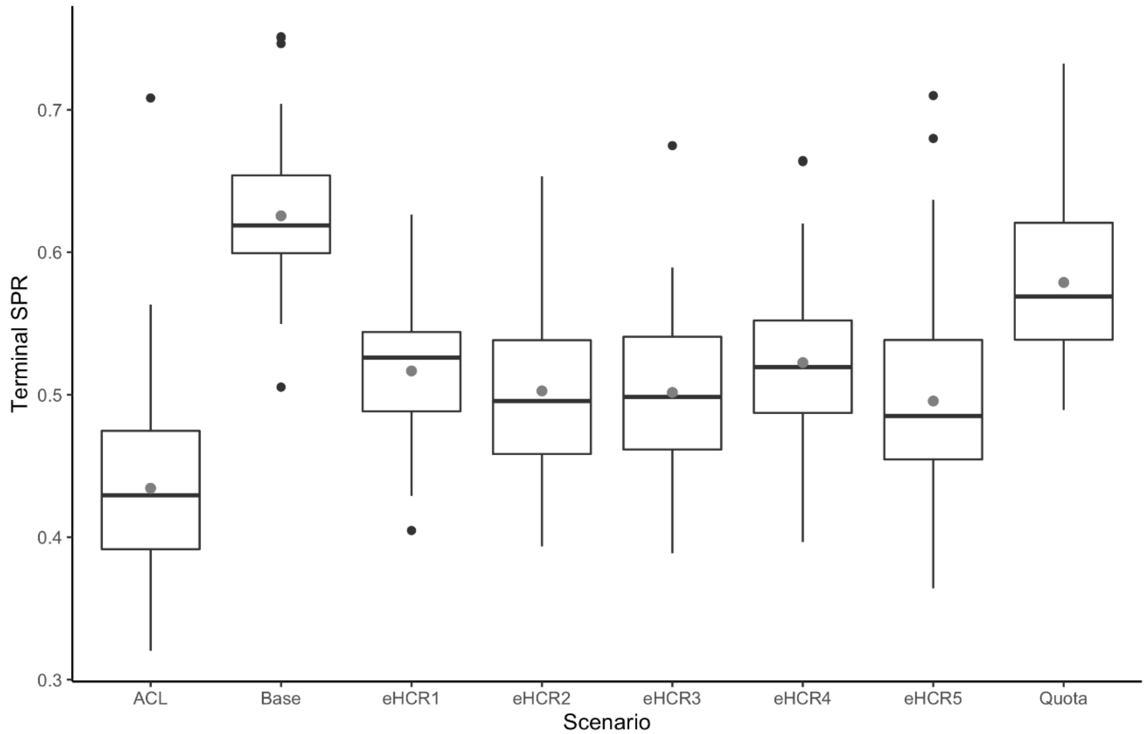

Figure 2.8 *Terminal SPRs*

Box and whisker plots of the terminal spawning potential ratio (SPR) values for each management strategy scenario. Grey dots represent the mean terminal SPR and the thick black bar represents the median.

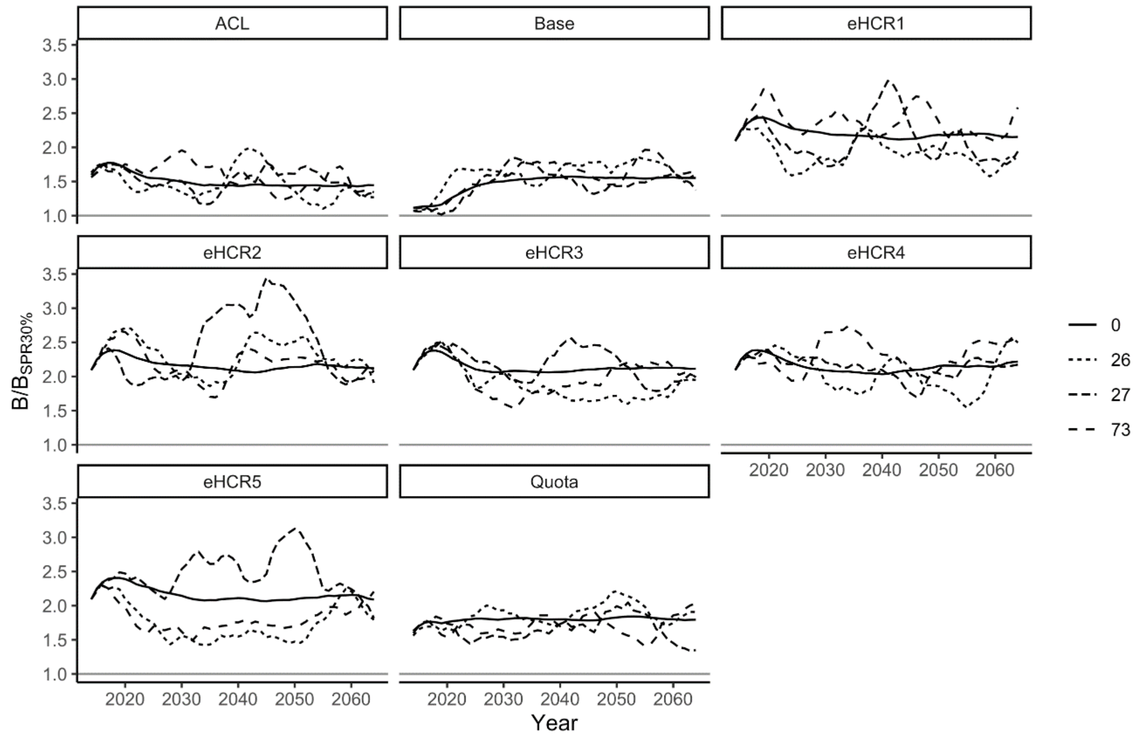

Figure 2.9 *Biomass Ratios*

$B/B_{SPR30\%}$ ratio of three randomly selected iterations (26, 27, and 73) and the mean $B/B_{SPR30\%}$ ratio (solid line, 0) for each management strategy. The solid grey line represents the line below which the population is considered overfished ($B/B_{SPR30\%} = 1$).

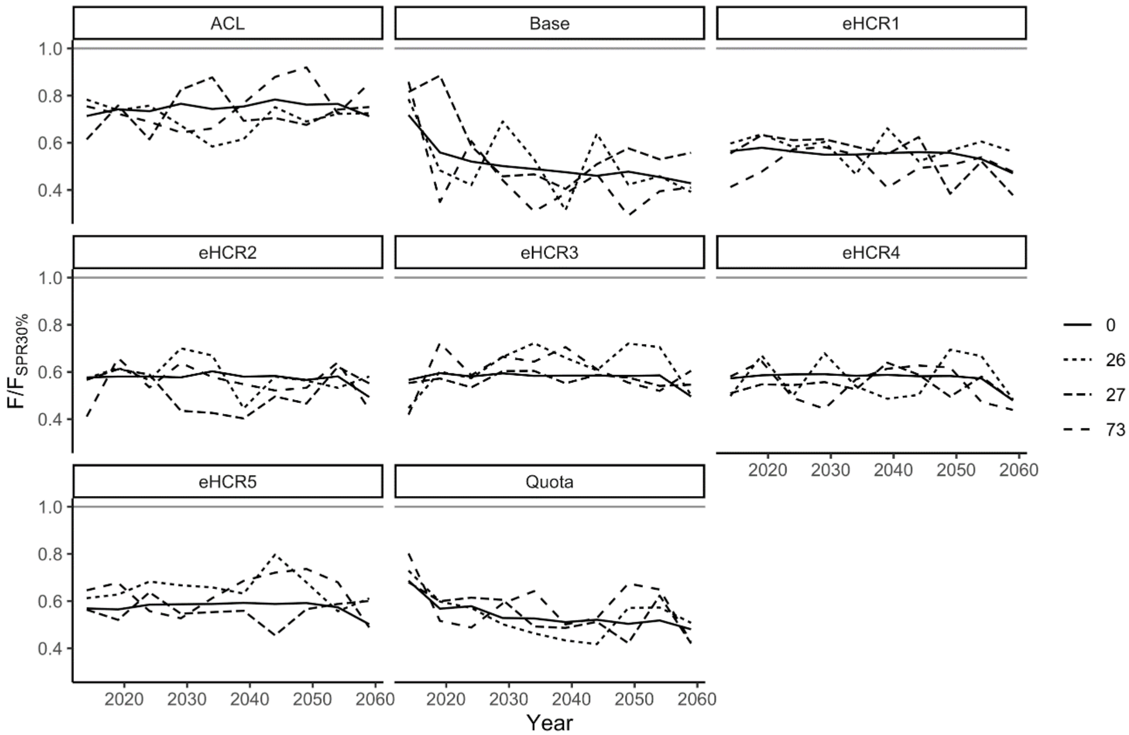

Figure 2.10 *Fishing Mortality Ratios*

$F/F_{SPR30\%}$ ratio of three randomly selected iterations (26, 27, and 73) and the mean (solid line, 0) $F/F_{SPR30\%}$ ratio for each management strategy. The solid grey line represents the line above which overfishing is occurring ($F/F_{SPR30\%} = 1$).

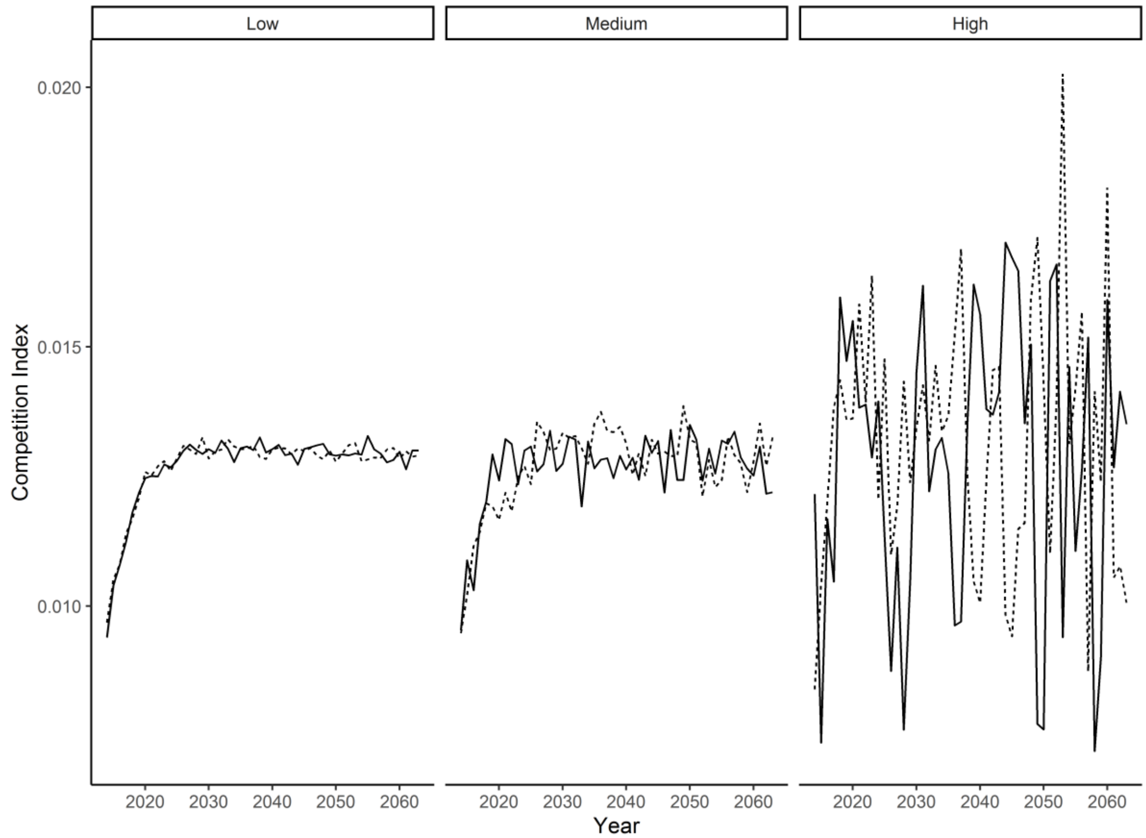

Figure 2.11 *Competition Index*

Competition index values used for two example trials with high (sd = 0.1), medium (sd = 0.01), and low (sd = 0.005) variability.

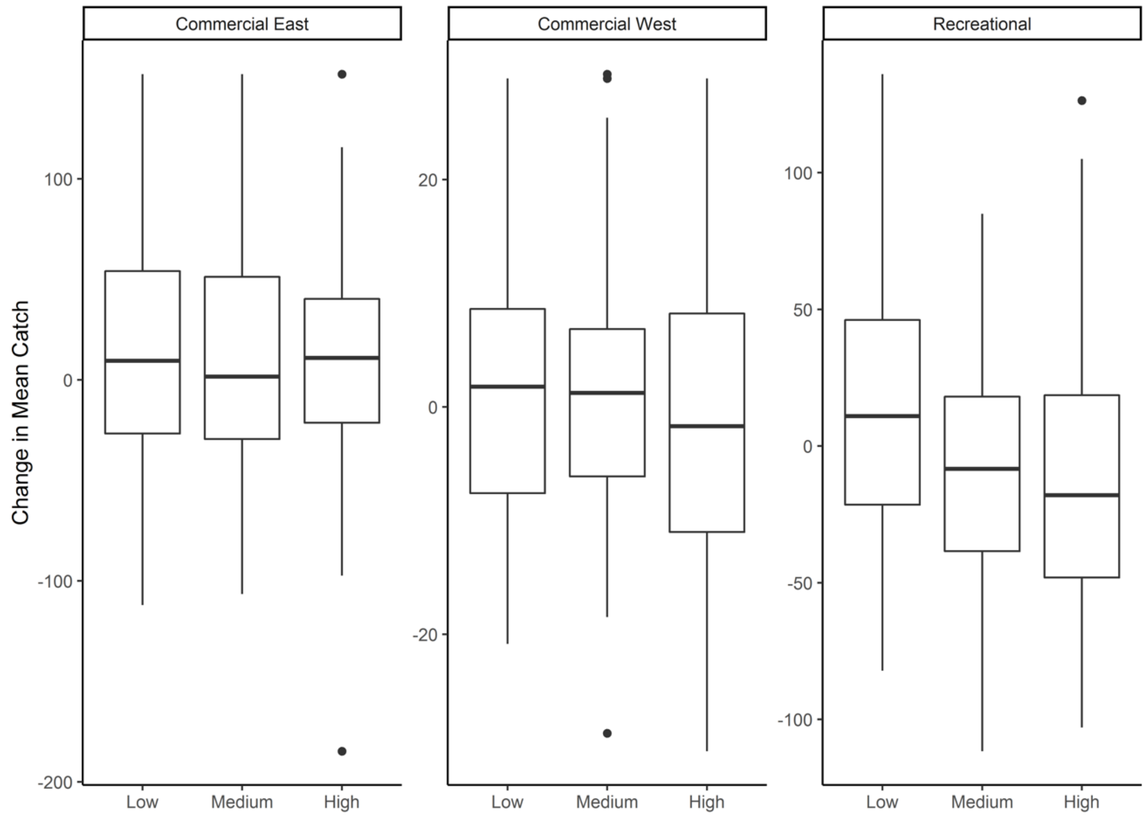

Figure 2.12 *Change in Mean Catch for ACL Rule*

Box and whisker plots showing the spread of the difference between the fixed scenario and the different levels of variability in the Red Snapper competition index for the ACL management strategy scenario.

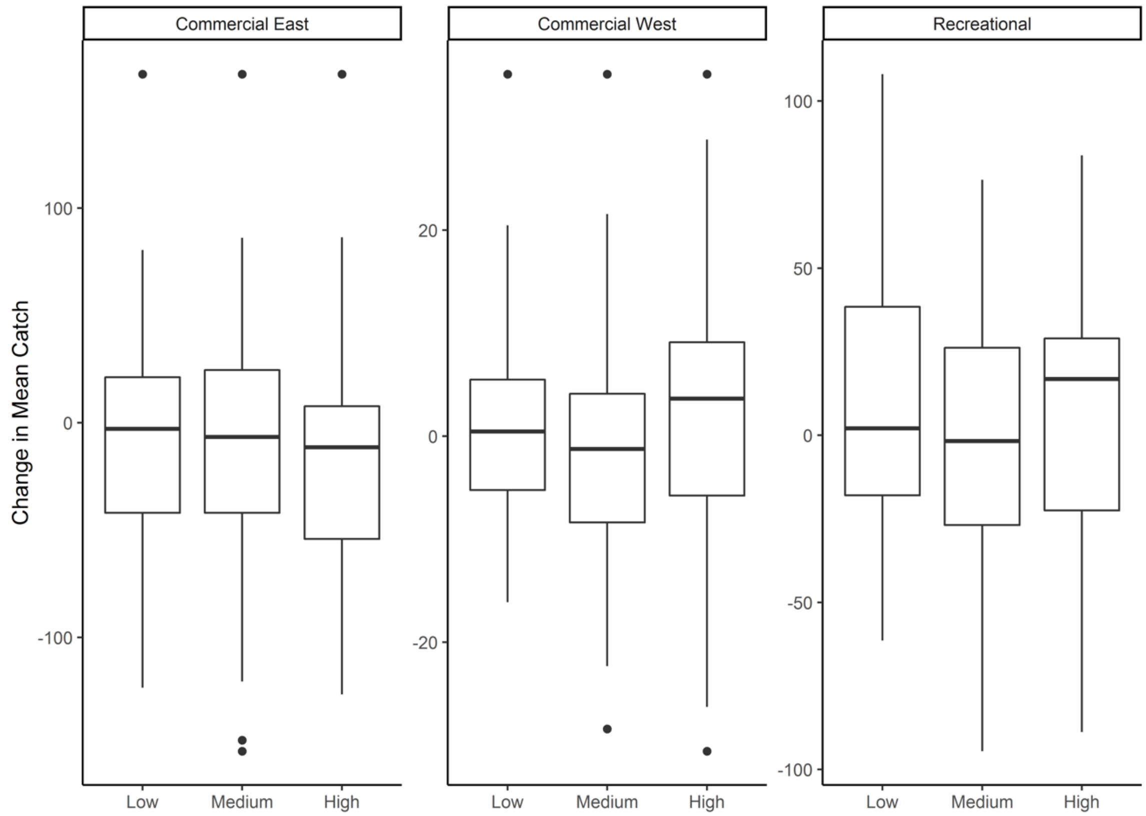

Figure 2.13 *Change in Mean Catch for Quota Rule*

Box and whisker plots showing the spread of the difference between the fixed scenario and the different levels of variability in the Red Snapper competition index for the Quota management strategy scenario.

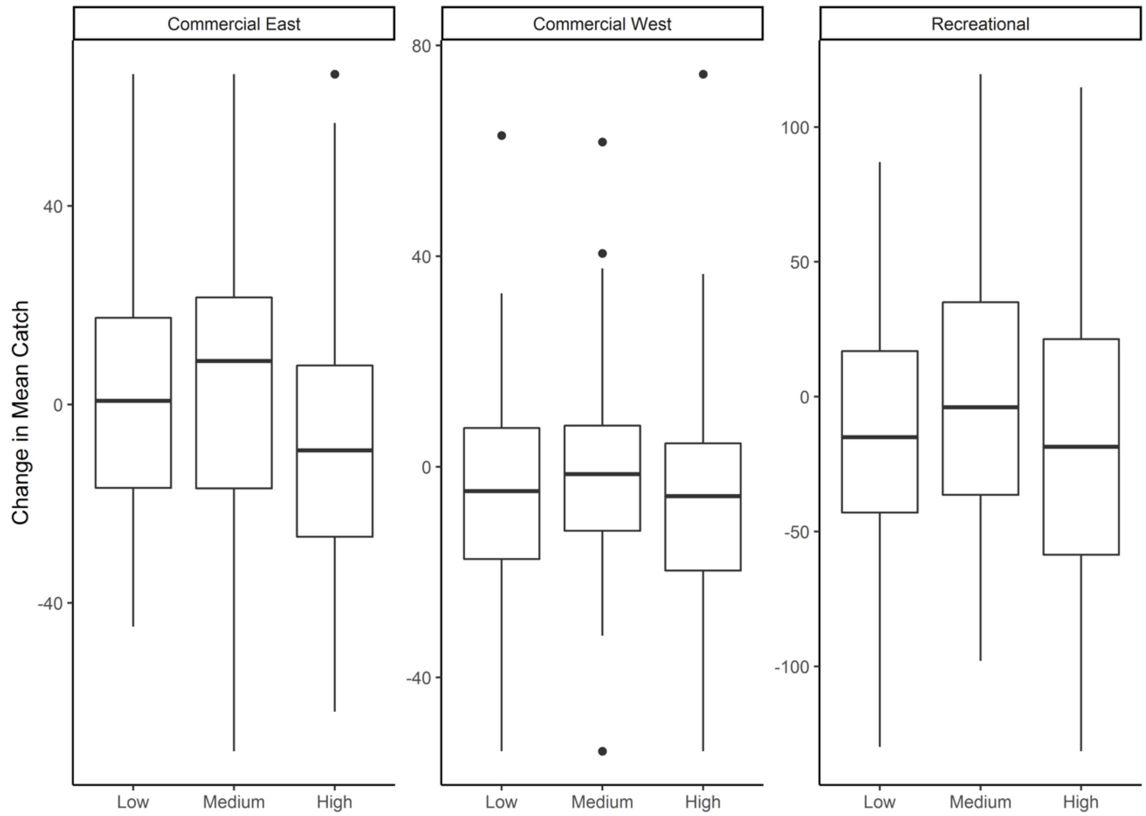

Figure 2.14 *Change in Mean Catch for eHCR1 Rule*

Box and whisker plots showing the spread of the difference between the fixed scenario and the different levels of variability in the Red Snapper competition index for the eHCR1 management strategy scenario.

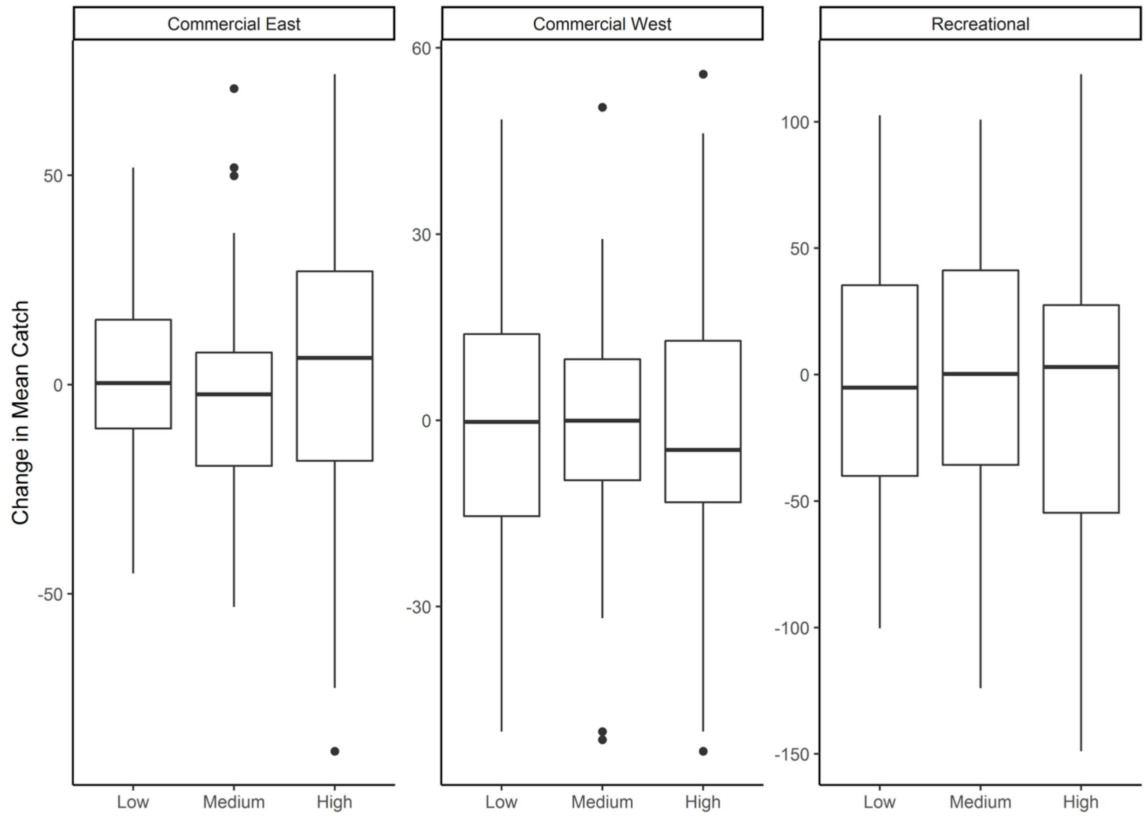

Figure 2.15 *Change in Mean Catch for eHCR2 Rule*

Box and whisker plots showing the spread of the difference between the fixed scenario and the different levels of variability in the Red Snapper competition index for the eHCR2 management strategy scenario.

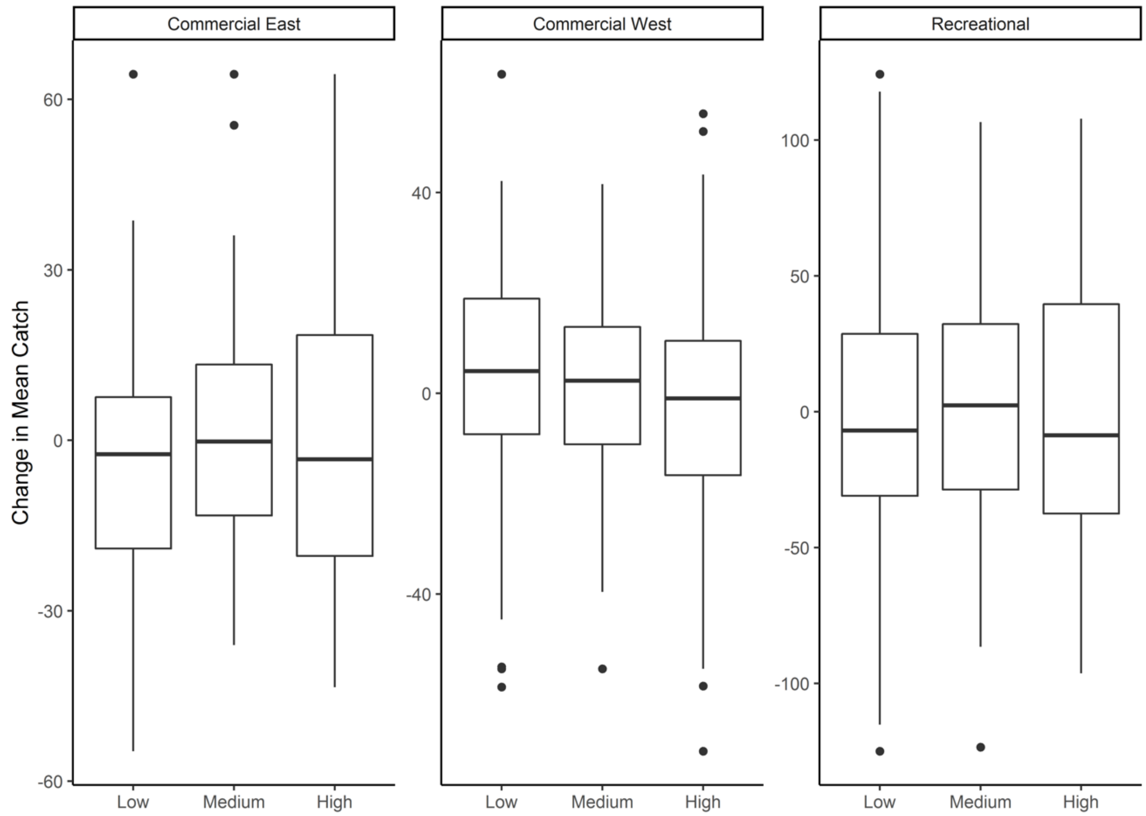

Figure 2.16 *Change in Mean Catch for eHCR3 Rule*

Box and whisker plots showing the spread of the difference between the fixed scenario and the different levels of variability in the Red Snapper competition index for the eHCR3 management strategy scenario.

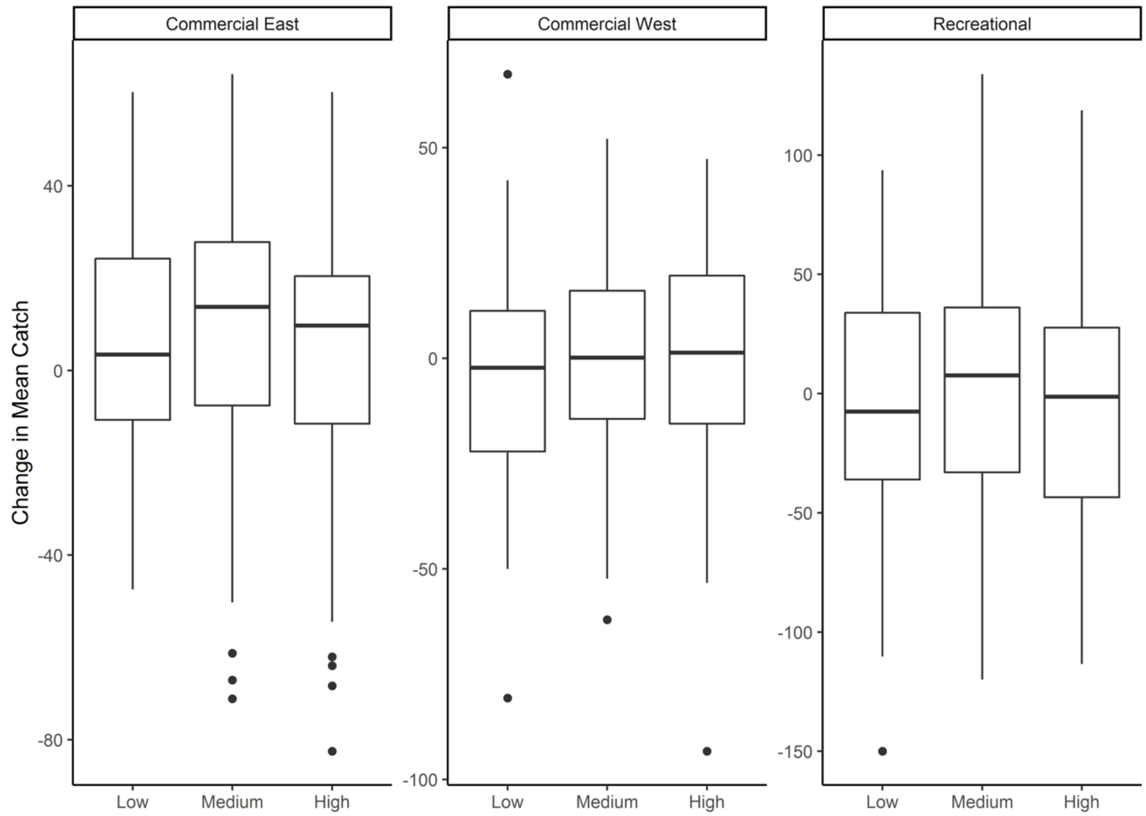

Figure 2.17 *Change in Mean Catch for eHCR4 Rule*

Box and whisker plots showing the spread of the difference between the fixed scenario and the different levels of variability in the Red Snapper competition index for the eHCR4 management strategy scenario.

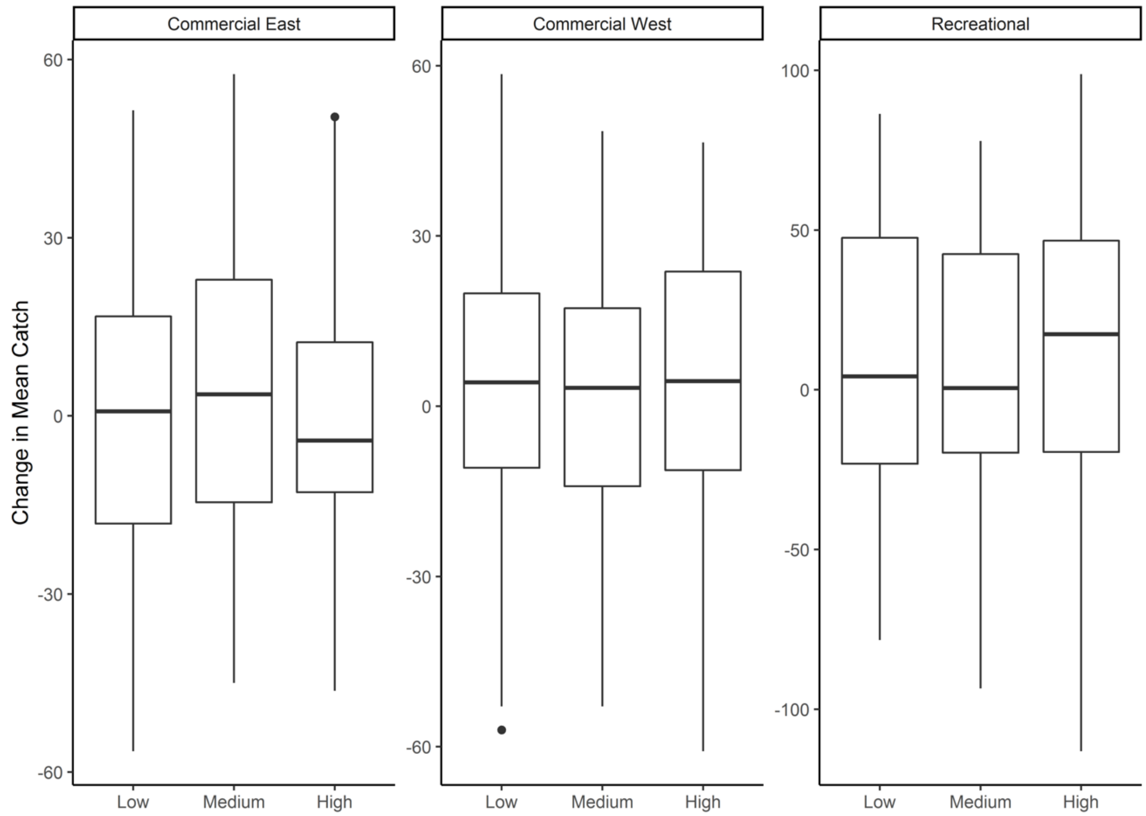

Figure 2.18 *Change in Mean Catch for eHCR5 Rule*

Box and whisker plots showing the spread of the difference between the fixed scenario and the different levels of variability in the Red Snapper competition index for the eHCR5 management strategy scenario.

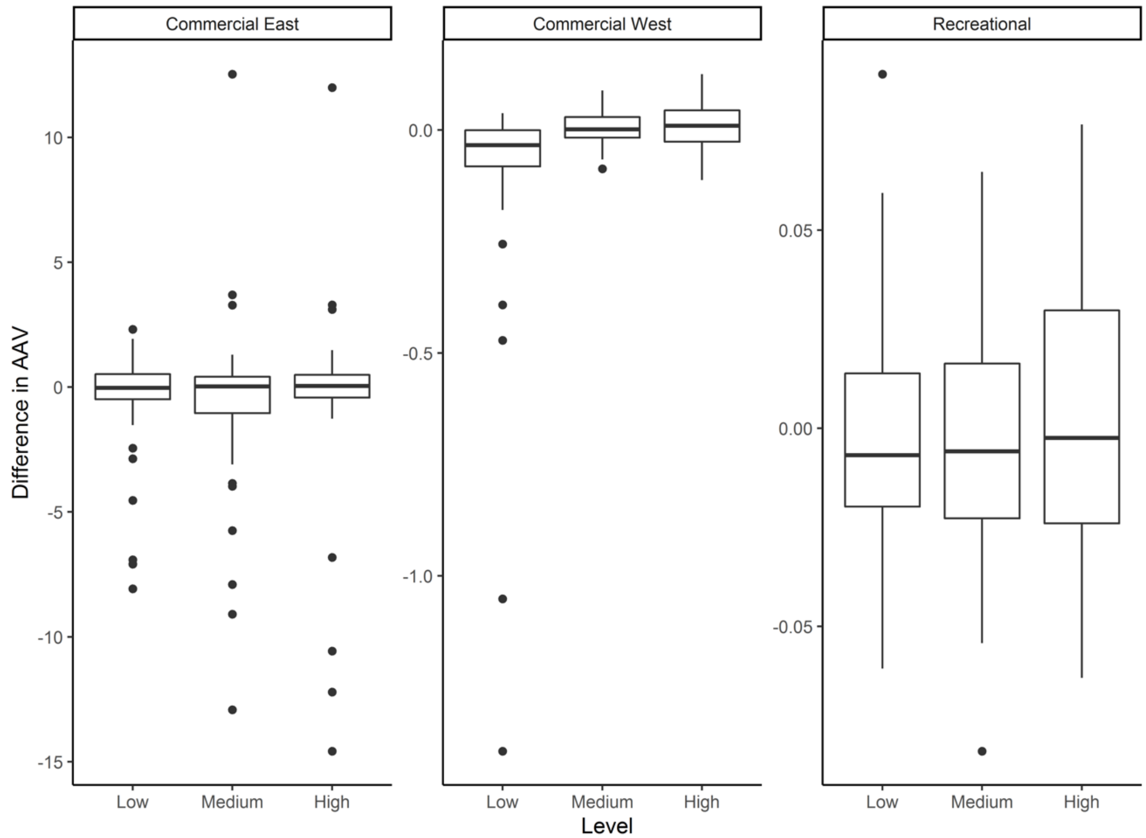

Figure 2.19 *Change in Mean AAV for ACL Rule*

Box and whisker plots showing the difference between the mean average annual variability (AAV) for the fixed scenario and the mean AAVs for different levels of variability in the Red Snapper competition index for the ACL management strategy.

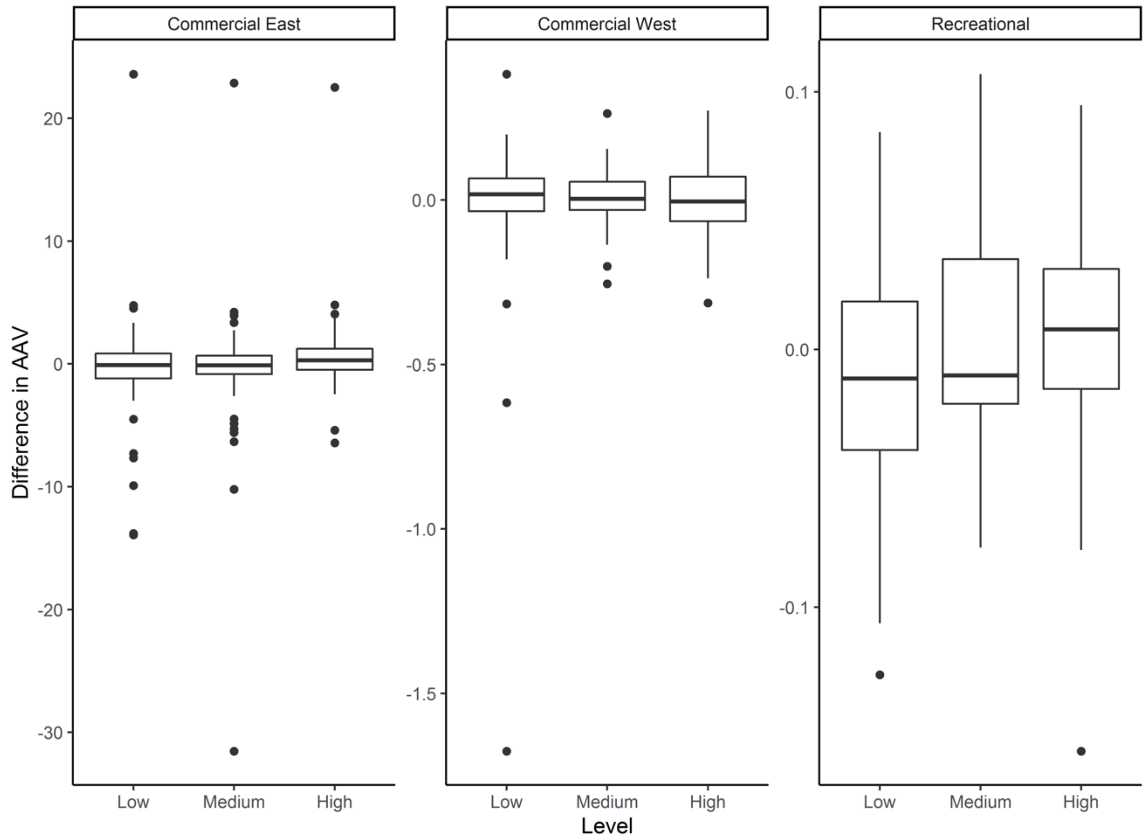

Figure 2.20 *Change in Mean AAV for Quota Rule*

Box and whisker plots showing the difference between the mean average annual variability (AAV) for the fixed scenario and the mean AAVs for different levels of variability in the Red Snapper competition index for the Quota management strategy. Four points in the CE fleet were removed because they were extreme outliers. Two points were from the low variability scenarios (323 and -1046), one from the medium variability scenario (319), and one from the high variability scenario (322).

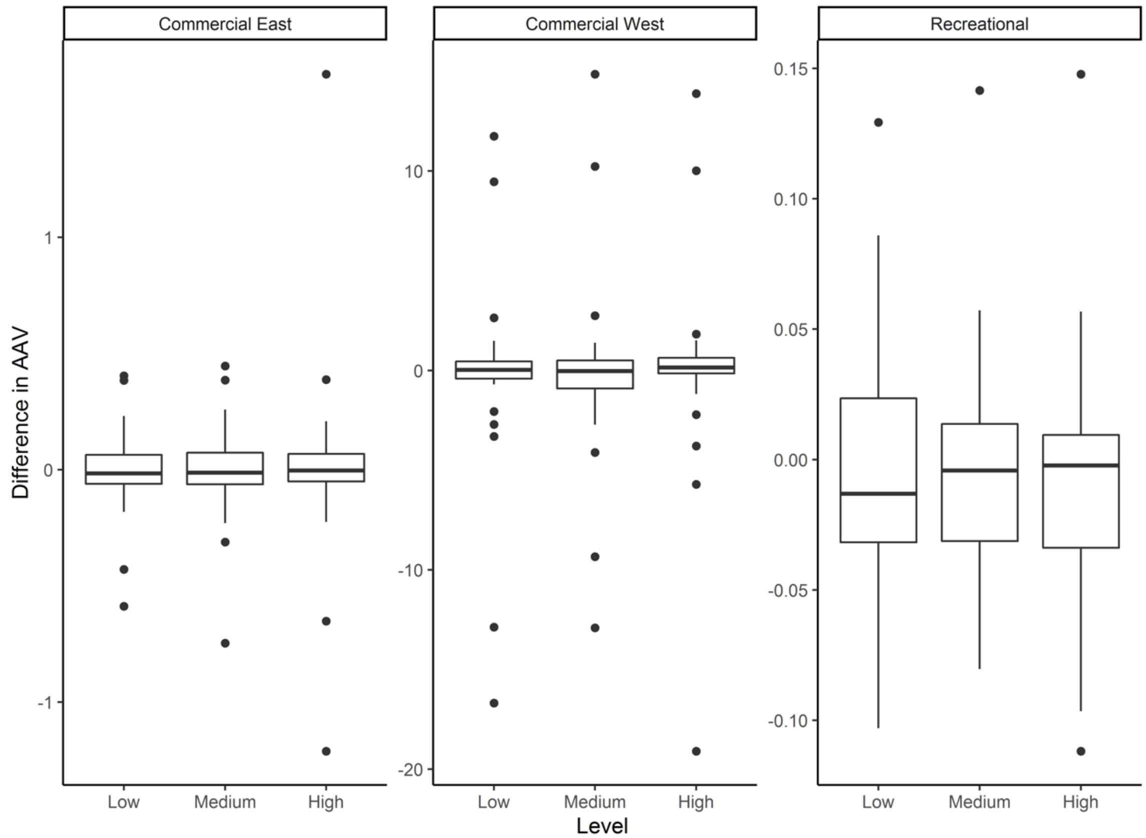

Figure 2.21 *Change in Mean AAV for eHCR1 Rule*

Box and whisker plots showing the difference between the mean average annual variability (AAV) for the fixed scenario and the mean AAVs for different levels of variability in the Red Snapper competition index for the eHCR1 management strategy.

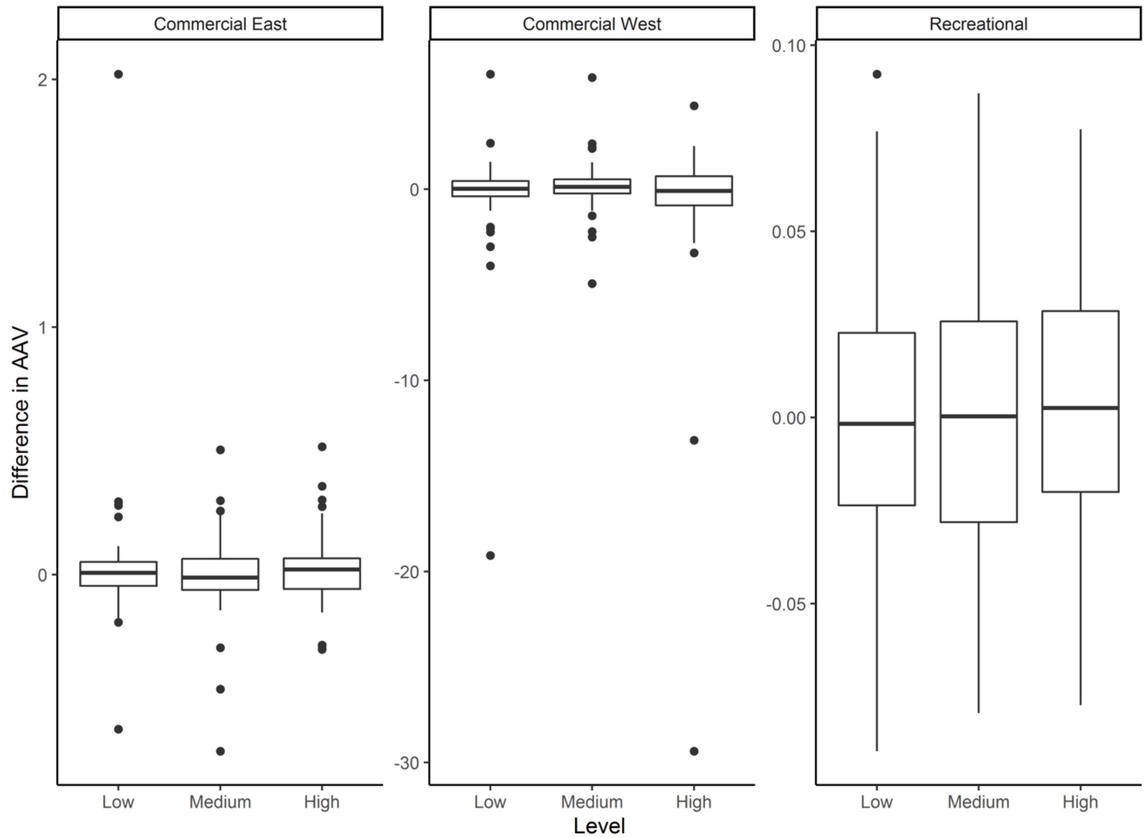

Figure 2.22 *Change in Mean AAV for eHCR2 Rule*

Box and whisker plots showing the difference between the mean average annual variability (AAV) for the fixed scenario and the mean AAVs for different levels of variability in the Red Snapper competition index for the eHCR2 management strategy.

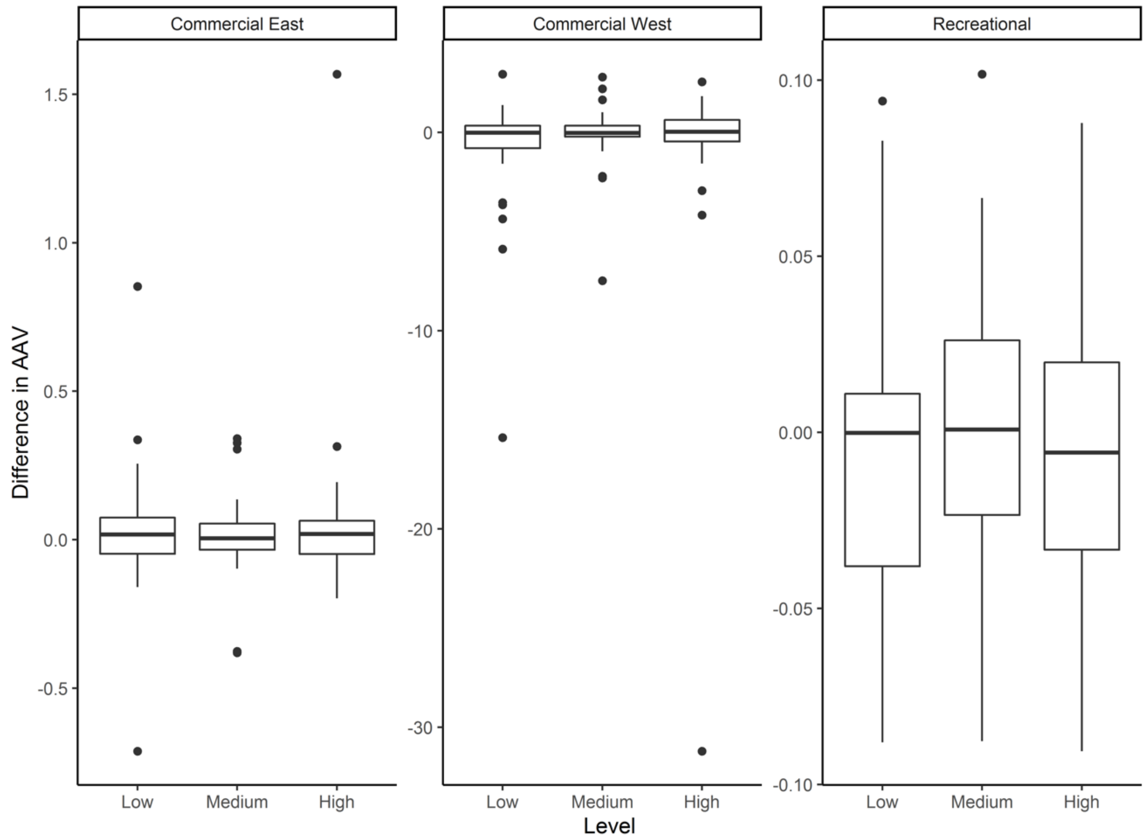

Figure 2.23 *Change in Mean AAV for eHCR3 Rule*

Box and whisker plots showing the difference between the mean average annual variability (AAV) for the fixed scenario and the mean AAVs for different levels of variability in the Red Snapper competition index for the eHCR3 management strategy.

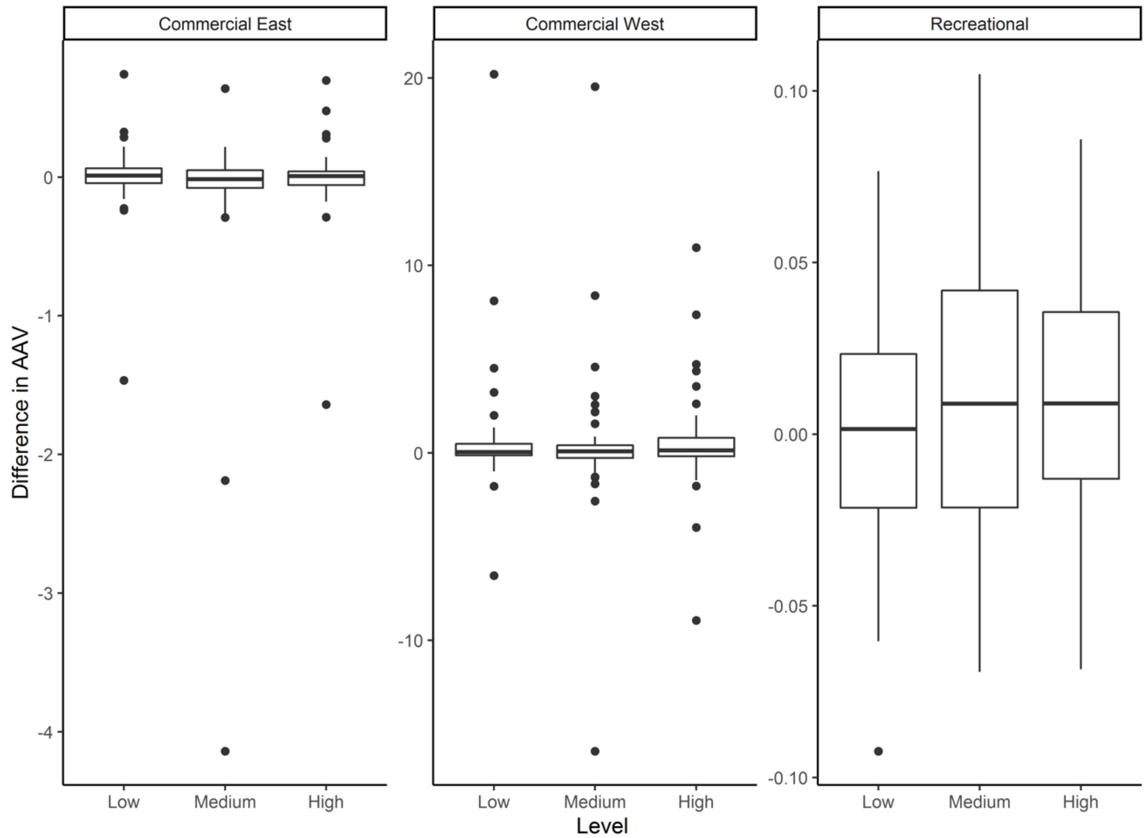

Figure 2.24 *Change in Mean AAV for eHCR4 Rule*

Box and whisker plots showing the difference between the mean average annual variability (AAV) for the fixed scenario and the mean AAVs for different levels of variability in the Red Snapper competition index for the eHCR4 management strategy.

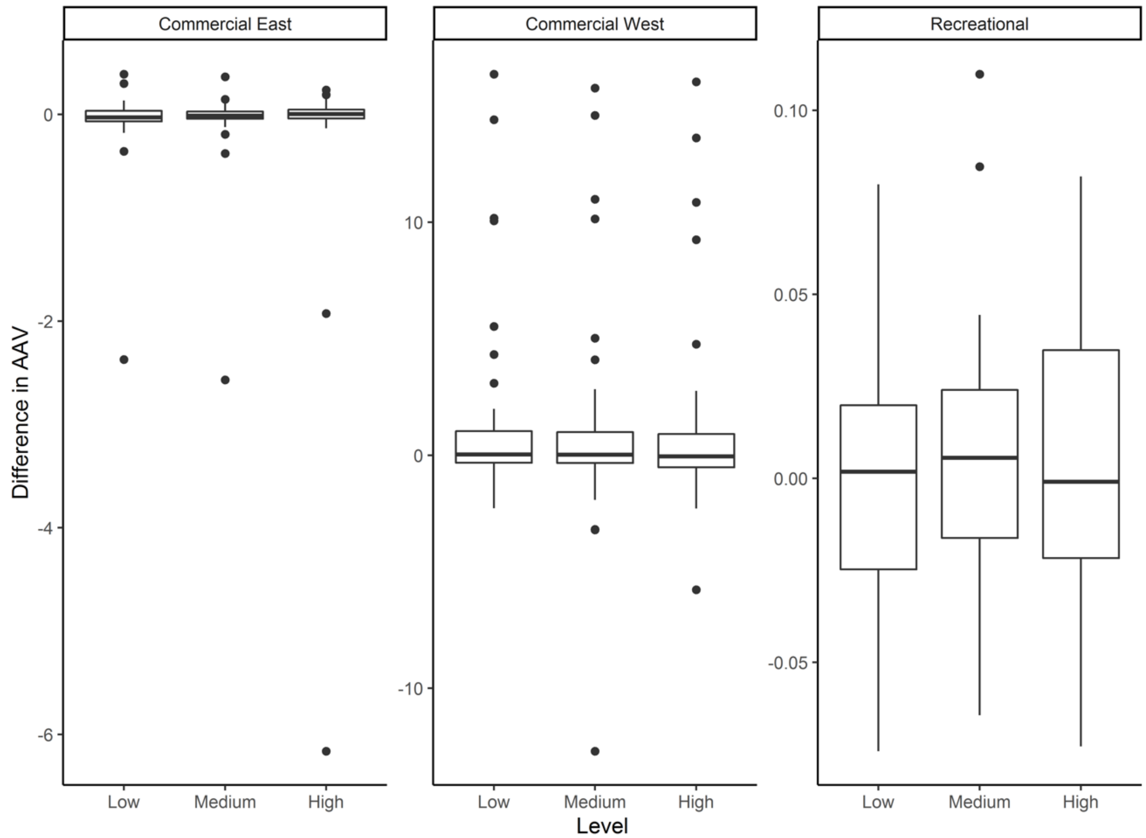

Figure 2.25 *Change in Mean AAV for eHCR5 Rule*

Box and whisker plots showing the difference between the mean average annual variability (AAV) for the fixed scenario and the mean AAVs for different levels of variability in the Red Snapper competition index for the eHCR5 management strategy. One point was omitted from the figure for the CW fleet because it was an extreme outlier. The data point omitted was for the high variability scenario and the difference in AAV was -1743.

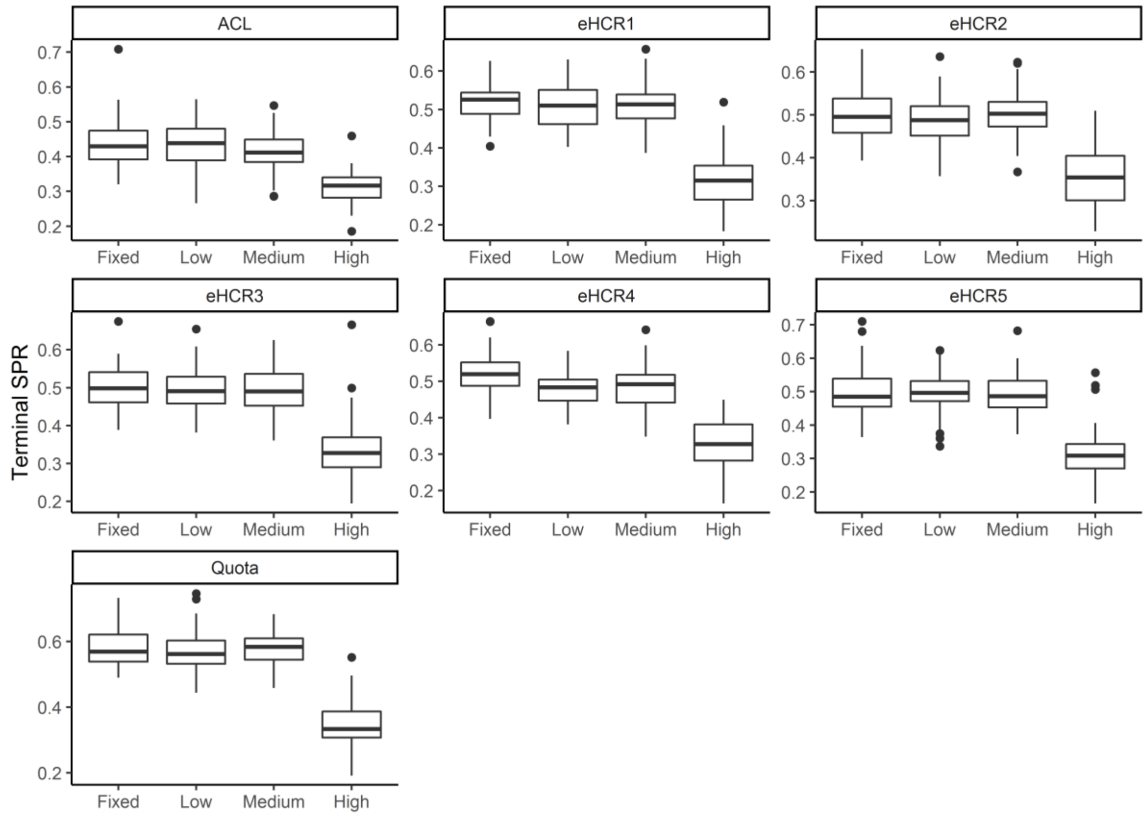

Figure 2.26 *Terminal SPRs for Sensitivity Analyses*

Box and whisker plots for terminal spawning potential ratio (SPR) values for each management strategy scenario. Fixed represents the "perfect knowledge" case and high, medium, and low represent the different levels of variability in the Red Snapper competition index.

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CHAPTER III – EVALUATING IMPACTS OF INCREASED RECREATIONAL TARGETING ON THE VERMILION SNAPPER STOCK IN THE GULF OF MEXICO

3.1 Introduction

Fisheries managers use input and output controls to attain sustainability of fish stocks. Input controls are regulations used to control fishing intensity and include bag limits, size limits, area closures, or shortened fishing seasons. Output controls are regulations used to control the magnitude of harvest and include quota and allocation level. Input controls can be effective in increasing stock biomass and preventing stocks from being overfished, however, they can have unintended consequences. In the recreational fishing sector, anglers select among a suite of fishes to target and will not stop fishing when regulations are imposed. Instead, they will switch their efforts to a different target species (Gentner 2004; Scheld et al. 2020). Recreational anglers and for-hire charter captains agree that in the Gulf of Mexico, "species substitution" occurs frequently (personal communication). Species substitution can undermine management efforts and may cause unexpected ecological and economic effects in a fishery (Sutton and Ditton 2005; Gentner and Sutton 2008). Recreational fishing is a major industry in the Gulf of Mexico (Keithly and Roberts 2017); estimates of expenditures for recreational fishing activities in the GOM exceeded $700 million, and at least 92,000 jobs are created as a direct result of the recreational fishing industry (Keithly and Roberts 2017). As regulations are changed and anglers switch their targets, economic impact will vary. For example, shortened fishing seasons can result in the loss of revenue.

Understanding angler decision-making behaviors is critical to designing effective regulations (Wilen 1979). One method that has been used to model angler choice are random utility models (RUM) (Gentner 2004; Hutton et al. 2004; Beville and Kerr 2008). RUM are used to understand the choice of an individual among a set of given options. The underlying assumption of any RUM is that anglers, when given *n* choices, will choose the one that maximizes their utility or provides them with the greatest satisfaction (Scheld et al. 2020). RUMs are used frequently in economics to determine the probability of a person choosing a particular option, given a set of conditions and to predict how changing a condition or adding an alternative option will change the probability of an individual selecting the particular option. In fisheries science, predictive RUMs can inform what influences anglers decisions and the areas of decision making are diverse and include decisions about fishing location (McConnell et al. 1995; Hutton et al. 2004; Hunt et al. 2007; Haab et al. 2008), species targeting (Gentner 2004; Haab et al. 2012), and target species substitution (Gentner 2004; Scheld et al. 2020). Random utility models allow inferences to be made about the influence that each attribute of a choice has on the utility of that option. For example, to model an individual's choice regarding which species to target, attributes may include fishing method, cost of the trip, expected catch, and current regulations such as bag limits or size limits. Attributes associated with the management policy for a particular species can also be included as predictor variables in the model. These are often evaluated in a BACI approach to understand the change in utility of a choice pre- and post-implementation of a management policy (Gentner 2004; Scheld et al. 2020). Thus, RUMs enable a prediction of how anglers' decisions differ due to policy changes. The method provides a framework for estimating angler preferences and their targeting behavior under a range of circumstances.

Limitations of multinomial logistic RUM have led to the development of alternative parameterizations of the RUM model. The first assumption of RUMs is homogenous preferences among participants. This means that the additional utility gained from a one unit change in an attribute is the same for all individuals sampled (Haab et al. 2012). The second assumption is independence from irrelevant alternatives (IIA). IIA means that the probability of an angler choosing option A over option B is independent of all other options. This assumption may be violated when latent or undetected groups of choices exist, where some options are more similar than they are to others. For example, an angler is more likely to switch between fishing site A and site B than switching from site A to site C if A and B are 2 miles apart and A and C are 10 miles apart. The mixed logit model is a flexible form that relaxes both assumptions. The mixed logit model allows for heterogeneity among anglers' preferences by estimating the preference parameters over parametric distributions (Train 2003). In some cases, mixed logit models have been found to better estimate angler preference than the multinomial version (Morey and Breffle 2000; Train 2003; Haab et al. 2008).

It is difficult to predict how anglers will respond to regulatory changes; however, simulation approaches can be used to evaluate expectations and their associated uncertainty. Agent-based models and integrated bioeconomic models have been used to evaluate policy implementation on recreational fishing (Gao and Hailu 2010) and predict optimal management policies based on angler characteristics (Arlinghaus and Mehner 2005; Johnston et al. 2010; Gao and Hailu 2012). Understanding characteristics of anglers (e.g. demographic, experience, location, or goal, catch oriented or consumptive oriented) can inform regulatory strategy implementation and lead to successful management of resources. A popular method of simulation testing used to evaluate the effectiveness of various management strategies under uncertainties of a stock or assessment model is management strategy evaluation (Punt et al. 2016). MSE is a flexible modeling framework that enables evaluation of the impacts of alternative management given some uncertainty in population dynamics, uncertainty in assessment model specification, or implementing alternative harvest strategies, to meet short- and long-term management objectives (Punt et al. 2016). MSE models can help scientists and managers identify and compare trade-offs of alternative harvest strategies, and determine which strategies provide the most long-term stability, sustainability, and profitability for all stakeholders (Punt et al. 2016). MSE studies with angler behavior have focused on quantifying the behavior of commercial anglers (Powell et al. 2016; Kuykendall et al. 2017) which may be more straightforward than quantifying the behavior of recreational anglers. In general, commercial anglers' main priority is to maximize profit while maintaining the resources and ecosystem that provides the resources they exploit. Recreational anglers are generally much more diverse in their motivations (Arlinghaus and Mehner 2005; Johnston et al. 2010; Goldsmith et al. 2018). Heterogeneity in motivation as well as socio-economic background and skill can make it difficult to predict group-wide behaviors. A benefit of using MSE to evaluate changes in recreational fishing on a stock is that the framework allows for testing alternative regulatory scenarios while incorporating uncertainty, in this case in fisher’s behavior, to get a range of possible outcomes under each scenario.

Vermilion Snapper's popularity in the Gulf of Mexico's recreational fishing sector has risen over the past decade. Since at least 1990, Vermilion Snapper has been among the top 25 species most frequently harvested in the Gulf of Mexico by recreational anglers (Keithly and Roberts 2017). One possible reason for this is that while other highly sought-after recreational reef fishes have experienced reduced bag limits or shortened fishing seasons, the regulations for Vermilion Snapper have remained constant over the past decade, making it popular among anglers that are indiscriminate. In 1997, a 20 reef-fish aggregate bag limit was established for species without a bag limit, which included Vermilion Snapper (SEDAR 2020). In 1998, the minimum size limit for Vermilion Snapper was increased from 8 inches to 10 inches in total length (TL). Regulations remained unchanged until 2005 when a rebuilding plan was established for Vermilion Snapper and the minimum total length was increased to 11 inches and within the 20 reef-fish aggregate, Vermilion Snapper were limited to 10 fish (SEDAR 2020). By 2007, the size limit was again reduced back to 10 inches TL and the 10 fish bag limit was repealed. In 2013, the 10 fish bag limit was reinstated and since then, the regulations have not changed (SEDAR 2020). From 2005 to 2017, the total recreational harvest of Vermilion Snapper has increased by three-fold (SEDAR 2020). In particular, 2011, 2013, and 2017 had particularly high landings (SEDAR 2020). Understanding the cause of increased landings and effort from the recreational sector is critical for creating effective management strategies for the Vermilion Snapper stock moving forward.

Two other popular recreational reef fish targets in the GOM are Red Snapper and Gray Triggerfish. The Red Snapper stock has exhibited major regulatory changes in the past two decades (Liu et al. 2017). Red Snapper provision an extremely popular commercial and recreational fishery and was heavily exploited since the establishment of the fishery in the late 1800s leading to a major collapse in the 1990s. This prompted regulations to protect and rebuild the stock in the 1980s but considerable increase in the stock abundance did not occur until the early 2000s. Strict bag limits, a five fish per angler per day, and shortened recreational seasons curbed overfishing and served to rebuild the stock. From 2006 to 2018, the recreational fishing season decreased from 194 days to six days (SEDAR 2018). Recreational anglers that would normally have fished for Red Snapper were limited to one or two weekends a year. The stock is still in a rebuilding phase that is expected to remain in effect until 2032 (SEDAR 2018). The overexploitation of Red Snapper and the consequent implementation of stricter regulations led to an increase in demand for the recreational harvest of Gray Triggerfish (Jefferson et al. 2019). Gray Triggerfish were not considered a desirable target until around the 1990s. They had a 12-inch TL minimum size limit and were included in the 20 reef-fish aggregate bag limit. The stock assessment in 2006 indicated that the stock was undergoing overfishing and a rebuilding management regime was implemented (SEDAR 2015). Following an updated assessment in 2011, the bag limit was reduced to two fish per angler per day and fishing season closures were implemented. In 2016 and 2018, the fishing season was shortened to 38 and 10 days respectively because of the persistent low stock abundance. Gray Triggerfish are currently under a rebuilding period that is expected to last until 2025 (SEDAR 2015). While the Red Snapper and Gray Triggerfish stocks are under rebuilding plans, anglers may choose to focus their efforts on more reliable targets with loose regulations, such as Vermilion Snapper.

In this study I, 1) estimate the relative change in recreational fishing allocation from Red Snapper and Gray Triggerfish to Vermilion Snapper as a response to changes in regulation (bag limit, shortened season, or size limit) 2) predict future recreational catch as a response to the three candidate regulation scenarios that vary in the duration of rebuilding periods for Red Snapper and Gray Triggerfish, and 3) incorporate the predicted catch into an MSE model that I developed (in Chapter Two of this dissertation) to account for multi-species interaction. This study will improve our understanding of the impact of species-substitution in the recreational sector on the Vermilion Snapper stock and allow an understanding of how robust management strategies are to potential increased substitution in the future.

3.2 Methods

3.2.1 MRIP Data

I used individual-level respondent data from the Marine Recreational Information Program (MRIP) dockside interviews. Information collected during angler interviews includes the primary and secondary targets of the angler's trip, the number of hours fishing, the number in the fishing party, fishing mode, area of fishing, and catch. I used only the information derived from trips that primarily targeted either Vermilion Snapper (VS), Red Snapper (RS), or Gray Triggerfish (GT). I filtered the data by retaining the interviews that met the following criteria:

1. Interviews conducted in Mississippi, Alabama, or the west coast of Florida,
2. Interviews associated with private and charterboat fishing modes,
3. Interviews that were not shore-based fishing or inshore waters,
4. Interviews that occurred after 2005.

The filtering criteria ensured that the data used best reflected the conditions under which anglers would be targeting Red Snapper, Vermilion Snapper, or Gray Triggerfish. 2005 was used as the cut-off because the regulations for both Red Snapper and Gray

Triggerfish were most variable between the years 2005 and 2017 as a response to low stock abundances (Table 3.1).

3.2.2 Random Utility Model

I developed random utility models (RUM) to predict the probability of an angler targeting Vermilion Snapper. In the multinomial model, utility is a random variable modeled for each choice *j* as:

$$u_j = v_j + \varepsilon_j \qquad [1]$$

where v_j is the indirect utility, or the observable utility, and ε_j is the random error component that provides heterogeneity of individuals. The probability of an angler choosing option *j* over option *k* is calculated as the probability that the utility of *j* is greater than the utility of *k*,

$$P_j = Pr\ (u_j > u_k). \qquad [2]$$

By assuming the error term follows a Type 1 extreme distribution, a logit model can be used to calculate the probability of option *j* as:

$$P_j = \frac{e^{v_j}}{\sum_{k=1}^{K} e^{v_k}} \qquad [3]$$

Indirect utility (*v*), for option *j* is calculated as:

$$v_j = f(x_j) = \beta_1 x_{j,1} + \beta_2 x_{j,2} \ldots + \beta_n x_{j,n}, \qquad [4]$$

where $x_{j,n}$ represents *n* number of attributes of that option (catch rate, cost of the trip, etc.) and β_n represents the relative weight for each attribute. The indicated target species (VS, RS, or GT) represents the choice *j*, and choice attributes included the number of days private recreational fishing was allowed in federal waters (fishing days), bag limits in the number of fish, and size limits in inches. Only management attributes were included in the model because they are the variables tested in the MSE to predict future recreational fishing effort. I quantified the relationship between attributes and species targeted by analyzing the sign of the model coefficients and calculating odds ratios. The sign of the coefficient represents the direction (negative or positive) of the effect and the odds ratio provides the relative change in probability of choosing one option over another. I calculated the odds ratios as:

$$odds_n = e^{\beta_n}. \tag{5}$$

I fit five models to the data (Table 3.2). The full, standard logit model (M1) included size limit, bag limit, and fishing days as alternate invariant covariates.

$$v_j = \beta_j SL_j + \beta_j BL_j + \beta_j FD_j + \varepsilon_j \tag{6}$$

The second model (M2) included all three covariates but fishing days varied across options, or was alternate-specific (α).

$$v_j = \beta_j SL_j + \beta_j BL_j + \alpha\beta_j FD_j + \varepsilon_j \tag{7}$$

In model three (M3), fishing days and size limit were alternate invariant and bag limit was alternate specific.

$$u_j = \beta_j SL_j + \alpha\beta_j BL_j + \beta_j FD_j + \varepsilon_j \tag{8}$$

Model four (M4) excluded fishing days and bag and size limits were alternate invariant.

$$u_j = \beta_j SL_j + \beta_j BL_j + \varepsilon_j \tag{9}$$

Models five through seven were structured the same as M2, M3, and M4 but included a random component. M5 was a mixed logit with the same structure of M2 but size and bag limits had normally distributed random effects (β_j'). M6 was the mixed logit version of M4, with random effects for both size and bag limits. M7 was the mixed logit version of M3 with random effects for size limit and fishing days. I compared all models using AIC and from the best model, I estimated the probability of an individual targeting Vermilion Snapper relative to Red Snapper or Gray Triggerfish each year between 2006 and 2017. I predicted future relative targeting probabilities based on size limit, bag limit, and fishing days that could occur in the future.

Once I estimated the probability of an angler targeting Vermilion Snapper, I fit the probability to the recreational catch for private and charterboat landings in the eastern GOM from 2006 to 2017 using linear regression. From that linear model, I predicted the eastern private and charterboat landings for 2018 to 2068 based on regulations from the future scenarios. It is unknown what the regulations for Red Snapper and Gray Triggerfish will be over the next 50 years, however, I simulated three possible scenarios to evaluate how robust each alternative management strategy is to them (Table 3.3). The first scenario assumed that both Red Snapper and Gray Triggerfish rebuilding would be successful in the expected timeframe, so the stricter regulations only last until 2032 and 2025 respectively. In the second scenario, both rebuilding periods lasted until 2035. In the third scenario, both rebuilding periods lasted until 2050. Whereas it is unlikely that both rebuilding periods would last until 2050, scenarios two and three were intended to indicate how robust the management strategies are to long-term landing changes for recreational anglers. During the rebuilding period, restrictions were slowly decreased so that by the end of the rebuilding period, regulations were back to the early 2000s.

3.2.3 MSE

I developed an MSE simulation model that included an operating and assessment model to test model-based and empirical HCRs on the Vermilion Snapper stock (Figure 3.1). The operating model simulates the population's dynamics and generates data that are used in the assessment model. The suite of HCRs are used to test alternative management strategies for the stock and the efficacy of each HCR is evaluated with the performance indices. All model runs were conducted on the High-Performance Computer at the University of Southern Mississippi.

3.2.3.1 Operating Model

3.2.3.1.1 Population Dynamics

To model the population dynamics of Gulf of Mexico Vermilion Snapper, I constructed an age-structured operating model (OM) composed of 15 age classes, ages zero to 14+. The operating model was similar in structure to that employed in the most recent stock assessment, SEDAR 67, with the exception of the stock-recruitment relationship. The SEDAR 67 assessment model used a Beverton-Holt stock-recruitment relationship, however in the OM used in this work, no stock-recruitment relationship was modeled. Because of the lack of depletion in the stock, steepness was not well estimated and the predicted stock-recruit curve was not very informative. The magnitude of annual recruitment was generated by random selection of the observed deviations from the mean historical recruitment reported in SEDAR 67. Initial population conditions (i.e. numbers-at-age) were established from estimates derived from Stock Synthesis 3.24 and fit to data from 1950 to 2017. Life-history parameters for natural mortality, and the weight-at-length and length-at-age relationships were fixed in the OM.

The population dynamics were calculated using the following equations:

$$N_{y,a} = \begin{cases} \hat{r} * e^{\delta} & a = 0 \\ N_{y-1,a-1}e^{-M_{a-1}} - C_{y,a-1} & 0 < a < A \\ N_{y-1,a-1}e^{-M_{a-1}} - C_{y,a-1} + N_{y-1,a-2}e^{-M_{a-2}} - C_{y,a-2} & a = A \end{cases} \quad [10]$$

where a is age in years, A is the age of the plus group (individuals 14 years and older), and y is the year. The numbers at age a and year y ($N_{y,a}$) are determined by the number at age a-1 in the previous year ($N_{y-1,a-1}$), the natural mortality at age a-1 (M_{a-1}) and the catch-at-age in the previous year ($C_{y-1,a-1}$). Spawning biomass was calculated as the numbers-at-age multiplied by the fecundity-at-age derived from the SEDAR 67 assessment.

3.2.3.1.2 Fishery Data

Four simulated fishing fleets operate in the OM: the eastern Gulf and western Gulf commercial fleets, one Gulf-wide recreational fleet, and a shrimp by-catch fleet. In the initial five years of the simulation, prior to the first assessment and imposition of scenario-specific harvest control rules, sector-specific landings were randomly drawn from a normal distribution based on the mean and standard deviation of catches from the years 2009 to 2017 for the eastern commercial fleet (CE) and western commercial fleet (CW), or 2011 to 2014 for the by-catch fleet (BC). These intervals were chosen for each fleet because they are assumed to represent current fishing practices (D. Goethel and M. Smith, National Marine Fisheries Science Center, personal communication). For example, because a reduction in effort and catch in the BC fleet occurred after 2010 compared to the historically higher levels, I assumed that this is representative of future effort (SEDAR 2020). Recreational landings were randomly drawn from a normal distribution with a mean of the predicted landings from the RUM model and a CV of 10%. Because the predicted landings only accounted for the eastern portion, I added 28% of that value to it to get the gulf-wide recreational landings. After the fifth year of the simulation, catch levels were determined by the harvest control rule and stock abundance estimates derived from the assessment. Total catch for the entire stock was calculated and the fleet-specific catch was determined by dividing the total catch by the mean historical catch proportion for each fleet. I used the predicted recreational landings unless the amount exceeded the amount allowed for the recreational fleet by the control rule. To maintain consistency with the formulation of the SEDAR assessment, catch was reported in biomass (mt) for the commercial fleets and numbers of fish for the recreational fleet and the shrimp bycatch fishery. Harvest rate (H y^{-1}) for each fleet was calculated for commercial fleets by:

$$H_{a,y,f} = \left(\frac{C_{f,y}}{\sum(N_{a,y} * S_{f,a} * W_a)}\right) \qquad [11]$$

or

$$H_{y,f} = \left(\frac{C_{f,y}}{\sum(N_{a,y} * S_{f,a})}\right) \qquad [12]$$

for the recreational and by-catch fleets, where $S_{a,f}$ is the selectivity-at-age for fleet f, $C_{f,y}$ is the total catch in year y for fleet f, and $N_{a,y}$ is the numbers-at-age. Catch-at-age was then calculated by:

$$C_{a,y,f} = \left(H_{y,f} * N_{a,y} * S_{f,a} * W_a\right)e^{\varepsilon}, \qquad \varepsilon \sim N(0, \sigma^2) \qquad [13]$$

for the CE and CW fleets or

$$C_{a,y,f} = \left(H_{y,f} * N_{a,y} * S_{f,a}\right)e^{\varepsilon}, \qquad \varepsilon \sim N(0, \sigma^2) \qquad [14]$$

for the REC and BC fleets. Uncertainty in catch (σ^2) was incorporated to account for implementation error by sampling the true catch from a normal distribution with a mean of the fleet-specific catch and a standard deviation reflective of historical catch standard deviation.

Simulated age composition was generated for the commercial and recreational catches using a multinomial distribution. Because sampling of age compositions is sporadic and inconsistent in the Vermillion Snapper fishery, an effective sample size of $n = 75$ was used every year. An assumption of the multinomial distribution is that each observation has an equal opportunity to be sampled and the only source of uncertainty is in the sample size. For simplicity, length composition data was not simulated.

3.2.3.1.3 Indices of Abundance

Indices of abundance were simulated for each fishing fleet, the SEAMAP Groundfish Survey (*SEAMAP Operations Manual for Trawl and Plankton Surveys* 2016), and the Reef Fish Video Survey (Campbell et al. 2014). Index values were calculated based on the biomass (or number) available to the fishery/survey and the catchability coefficient estimated from the assessment report. Catchability was fixed throughout the projection period in the OM. Index values were log-normally distributed with fleet- or survey-specific error. I converted the numbers-at-age to numbers-at-length using the age-length key derived from the SEDAR 67 assessment because the indices of abundance for the fishery-independent surveys are based on the numbers-at-length. Twelve length bins were used, starting at 1 cm up to 55 cm in 5 cm increments.

3.2.3.1.4 Selectivity

I used selectivity parameter estimates for each fishing fleet and survey from SEDAR 67. Age composition data is not available for the BC fleet, so a fixed selectivity was used with 100% vulnerability for age-1, 30% for age-2, 3% for age-3 and 0% for ages-4+ (SEDAR 45, 2016). For EC and WC, a logistic selectivity function was used, and a domed-shaped, double normal function was used for the REC fleet. Selectivity for both commercial fleets was modeled for the time period after 2007 when Red Snapper individual fishing quotas were implemented. The domed-shaped double normal selectivity function was also used for SEAMAP Groundfish Survey and Reef Fish Video Survey. The age-based logistic selectivity function is:

$$S_{f,a} = \left(1 + e^{-\ln(19)(L'_a - \beta_{1,f})/\beta_{2,f}}\right)^{-1} \quad [15]$$

where $\beta_{1,f}$ is the size-at-50%-selectivity, and $\beta_{2,f}$ is the difference between the size-at-95%-selectivity and that at 50%-selectivity. The length-based double normal selectivity function is defined as:

$$S_{f,l} = asc_{f,l}(1 - j_{1,f,l}) + j_{1,f,l}\left((1 - j_{2,f.l}) + j_{2,f.l}dsc_{f,l}\right) \quad [16]$$

where the ascending (*asc*), joiner (j_1 and j_2), and descending (*dsc*) functions are:

$$asc_{f,l} = (1 + e^{-\beta_{5,f}})^{-1} + (1 - \left(1 + e^{-\beta_{5,f}}\right)^{-1})\frac{e^{\left(\frac{-(L'_l - \beta_{1,f})^2}{e^{\beta_{3,f}}}\right)} - t1_{min,f}}{1 - t1_{min,f}} \quad [17]$$

$$dsc_{f,l} = 1 + \left(\left(1 + e^{-\beta_{6,f}}\right)^{-1} - 1\right)\frac{e^{\left(\frac{-(L'_l - peak_{2,f})^2}{e^{\beta_{4,f}}}\right)} - 1}{t2_{min,f} - 1} \quad [18]$$

$$j_{1,f,l} = \left(1 + e^{\left(-20\frac{L'_l - \beta_{1,f}}{1+\left|L'_l - \beta_{1,f}\right|}\right)}\right)^{-1} \quad [19]$$

$$j_{2,f,l} = \left(1 + e^{\left(-20\frac{L'_l - peak_{2,f}}{1+\left|L'_l - peak_{2,f}\right|}\right)}\right)^{-1} \quad [20]$$

and $t1_{min}$ and $t2_{min}$ are defined as:

$$t1_{min,f} = e^{\left(-\frac{\left(L_{min} - \beta_{1,f}\right)^2}{e^{\beta_{3,f}}}\right)} \quad [21]$$

$$t2_{min,f} = e^{\left(-\frac{\left(L'_{max} - peak_{2,f}\right)^2}{e^{\beta_{4,f}}}\right)} \quad [22]$$

3.2.3.1.5 Uncertainty

Uncertainty was incorporated into the OM in multiple components. Process error in recruitment was modeled with a normal distribution, to simulate the observed annual variations. Implementation error was modeled with a normal distribution in the projected catch to simulate variability in annual catch for fleets that harvest more or less than their allotted limits. Observation error was modeled with a lognormal distribution for the indices of abundance.

3.2.3.1.6 Competition Index

An index of Red Snapper competition was created based on estimates of Red Snapper abundance from the most recent stock assessment. I assumed that ecosystem carrying capacity (*K* mt) is the sum of Vermilion Snapper virgin biomass and the mean

Red Snapper biomass from 1940 to 1950. This period represents a period before heavy Red Snapper exploitation and coincides with the initial year of the Vermilion Snapper assessment. Red Snapper biomass relative to K was used as the index for competition and was projected to 2116 based on estimates from an age-structured catch-at-age model, and fishing at a level to reach recovered biomass by 2032. In the OM, the number of Vermilion Snapper that died due to the Red Snapper competition was accounted for by assigning the fish to a fishing fleet with the harvest rate being determined by the index value for year y.

3.2.3.2 Assessment Model

I used a statistical-catch-at-age model, Stock Synthesis 3.24 (SS), for the assessment model in the simulation. The assessment model was parameterized in the same way as the most recent stock assessment, SEDAR 67, except for three differences. First, the stock-recruitment parameters were fixed in the model to the estimated values from SEDAR 67, to aid with convergence. Second, an additional discard fleet was included in the model and used as a proxy for Red Snapper competition-induced mortality. Third, the commercial CPUE index was included from 2017 to the end of the simulation. Previous studies have shown that a method for including sources of natural mortality into older versions of SS models (versions earlier than 3.3) is to incorporate an index to simulate a fishing fleet and allow SS to estimate the numbers killed (Sagarese et al. 2015). To reflect the current assessment cycle frequency, an assessment was performed every five years. However, unlike the current cycle, all data were available up to the year before the assessment (e.g. if the assessment was performed in 2022, all data through 2021 were included). Data included in the assessment model included the magnitude of catch for the commercial and recreational fleets (CE, CW, REC), magnitude of discard for the shrimp by-catch fleet and the Red Snapper fleet, CPUE indices for commercial, recreational, shrimp by-catch, and Red Snapper fleets, as well as for the SEAMAP Groundfish survey, and the Reef Fish Video Survey. Age composition data were included for the three commercial and recreational fleets. The assessment was performed with new data and model convergence was checked. Once the model converged, the target F_{SPR} was checked and if it was not at least 30% (the limit reference point), the model was run iteratively changing the target SPR parameter until the target F_{SPR} was realized. After the assessment was run, management reference points were checked to determine catch limits and if a rebuilding plan should be implemented.

3.2.3.3 Harvest Control Rules

I evaluated and compared both model-based and empirical harvest control rules (HCR) as means for managing the Vermilion Snapper stock (Table 3.4). The model-based HCRs used an age-structured assessment model (Stock Synthesis) to evaluate the stock status and set catches. From the assessment model, values of overfishing level (OFL) and acceptable biological catch (ABC) were estimated. ABC was calculated as 75% of the OFL. The ABC was proportionally allocated between the three fishing fleets as follows: CE = 35%, CW = 17%, and REC = 48%. These fixed proportions p_f were based on the mean proportions for the final five years of catch data (2013 to 2017). The empirical HCR did not use output from the assessment model. Instead, annual catches were determined by the indices of abundance and CPUE from the fisheries and surveys. To align with the current management strategy, the base HCR was a constant conditional catch rule set at the current quota. After every assessment period, the status of the stock was evaluated and if it was not overfished, the quota for the next five years was not changed, and fishing continued similar to historical levels. The constant quota was set at 3,110,000 lbs (1,555 mt), the most recent target set in the Gulf of Mexico. However, if the stock was overfished, the quota was reduced until the next assessment, coincident with the current NOAA Fisheries' regulatory approach to determine rebuilding periods. Overfished status was defined as the spawning potential ratio (SPR) of the stock below 30% of unfished population levels. $SPR_{30\%}$ was one of the three MSY proxies used in the previous assessment and was established as an acceptable MSY proxy (SEDAR 2020). To calculate the reduced quota, the stock dynamics were projected with no fishing to determine the time taken to reach an SSB of 30%. If the time required to rebuild (T_{min}) was less than ten years, T_{target} was set to ten years. If the time required was longer than ten years, the maximum time (T_{max}) allowed for rebuilding was calculated as T_{min} plus one generation time (seven years) (SEDAR 2020). Catch was calculated based on the level of fishing mortality required to rebuild the stock within the given period. Total catch was calculated and then allocated amongst the three fisheries based on the respective proportions. At the next assessment period, if the stock was still overfished but on track to rebuild by T_{target}, the catch magnitudes from the previous assessment were kept. If the stock did not recover to $SPR_{30\%}$, catch was further reduced using the methods described above. If the stock was above $SPR_{30\%}$, the catch was no longer reduced and was set to the original quota.

Two alternative harvest control rules were evaluated, a constant conditional catch set to the annual catch limit (ACL) and an empirical rule that was based on the indices of abundance. The constant conditional catch HCR was set to the annual catch limit (ACL), which was calculated as 75% of the overfishing limit (OFL). If the stock was identified to be overfished after an assessment, the ACL was reduced using the same methods described for the quota HCR. Otherwise, the total catch was set to the ACL and allocations were established by proportional division among each fleet. The empirical HCR was derived by modeling each of the indices from the previous *n* years (*n* = 5) using linear regression. Total allowable catch (TAC) was calculated by multiplying the slope of the fitted regression line (m_i) by the moving average of the previous 5 years' catch ($\bar{C}_{y-5,y}$) and the respective weighting for each index (w_i):

$$TAC = \bar{C}_{y-5,y}\left(\sum_{i=1}^{I} w_i(1 + m_i)\right) \quad [23]$$

The TAC was capped at the current quota (1,555 mt) for all scenarios. Different weightings of the indices were evaluated with sensitivity analyses (Table 3.5). In the first two scenarios, only fishery CPUE indices were considered when calculating the TAC. The third scenario considered only the survey and competition indices. The fourth scenario included all indices with approximately even weightings. Surveys were weighted slightly heavier, 0.15 compared to 0.14, to make the weighting equal 1 and because they are more reliable as an index of the population abundance than fishing CPUE indices. The fifth scenario uses only the Red Snapper index to determine catch for the following years.

3.2.3.4 Management Objectives

The current status of the Vermilion Snapper population is estimated to be above the target biomass level and therefore the management objectives for this project are to maintain the population above MSST, exploit the stock by allowing for greater catch when possible, and effectively implement rebuilding strategies if the biomass falls below the limit (MSST).

3.2.3.5 Performance Indices

To assess and compare the effectiveness of each harvest control rule in meeting the management objectives, I analyzed a suite of performance indices. To evaluate the impact of the management strategy scenario on the fishery, I compared median catches and calculated average annual variability (AAV) of 100 trials of each management strategy scenario. To evaluate the impact of a management strategy on the stock, I calculated the terminal spawning potential ratio ($SPR_{terminal}$) where $SPR_{terminal}$ is the ratio of the SSB in year y to the virgin SSB, the probability of the stock being overfished ($B/B_{SPR30\%}$) at least once over n trials, and the probability of overfishing occurring ($F/F_{SPR30\%}$) at least once over n trials.

3.3 Results

Red Snapper was the most frequently reported primary target in the MRIP survey of the three species (92%), followed by Vermilion Snapper (4%), and then Gray Triggerfish (3.5%) (Table 3.6). The number of trips targeting Red Snapper primarily was greatest in the earlier years (2006 and 2007) and the later years (2016 to 2018) with a substantial decrease in the interim (Figure 3.2). The number of trips primarily targeting Vermilion Snapper increased over time, reaching a maximum in 2017. The number of trips primarily targeting Gray Triggerfish stayed relatively steady since 2006 except for the years 2011, 2016, and 2018, which had an unusually large number of trips.

3.3.1 RUM Analysis

For the five multinomial and mixed logit models developed, I found variation in model performance. The two alternate-specific models, M2 and M3, performed similarly well and the alternate-invariant models, M1 and M4, both performed poorly. M5, with alternate-invariant size and bag limits and alternative-specific fishing days, had an AIC value similar to that of M2. In M2, species targeting was significantly influenced by size limit, bag limit, and fishing days (Table 3.7). To understand the relationship between attributes and species targeting, I analyzed both the sign of the coefficient and the odds ratio. The factor "size limit" negatively impacted species targeting, bag limit positively affected species targeting, and fishing days negatively affected targeting for Gray Triggerfish relative to Vermilion Snapper but positively affected targeting for Red Snapper relative to Vermilion Snapper. As size limit increased for a given species, the probability of an angler targeting that species decreased. As the bag limit increased for a given species, the probability of an angler targeting that species increased. The alternate-specific variable fishing days had opposite impacts on Gray Triggerfish and Red Snapper. As the number of fishing days in the season increased, the probability of an angler targeting Gray Triggerfish relative to Vermilion Snapper decreased, however, as the number of fishing days increased an angler was more likely to target Red Snapper than Vermilion Snapper. The log odds ratio showed that for one-inch change in size limit, an individual is 15% less likely to target that species and for a one fish change in the bag limit, an angler is 9% more likely to target that species. The number of fishing days had a much smaller impact, a change in one day less than 1% change in an angler targeting either Gray Triggerfish or Red Snapper over Vermilion Snapper. Because season lengths can vary by tens to hundreds of days, fishing days could end up having a large impact on the overall targeting probability. I used M2 to predict the probability of targeting Vermilion Snapper by fitting the model to new data, which included the future regulations for each scenario.

3.3.2 Mixed logit model

In the mixed logit model, the standard deviations of the random variables (size and bag limit) were not statistically significant (p-value = 0.713 and p-value = 0.828 respectively). Because the standard deviations were not significant, the random effect was not statistically significant. Similar to M2, all covariates were statistically significant. As the size limit increases for a species by one inch, the probability of anglers targeting it decreased by 15%. As the bag limit increased by one individual, the probability of targeting that species increased by 5.7%. The probability of targeting Red Snapper over Vermilion Snapper increased by 0.84% when fishing days are increased by one day but the probability of targeting Gray Triggerfish over Vermilion Snapper decreased by 0.30% when fishing days are increased by one day.

3.3.3 Predicted recreational landings

From M2, I estimated the probability of an angler targeting Vermilion Snapper relative to the other two species for the years 2006 to 2017. Estimated probabilities ranged from 87.7% to 97.2% for Red Snapper, 1.2% to 6.9% for Vermilion Snapper, and 1.6% to 7.2% for Gray Triggerfish (Figure 3.3). From 2013, the relative probability of an angler targeting Vermilion Snapper steadily increased, and the relative probability of an angler targeting Red Snapper decreased. The linear regression that fit the estimated probability of an angler targeting Vermilion Snapper to the annual eastern private and charterboat landings was statistically significant (p-value = 0.033, $R^2 = 0.315$). The estimated landings followed the general trends of the true landings and most true landing values were within the 95% confidence interval (Figure 3.4).

The forecasted recreational landings for Vermilion Snapper did not differ much between scenarios one and two (Figure 3.5). Landings predicted under scenario three followed the same trends as predicted landings under the other scenarios but for longer periods of time (Figure 3.5). Under scenario three, anglers targeted Vermilion Snapper much more than in the other two scenarios between the years of 2026 and 2059 so landings declined more gradually. By the terminal four years, landings for all three scenarios were approximately equal. Under scenario one, the predicted relative probability of targeting Vermilion Snapper started at 6.8% in 2018 and declined to 4.6% by 2068 (Figure 3.3). The predicted landings for Vermilion Snapper ranged from 929,000 fish to 1,258,000 fish (Figure 3.5). The predicted relative probability of targeting Red Snapper started at 88% in 2018 and gradually increased to 92.7% by 2068 (Figure 3.3). The predicted relative probability of targeting Gray Triggerfish started at 4.9% in 2018 and increased over the first 11 years then gradually declined to 3.6% by 2068 (Figure 3.3). Under scenario two, the predicted future relative probability of targeting Vermilion Snapper started at 6.8% in 2018 and declined to 4.6% by 2068 (Figure 3.3). Predicted landings for Vermilion Snapper ranged between 930,000 fish and 1,257,000 fish (Figure 3.5). The predicted relative probability of targeting Red Snapper started at 88% in 2018 and gradually increased to 92.0% by 2068 (Figure 3.3). The predicted relative probability of targeting Gray Triggerfish started at 5% in 2018 and increased over the first 11 years then gradually declined to 3.3% by 2068 (Figure 3.3). Under scenario three, the predicted relative probability of targeting Vermilion Snapper started at 6.8% in 2018 and declined to 4.6% by 2068 (Figure 3.3). Predicted landings for Vermilion Snapper ranged between 931,000 and 1,253,000 fish (Figure 3.5). The predicted relative probability of targeting Red Snapper started at 88.2% in 2018 and gradually increased to 92.1% by 2068 (Figure 3.3). The predicted relative probability of targeting Gray Triggerfish started at 5% in 2018 and steadily declined to 3.3% by 2068 (Figure 3.3).

3.3.4 MSE

All harvest control rules effectively maintained the population above MSST and effectively implemented rebuilding strategies if it was necessary, for each of the three scenarios. The population fell below MSST during one trial under eHCR3 and scenario one. The population was below MSST for five years but recovered to above MSST by the next assessment year. I performed 100 trials for each HCR per scenario, however, because of the non-convergence of the assessment model, not all 100 trials ran to completion. For scenario one, between 84 - 94% of trials ran to completion (Table 3.8). For scenario two, between 84 – 92% of trials ran to completion (Table 3.8). For scenario three, between 85-92% of trials ran to completion (Table 3.8).

Commercial catch was influenced more by the harvest control used and the recreational catch was influenced by the scenario implemented. The commercial fleets experienced the greatest variability in catch between HCR. The ACL rule had the highest catches for both the eastern and western commercial fleets (Figures 3.6 and 3.7). The median catches were approximately 1.5 times greater with the ACL rule than the other rules for the CE fleet (Figure 3.6) and approximately 2 times greater with the ACL rule for the CW fleet (Figure 3.7). The Quota rule had the second-highest median landings, but the difference was much smaller for both CE and CW fleets. Both fleets did have a few extremely large outliers that were equal in magnitude to ACL catches. Under the empirical rules, eHCR1 generally had the greatest median catches for the CE fleet and eHCR2 allowed the greatest median catches for the CW fleet (Figures 3.6 and 3.7). This pattern held true under all three scenarios. The ACL rule resulted in the greatest recreational landings under all three scenarios, however, the difference between landings under the ACL rule and landings under the other six rules was much smaller than for the difference between landings of the commercial fleets (Figure 3.8). The third scenario had the greatest difference in recreational landings among the HCR. Additionally, median landings under all rules were greater in scenario three than for scenarios one and two. Average annual variability was smallest for the recreational landings and greatest for the eastern commercial fleet (Figures 3.9 and 3.10). For the CE fleet, AAV was the smallest under the ACL rule for all three scenarios. AAV was greatest under eHCR2 for scenario two and greatest under eHCR4 for scenario three.

None of the seven HCR had a negative impact on the stock. Overfishing never occurred out of the 1,858 completed (i.e. successfully converged) trials. The probability of the stock being overfished at least once was less than 0.0005%. The stock was overfished in only one trial in scenario one and never in scenario two or three. This occurred under the eHCR3 rule and within five years, the stock had recovered so that it was no longer overfished. All HCR achieved terminal SPR greater than the limit reference point of 0.30 for all three scenarios (Figure 3.11). Under the ACL rule, there was one trial that had a terminal SPR of 0.32 which was the lowest SPR of all trials. Terminal SPRs were generally highest for scenario two and lowest for scenario three.

Median terminal SPR for scenario one was greatest under eHCR4 and lowest under ACL rule. Median terminal SPR for scenario two was greatest under eHCR3 and lowest under ACL rule. Median terminal SPR for scenario three was greatest under eHCR1 and lowest under ACL rule.

3.4 Discussion

Fish stocks are influenced by environmental, biological, and anthropogenic factors, and understanding the impact that each has on a stock is complicated. Understanding and being able to predict anthropogenic influences such as removal and fishing effort is essential for proper long-term management of recreationally and commercially exploited stocks. In the Gulf of Mexico, little is known about the ecological and anthropogenic influences on the Vermilion Snapper population (Johnson et al. 2010; Davis et al. 2015b). By better understanding the impacts of ecological pressures, scientists can reduce uncertainty in assessment models which leads to improved estimates of biomass and productivity. Concurrently, a better understanding of anthropogenic pressures can help managers allocate resources more effectively to support viable fisheries and long-term sustainability (Criddle et al. 2003; Hunt et al. 2007).

In this study, I modeled recreational species targeting and species substitution with a random utility model. I then coupled the output of the RUM with a management strategy evaluation to estimate the impact of future recreational fishing in combination with intraspecific competition impacts on the Gulf of Mexico Vermilion Snapper population. The results of the RUM suggest that species substitution occurs with anglers targeting either Red Snapper, Gray Triggerfish, or Vermilion Snapper. I found that in years where Red Snapper and Gray Triggerfish had changes in regulations, the relative probability of targeting either of them decreased while the relative probability of targeting Vermilion Snapper increased. Changes in the Red Snapper fishing season length have direct consequences on the probability of anglers targeting Vermilion Snapper (Figure 3.12). This factor should be taken into consideration when setting annual regulations and restrictions for both Red Snapper and Vermilion Snapper. By understanding this relationship, managers can account for potential shifts in effort towards Vermilion Snapper and implement proactive management. Red Snapper targeting probability was also directly impacted by changes in Gray Triggerfish bag limits. Negative changes in the bag limit resulted in a noticeable increase in the probability of targeting Red Snapper. Again, managers should consider this factor when making regulations. As expected, the behavioral decisions of anglers are complicated and conditional on many factors (Gentner 2004; Haab et al. 2012), of which only a few were included in this analysis. However, beginning to understand and account for species substitution in recreational fisheries can help managers be more proactive when setting regulations.

The length of the fishing season and the bag limit significantly influenced angler's target choice. Size limit was not significant; however, this is not surprising because size limits do not change frequently, unlike fishing season that has been extremely dynamic for both Red Snapper and Gray Triggerfish over the past decade. Interestingly, fishing season length and bag limit had opposite effects depending on the species. For example, increases in the fishing season negatively impacted the probability of targeting Gray Triggerfish over Vermilion Snapper but positively impacted the probability of targeting Red Snapper over Vermilion Snapper. This suggests that anglers prefer Red Snapper over

Vermilion Snapper but prefer Vermilion Snapper over Gray Triggerfish given longer fishing seasons. Conversely, increases in the bag limits positively impacted the probability of targeting Gray Triggerfish over Vermilion Snapper but negatively impacted the probability of targeting Red Snapper over Vermilion Snapper. This result is surprising because I expected Red Snapper would be targeted more if bag limits increased considering it is such a popular fishery. One possible explanation for this result is that between 2006 and 2017 the bag limit for Red Snapper only changed once, from five to two and it was early in the period used. This decrease is small compared to the bag limit change for Gray Triggerfish that dropped from 20 fish to two. The Red Snapper bag limit changed in 2008 and remained at two through 2018, so there were only two years of data when the bag limit was five compared to the 11 years when the bag limit was two. These two differences may contribute to why the effects of bag limits were opposite, and perhaps if earlier years of data were included, the impact of bag limit on Red Snapper targeting would be better estimated.

The findings of this study, that recreational anglers will substitute their target species when regulations tighten, support previous studies from both the Gulf of Mexico and other regions around the world (Hunt et al. 2002; Gentner 2004; Scheld et al. 2020). In an earlier, but similar study, Gentner (2004) used a stated preference approach to evaluate species substitution for four species or groups. Gentner (2004) also found stricter regulations caused anglers to switch from one species to another in the Gulf of Mexico and South Atlantic. He estimated that reducing the bag limit for Red Snapper by two fish would decrease the number of trips targeting Red Snapper by 5% and increase the trips targeting King Mackerel and Dolphin (Gentner 2004). In my analysis, a reduction in the bag limit of Red Snapper by three fish reduced the probability that an angler would target Red Snapper over Vermilion Snapper or Gray Triggerfish by 5.3%. Both studies support recreational species substitution among Red Snapper anglers. Additionally, the findings of this study support Sutton and Ditton's (2005) the conclusion that anglers strategically substitute one species for another found in the same location. Gray Triggerfish, Vermilion Snapper, and Red Snapper all share habitats so this likely occurs for these three species as well as others not included in this study. One difference between this study and others that looked at species substitution is that other studies included angler demographic variables (Sutton and Ditton 2005; Haab et al. 2012; Scheld et al. 2020). Sutton and Ditton (2005) found that in the Gulf of Mexico, age, education level, and gender significantly influence an angler's willingness to substitute species. Whereas angler demographic attributes were not included in the RUMs in this study, they are undoubtedly important for understanding angler motivations and preferences. Sutton and Ditton (2005) also noted that the significant drivers varied between Florida and Texas and that target-switching behavior is not consistent across populations and fisheries. I did not account for any spatial differences in the RUMs but Sutton and Ditton (2005) suggest that FL anglers are more flexible and willing to substitute their target species. Other studies quantified angler's welfare and willingness to pay as an economic analysis of the substitutability of recreational targets. Willingness to pay analyses quantify how much an individual is willing to pay to catch and keep one additional fish. At some point, an individual is no longer willing to pay more and would rather switch targets. Haab et al. (2012) estimated the willingness to pay for one additional Red Snapper ranged from $32 to $123. Understanding the economic value of each target species to anglers can provide a deeper understanding of what motivates them to switch target species and when. For popular sport fish such as Red Snapper, individuals are willing to pay more before they change targets compared to a species such as Seatrout, where the willingness to pay ranged between $7 and $12 (Haab et al. 2012).

From the MSE simulation, I found that the Vermilion Snapper population is resilient to the predicted recreational catches and intraspecific competition from Red Snapper under the current harvest control rule. The Quota rule, which reflects the current HCR, maintained the biomass above MSST during all scenarios, and the stock was never overfished or experienced overfishing. This HCR is sustainable long-term and can maintain adequate biomass levels of the population when accounting for intraspecific competition. If the management of Vermilion Snapper continued as it is now for the next 50 years, it is unlikely the stock would face a major collapse or need to go into a rebuilding period. The Quota rule not only worked well for the stock, but it also met fishery objectives of maintaining high catches and reducing interannual variability for both the commercial and recreational sectors.

Alternative HCRs were as effective in maintaining the population above MSST and preventing overfishing as the Quota rule. As expected, the trade-off of greater landings under the ACL rule resulted in reduced biomass of the stock, however, the biomass levels remained well above MSST, which suggests that the stock can support larger removal than it currently is experiencing. Empirical rules were as effective in achieving management objectives as the model-based rules. Empirical rules have been tested and implemented in many fisheries to date and have proven effective for managing data-limited and data-moderate stocks (Rademeyer et al. 2008; De Moor et al. 2011; Punt et al. 2012). In scenarios two and three, empirical rules served to maintained biomass as high as or higher than both the Quota and ACL rules. Empirical rule three consistently performed well for all of the performance metrics for all three scenarios. While the landings for the CW fleet were not the highest under eHCR3, the AAV was generally lower under eHCR3 than the other eHCR, which may make it a preferable choice for commercial fishermen because it provides more stability and consistency from year-to-year. However, empirical rules are not entirely trustworthy. Simulations have shown that rules that rely on catch rates can be very misleading (Punt and Campbell 2001). High inter-annual variability in catch rate can cause rules to be triggered earlier than they should. For example, eHCR1 performed poorly, particularly in scenario one, due to greater AAV for commercial fleets. One method of dampening noise from inter-annual variability is to use the natural logarithm of the catch average to improve the efficacy of the empirical rules (Plagányi et al. 2018). While often the preferred control rules include information from both fishery-dependent and fishery-independent sources (Plagányi et al. 2018), one of the more effective empirical rules in this study only used fishery-independent survey data. Excluding fishery-dependent CPUE indices is supported in the most recent Vermilion Snapper stock assessment (SEDAR 2020). In SEDAR 67 (2020), the commercial CPUE indices time series was truncated after 2007 because of difficulty in standardizing the indices post-Red Snapper IFQ implementation and there was very little impact on the population estimations from excluding them. A major concern of using fishery-dependent CPUE data is that they often exhibit hyperstability, where the population declines faster than the indices as a result of changes in technology or targeting behaviors (Hilborn and Walters 1992; Erisman et al. 2011). An additional benefit of using empirical rules is that they can be applied quickly (Plagányi et al. 2018). Hutniczak et al. (2019) suggest that stocks with large directed recreational sectors may need more frequent updating of assessment. If recreational fishing effort for Vermilion Snapper does continue to increase in the future, more frequent assessments may be necessary. However, this takes time and resources, which are often limited. The results of this study suggest that extending the time between formal assessments and using an empirical rule based on fishery-independent surveys in the interim would be sufficient for the GOM Vermilion Snapper stock.

In addition to the previously mentioned limitations, there were others in this study. The MRIP survey data that was used to fit the utility model is only available for Mississippi, Alabama, and Florida in the Gulf; Texas and Louisiana have their versions of recreational surveys and those data are not directly comparable to the MRIP data. Ideally, if there was just one survey for the entire Gulf of Mexico, that would allow us to estimate total Gulf-wide recreational landings instead of having to estimate the eastern and western landings separately. Second, the probabilities of selecting any of the given options are all relative to each other. We cannot say that recreational anglers have a 3% probability of targeting Vermilion Snapper: we have to say that given the option to target Red Snapper, Gray Triggerfish, or Vermilion Snapper, recreational anglers have a 3% probability of targeting Vermilion Snapper over Red Snapper or Gray Triggerfish. Had we chosen different alternative targets, we would have gotten different probabilities of targeting Vermilion Snapper. Future studies could examine how targeting probabilities change based on the alternative choices and examine the Red Snapper Vermilion Snapper switching dynamic more closely. Another problem with the RUM is that because the

MRIP data was so heavily skewed towards Red Snapper (12,355 Red Snapper trips and 535 Vermilion Snapper trips), the model had trouble predicting when the angler would target another species besides Red Snapper from the original dataset. Finally, the RUM model did not include any trip attributes that have been shown to have effects on targeting in other utility models (Criddle et al. 2003; Haab et al. 2008; Scheld et al. 2020). I only used policy attributes in the model because there are infinite possible future scenarios for how trip costs or weather might change. I also wanted to look explicitly at how regulations are influencing species substitution for Gulf anglers. Including trip attributes likely would have improved the fit of the model but to use the model to predict future catches, I limited it to only include policy attributes.

Future research should continue to develop the utility model by including trip attributes to better understand current and past angler targeting behaviors. Additionally, including more species or species complexes as alternatives should be investigated. Some work has been done to compare the targeting of different species groups in the Gulf of Mexico (Gentner 2004; Haab et al. 2012) but more research on what drives anglers' decision making would be useful for future ecosystem approaches to management. Also, creating a specific survey asking anglers to choose between a suite of trip options (including target species, trip costs, regulations, etc.) would provide more direct data that could be included in the utility model. MRIP data is convenient to use because it is available for many years and is a standardized survey, however, there are limitations to the data that could be minimized if a specific survey was developed. It would also potentially provide a more balanced data set, which would improve predictions from the RUM.

The results from this study can provide insight into recreational anglers' behavior and support long-term assessment and management of Vermilion Snapper. We can begin to understand recreational anglers' choices using random utility models to identify what factors drive their decisions. I found that for GOM anglers choosing between Red Snapper, Gray Triggerfish, and Vermilion Snapper, bag limits and fishing season are significant factors but the relationships between them are nuanced. Additionally, in years where regulations were tightened for either Gray Triggerfish or Red Snapper, there was a resulting increase in the probability of targeting Vermilion Snapper. Lastly, the current harvest control rule can effectively manage the Vermilion Snapper stock for the long term but it is not the only effective HCR for the stock and alternative rules should be considered to save time or increase catches for commercial and recreational sectors.

Table 3.1 *Recreational Regulations*

Year	GT			RS			VS		
	Bag limit	Size Limit	Fishing Days	Bag Limit	Size Limit	Fishing Days	Bag Limit	Size Limit	Fishing Days
2006	20	12	365	5	16	194	10	11	365
2007	20	12	365	5	16	194	10	11	365
2008	20	14	365	2	16	65	10	10	365
2009	20	14	365	2	16	75	10	10	365
2010	20	14	365	2	16	77	10	10	365
2011	20	14	365	2	16	48	10	10	365
2012	20	14	181	2	16	46	10	10	365
2013	2	14	304	2	16	42	10	10	365
2014	2	14	304	2	16	9	10	10	365
2015	2	14	304	2	16	10	10	10	365
2016	2	14	38	2	16	11	10	10	365
2017	2	14	151	2	16	42	10	10	365
2018	1	15	10	2	16	6	10	10	365

Recreational fishery regulations for Gray Triggerfish (GT), Red Snapper (RS), and Vermilion Snapper (VS). Bag limit is in number of fish, size limit is in inches, and fishing days is the number of days for private recreational fishing was allowed in Federal waters.

Table 3.2 *Random Utility Models*

Model	Alternate Invariant	Alternate Variant	Random Effects
M1	Size Limit, Bag Limit, Fishing Days		
M2	Size Limit, Bag Limit	Fishing Days	
M3	Fishing Days, Size Limit	Bag Limit	
M4	Size Limit, Bag Limit		
M5	Size Limit, Bag Limit	Fishing Days	Size Limit, Bag Limit
M6	Size Limit, Bag Limit		Size Limit, Bag Limit
M7	Size Limit, Fishing Days	Bag Limit	Size Limit, Fishing Days

The five random utility models fit to the data.

Table 3.3 *Future Management Regulations*

	Scenario 1						Scenario 2						Scenario 3					
	GT			RS			GT			RS			GT			RS		
Year	Bag Limit	Size Limit	Fishing Days	Bag Limit	Size Limit	Fishing Days	Bag Limit	Size Limit	Fishing Days	Bag Limit	Size Limit	Fishing Days	Bag Limit	Size Limit	Fishing Days	Bag Limit	Size Limit	Fishing Days
2018	1	15	10	2	16	6	1	15	10	2	16	6	1	15	10	2	16	6
2019	1	15	10	2	16	6	1	15	10	2	16	6	1	15	10	2	16	6
2020	1	15	10	2	16	6	1	15	10	2	16	6	1	15	10	2	16	6
2021	1	15	20	2	16	6	1	15	20	2	16	6	1	15	10	2	16	6
2022	1	15	20	2	16	6	1	15	20	2	16	6	1	15	10	2	16	6
2023	1	15	30	2	16	6	1	15	30	2	16	6	1	15	10	2	16	6
2024	1	15	30	2	16	6	1	15	30	2	16	6	1	15	10	2	16	6
2025	1	15	40	2	16	6	1	15	30	2	16	6	1	15	10	2	16	6
2026	2	14	50	3	16	8	1	15	30	3	16	8	1	15	10	2	16	7
2027	2	14	50	3	16	8	1	15	30	3	16	8	1	15	10	2	16	7
2028	2	14	50	3	16	8	1	15	30	3	16	8	1	15	20	2	16	7

Table 3.3 (continued) *Future Management Regulations*

2029	2	14	50	4	16	8	1	15	40	4	16	8	1	15	20	2	16	7
2030	2	14	50	4	16	8	1	15	40	4	16	8	1	15	20	2	16	7
2031	2	14	50	4	16	8	1	15	40	4	16	8	1	15	20	2	16	7
2032	2	14	50	4	16	8	1	15	40	4	16	8	1	15	20	3	16	7
2033	2	14	50	5	16	10	2	14	40	5	16	10	1	15	20	3	16	7
2034	2	14	50	5	16	10	2	14	50	5	16	10	1	15	20	3	16	8
2035	2	14	50	5	16	10	2	14	50	5	16	10	1	15	20	3	16	8
2036	2	14	50	5	16	10	2	14	50	5	16	10	1	15	20	3	16	8
2037	2	14	50	5	16	15	2	14	50	5	16	15	1	15	20	3	16	8
2038	2	14	50	5	16	15	2	14	50	5	16	15	1	15	20	3	16	8
2039	2	14	50	5	16	15	2	14	60	5	16	15	1	15	30	3	16	8
2040	2	14	50	5	16	15	2	14	60	5	16	15	1	15	30	3	16	8
2041	2	14	50	5	16	20	2	14	60	5	16	20	1	15	30	4	16	8

Table 3.3 (continued) *Future Management Regulations*

2042	2	14	50	5	16	20	2	14	60	5	16	20	1	15	30	4	16	9
2043	2	14	50	5	16	20	2	14	60	5	16	20	1	15	30	4	16	9
2044	2	14	50	5	16	20	2	14	60	5	16	20	1	15	30	4	16	9
2045	2	14	50	5	16	25	2	14	60	5	16	25	1	15	30	4	16	9
2046	2	14	50	5	16	25	2	14	70	5	16	25	1	15	30	4	16	9
2047	2	14	50	5	16	25	2	14	70	5	16	25	1	15	30	4	16	9
2048	2	14	50	5	16	25	2	14	70	5	16	25	1	15	30	4	16	9
2049	2	14	50	5	16	30	2	14	70	5	16	30	1	15	30	4	16	9
2050	2	14	50	5	16	30	2	14	70	5	16	30	2	14	40	5	16	10
2051	2	14	50	5	16	30	2	14	70	5	16	30	2	14	40	5	16	10
2052	2	14	50	5	16	30	2	14	70	5	16	30	2	14	40	5	16	10
2053	2	14	50	5	16	30	2	14	70	5	16	30	2	14	40	5	16	10
2054	2	14	50	5	16	35	2	14	80	5	16	35	2	14	40	5	16	10

Table 3.3 (continued) *Future Management Regulations*

2055	2	14	50	5	16	35	2	14	80	5	16	35	2	14	40	5	16	20
2056	2	14	50	5	16	35	3	14	80	5	16	35	3	14	60	5	16	20
2057	2	14	50	5	16	35	3	14	80	5	16	35	3	14	60	5	16	20
2058	2	14	50	5	16	35	3	14	80	5	16	35	3	14	60	5	16	20
2059	2	14	50	5	16	40	3	14	90	5	16	40	3	14	60	5	16	20
2060	2	14	50	5	16	40	3	14	90	5	16	40	3	14	80	5	16	30
2061	2	14	50	5	16	40	3	14	90	5	16	40	3	14	80	5	16	30
2062	2	14	50	5	16	40	3	14	90	5	16	40	3	14	80	5	16	30
2063	2	14	50	5	16	40	3	14	90	5	16	40	3	14	80	5	16	30
2064	2	14	50	5	16	40	3	14	90	5	16	40	3	14	100	5	16	30
2065	2	14	50	5	16	40	3	14	90	5	16	40	3	14	100	5	16	40
2066	2	14	50	5	16	40	3	14	100	5	16	40	3	14	100	5	16	40
2067	2	14	50	5	16	40	3	14	100	5	16	40	3	14	100	5	16	40

Table 3.3 (continued) *Future Management Regulations*

2068	2	14	50	5	16	40	3	14	100	5	16	40	3	14	100	5	16	40

Table 3.4 *Harvest Control Rules*

HCR	**Equation**
Quota	Quota = 1,555 mt
ACL	ACL = .75*OFL
Empirical Rule	$TAC = \bar{C}_{y-5,y} * \sum_{i=1}^{I} w_i * (1 + m_i)$

The three harvest control rules tested and their equations.

Table 3.5 *Empirical Harvest Control Rules*

Scenarios	CE	CW	REC	BC	COMP	VIDEO	SEAMAP
eHCR1	0.33	0.33	0.34	0	0	0	0
eHCR2	0	0	1	0	0	0	0
eHCR3	0	0	0	0	0.34	0.33	0.33
eHCR4	0.14	0.14	0.14	0.14	0.14	0.15	0.15
eHCR5	0	0	0	0	1	0	0

The five empirical rules tested in the simulation and the weighting given to each index. Indices used included catch-per-unit-effort indices for the eastern commercial (CE), western commercial (CW), and recreational (REC) fisheries, an effort index for the shrimp by-catch fishery (BC), and indices of abundance for the competition index (COMP), reef fish video survey (VIDEO) and the SEAMAP groundfish survey (SEAMAP).

Table 3.6 *Number of Targeted Trips*

Species	N trips as primary
Gray Triggerfish	404
Red Snapper	12355
Vermilion Snapper	535

The number of trips that Gray Triggerfish, Red Snapper, or Vermilion Snapper were reported as the primary target between 2006 and 2018.

Table 3.7 *RUM Model Coefficient Estimates*

Coefficient	Estimate	Std. Error	P-value
Gray Triggerfish (intercept)	1.048873	0.37555	0.00522*
Red Snapper (intercept)	3.958714	0.483283	2.220E-16***
Size Limit	-0.16786	0.081718	0.03996*
Bag Limit	0.056409	0.006985	6.66134E-16***
GT: Fishing Days	-0.00307	0.000478	1.4096E-10***
RS: Fishing Days	0.008211	0.000841	0***

Coefficient estimates, standard error and p-values for the random utility model. *** indicates significance at 0.0001, ** indicates significance at 0.001 and * indicates significance at 0.01.

Table 3.8 *Number of Incomplete Trials*

HCR	Scenario 1	Scenario 2	Scenario 3
ACL	13	11	15
E1	6	8	8
E2	16	13	14
E3	9	16	12
E4	14	11	11
E5	9	11	10
Quota	9	12	14

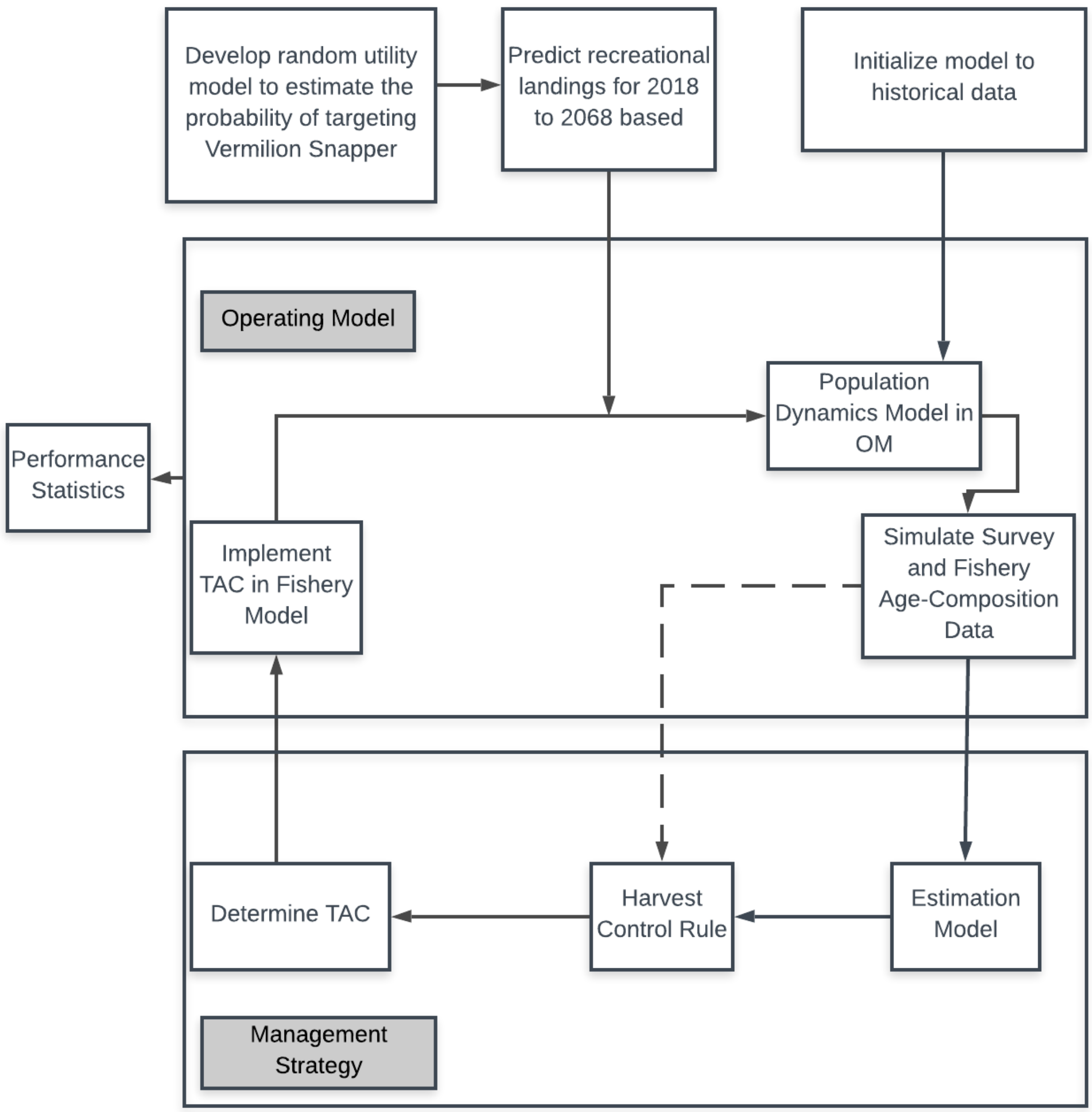

Figure 3.1 *MSE Simulation Process*

A representation of the MSE process. The operating model simulates the population and fishery dynamics. Data generated in the operating model are put into the management strategy component and the catch limits are determined using model-based or empirical harvest control rules. Performance indices are calculated at the end of the 50-year simulation period and are used to compare different management strategies.

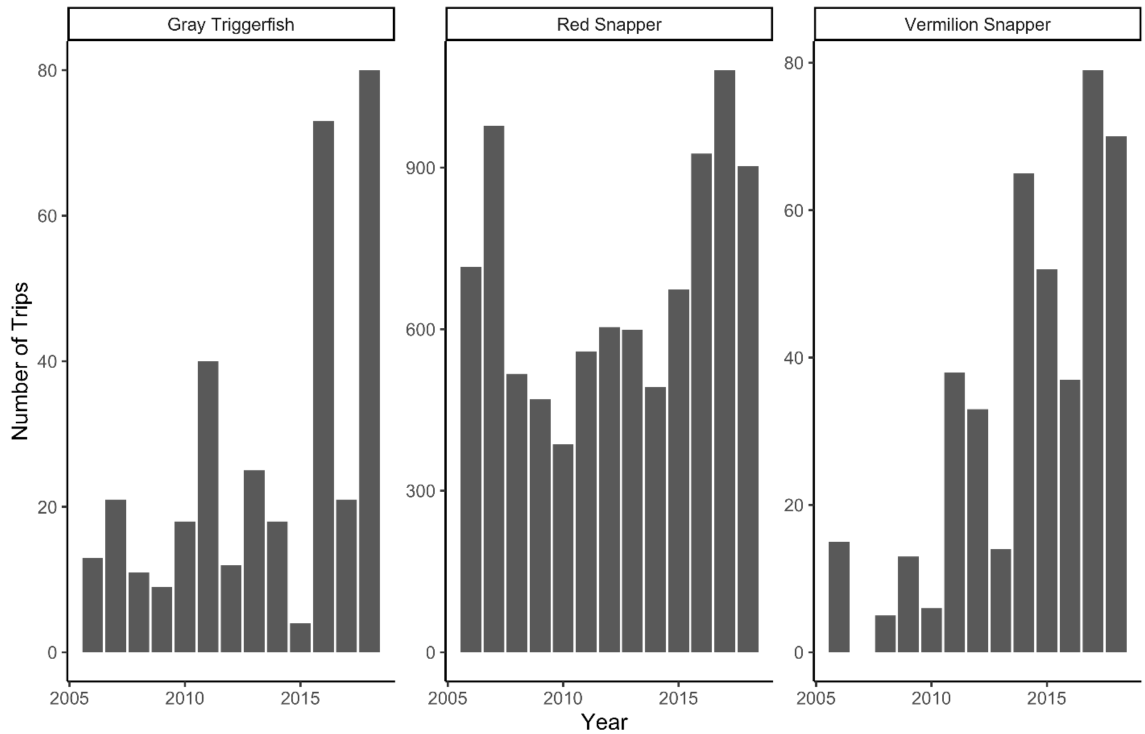

Figure 3.2 *Number of Trips*

Number of trips counted by survey for Gray Triggerfish, Red Snapper, and Vermilion Snapper between 2006 and 2018.

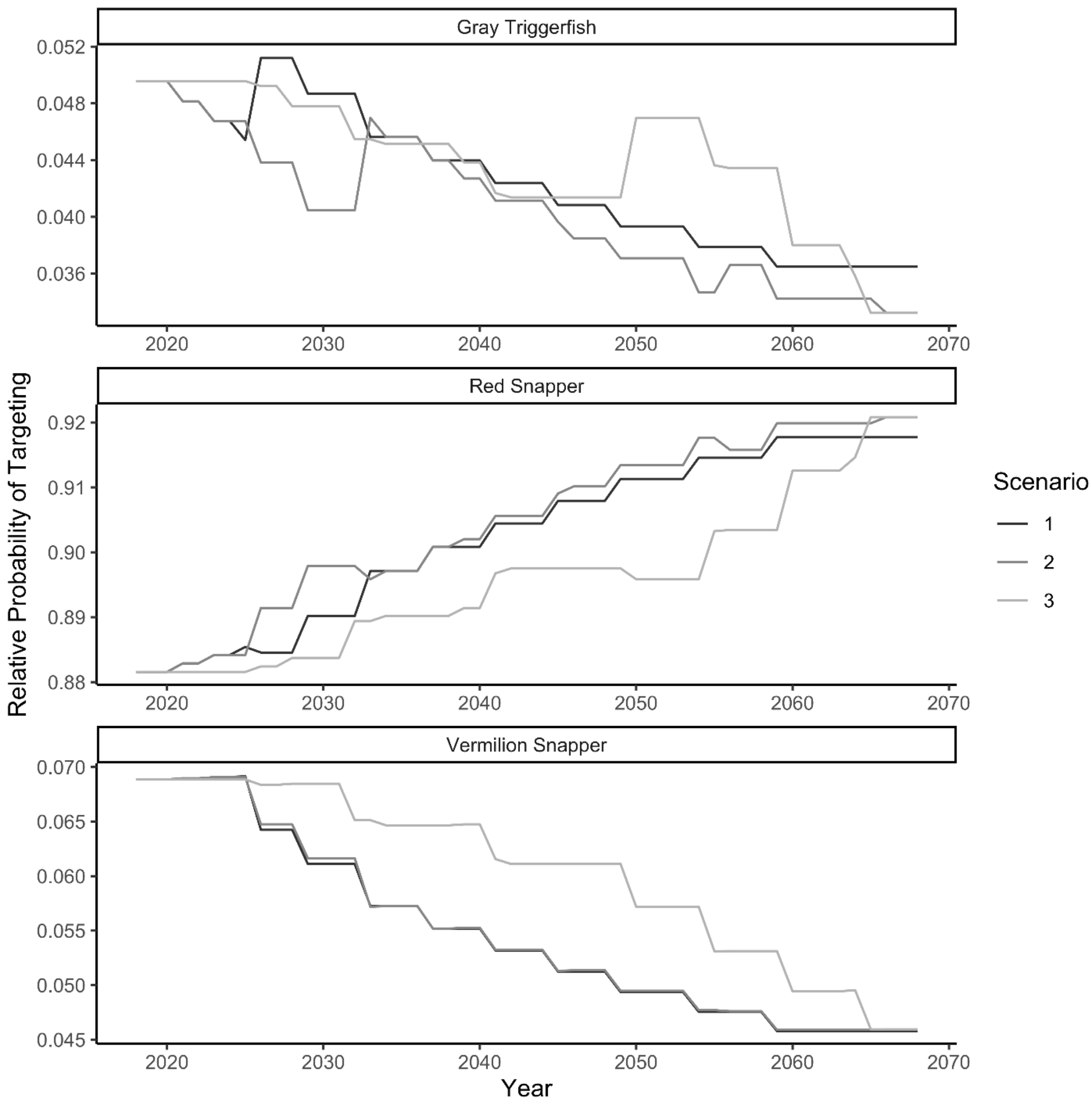

Figure 3.3 *Predicted Relative Probability of Targeting*

Predicted relative probabilities of targeting Gray Triggerfish, Red Snapper, and Vermilion Snapper from 2017 to 2067 for the three regulation scenarios.

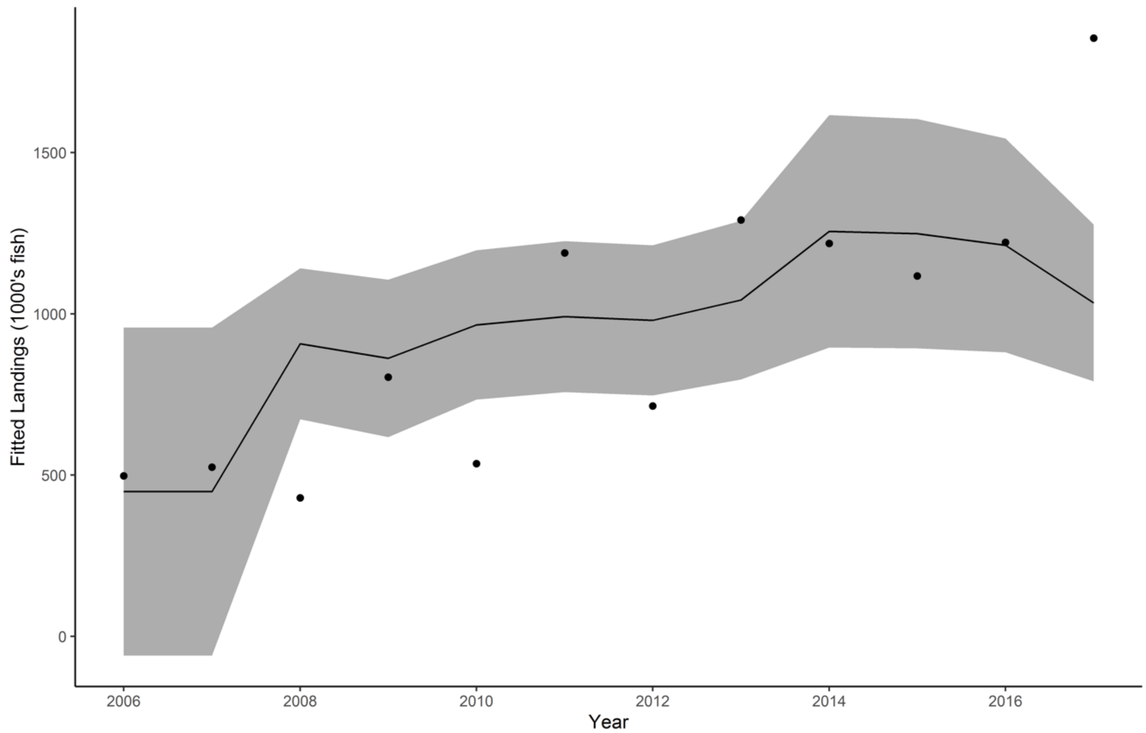

Figure 3.4 *Predicted Recreational Landings*

Observed (points) and fitted (line) recreational landings for 2006 to 2017 as fit by the linear regression model. The linear regression fit moderately well with $r^2 = 0.377$ and p-value = 0.033.

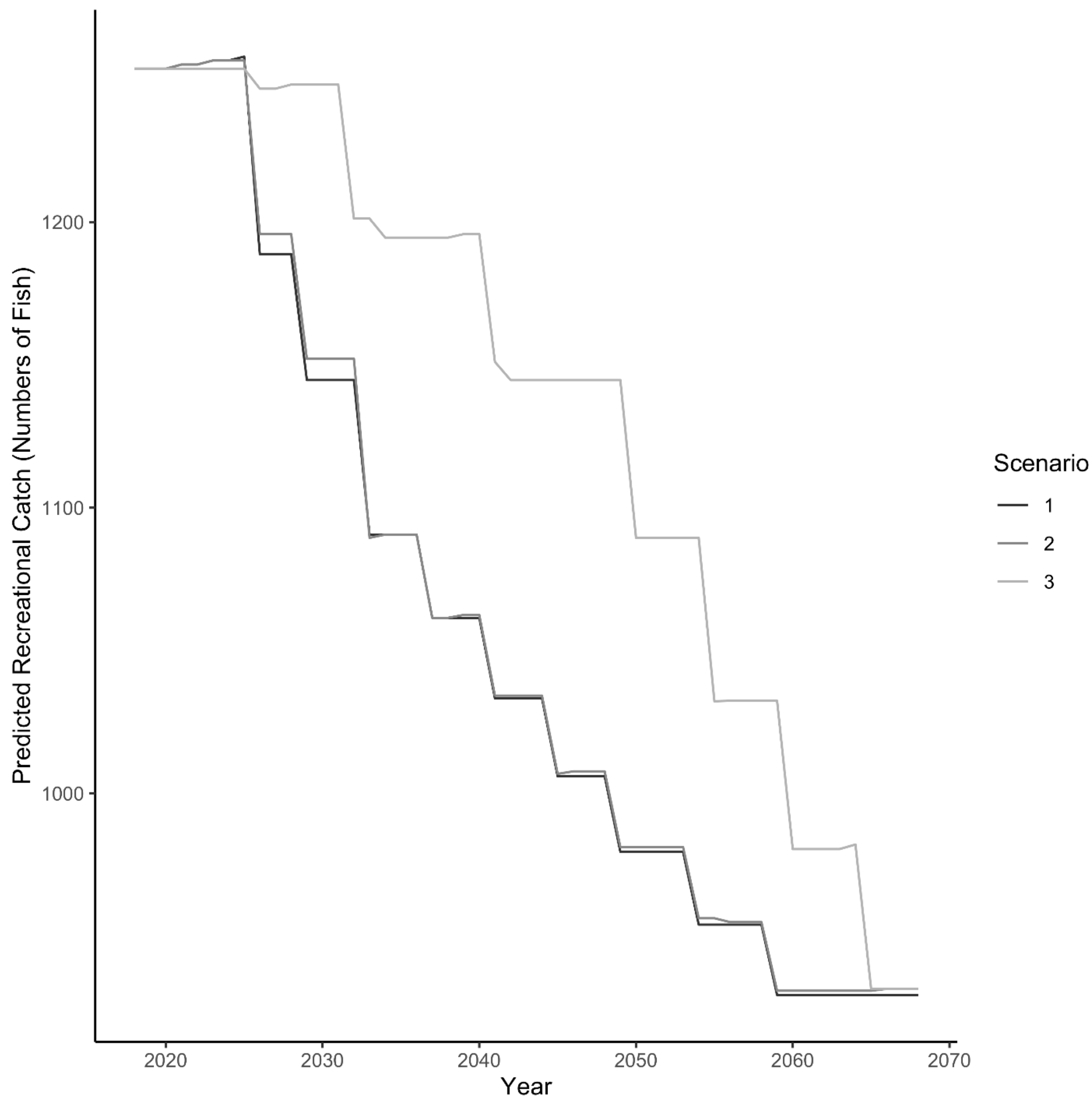

Figure 3.5 *Predicted Recreational Catch Under 3 Regulation Scenarios*

Predicted recreational catch as estimated with linear regression for the three regulation scenarios.

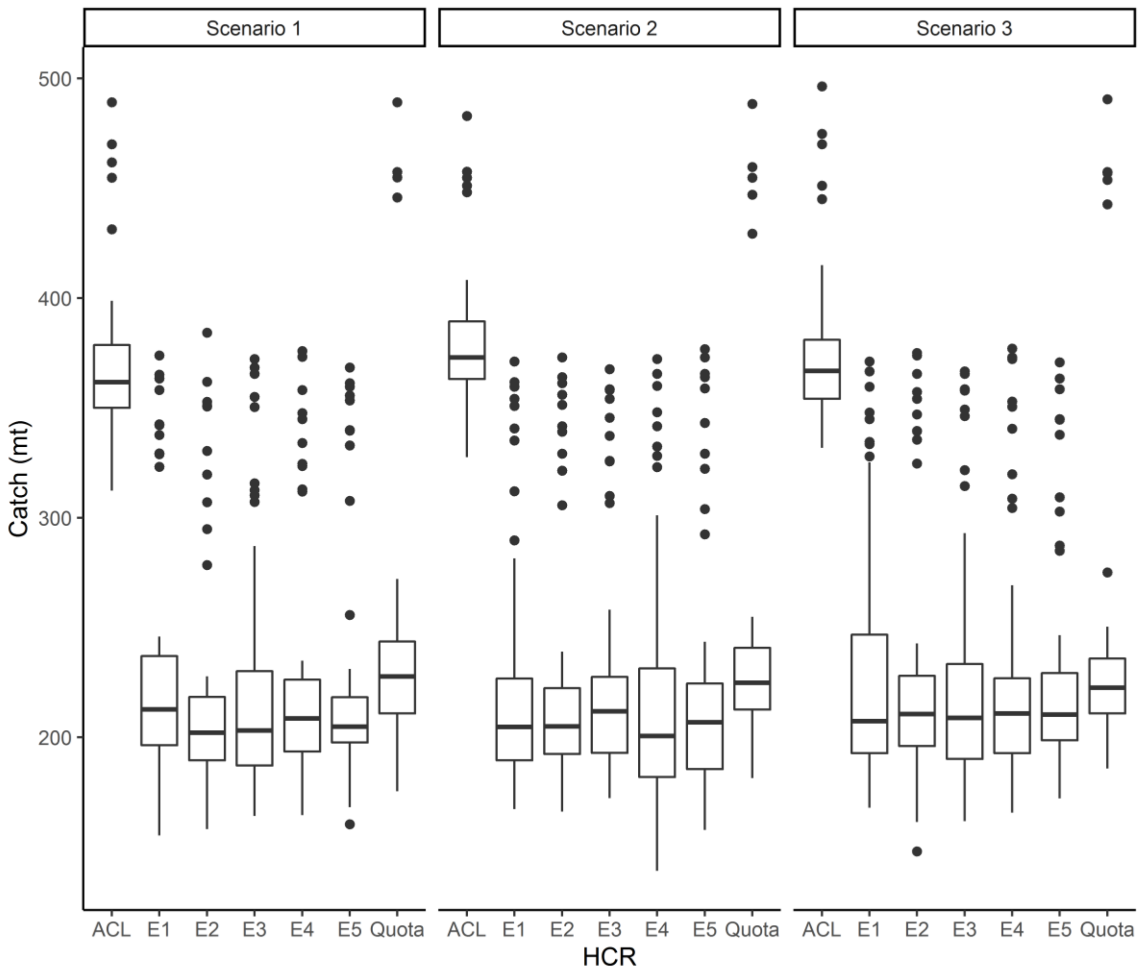

Figure 3.6 *Eastern Commercial Catch*

Median catch (in metric ton) for CE fleet over projection period under each HCR and Scenario.

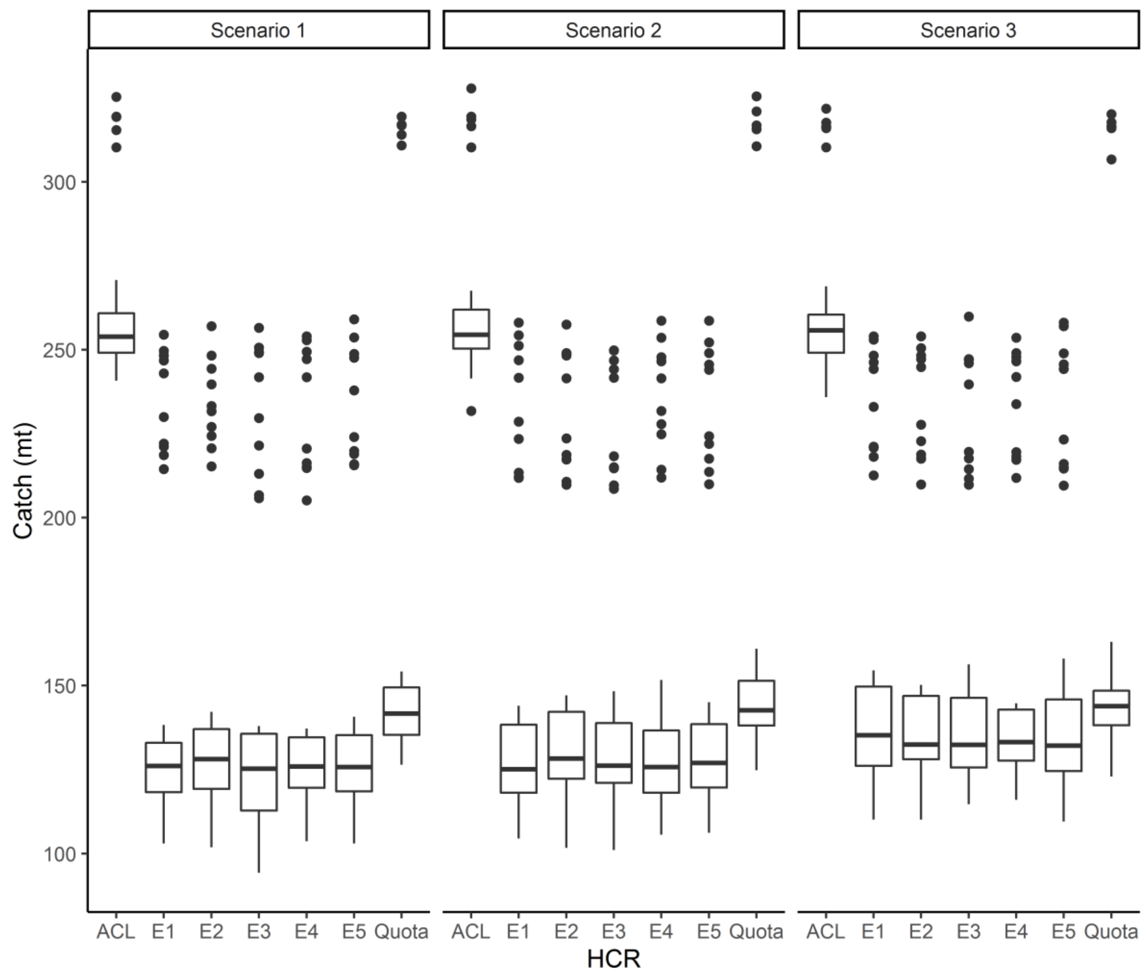

Figure 3.7 *Western Commercial Catch*

Median catch (in metric ton) for CW fleet over projection period under each HCR and Scenario.

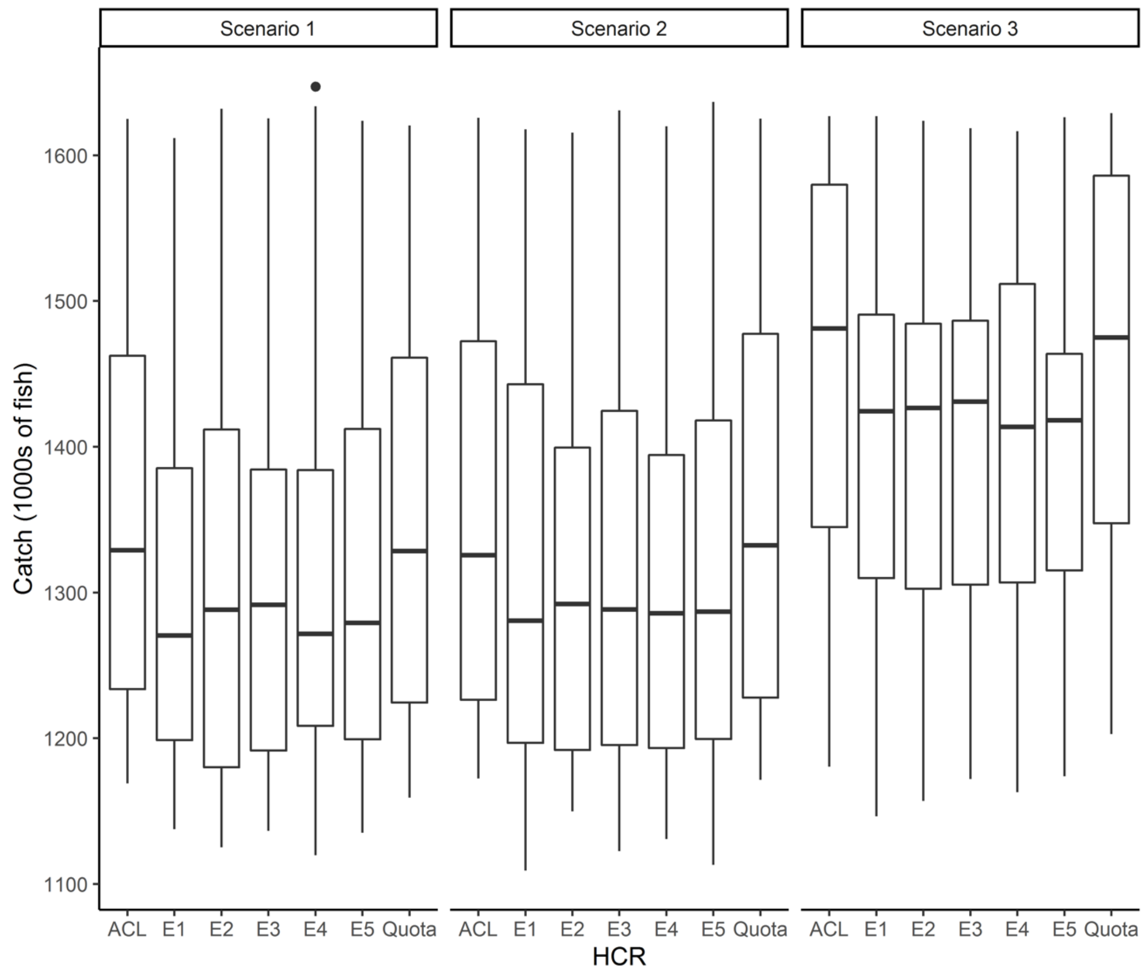

Figure 3.8 *Recreational Catch*

Median catch (in thousands of fish) for recreational fleet over projection period under each HCR and Scenario.

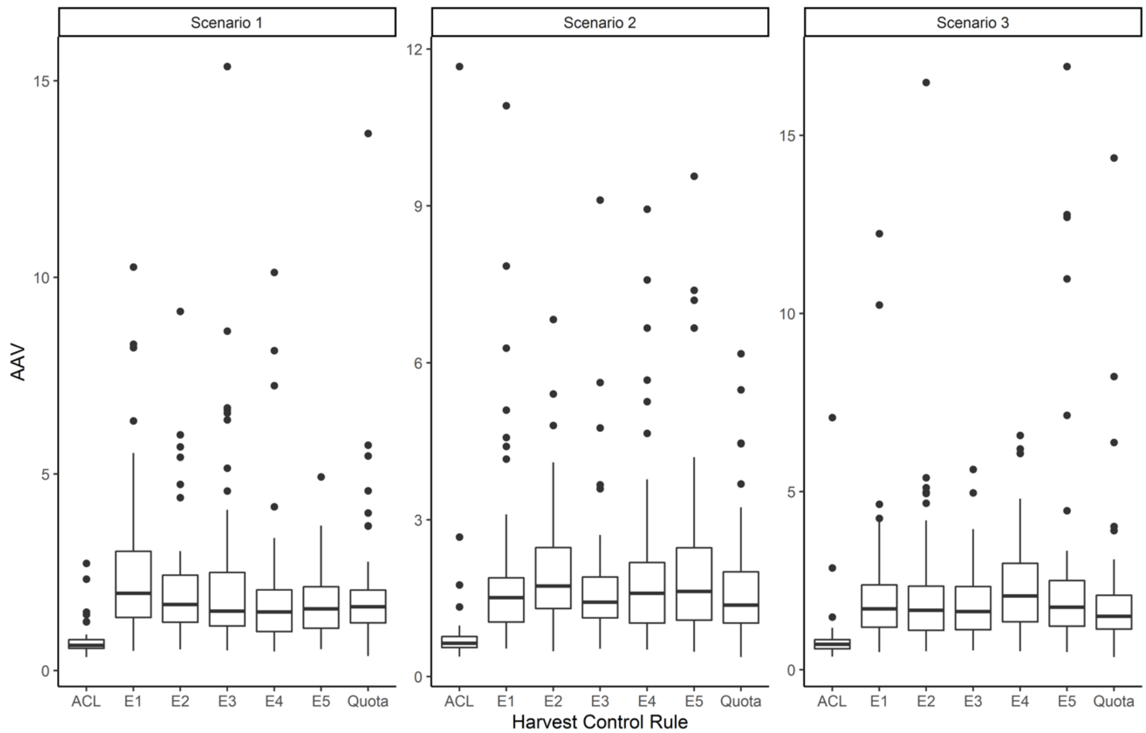

Figure 3.9 *Average Annual Variation of Eastern Commercial Landings*

Average annual variation of CE catch under each HCR and Scenario.

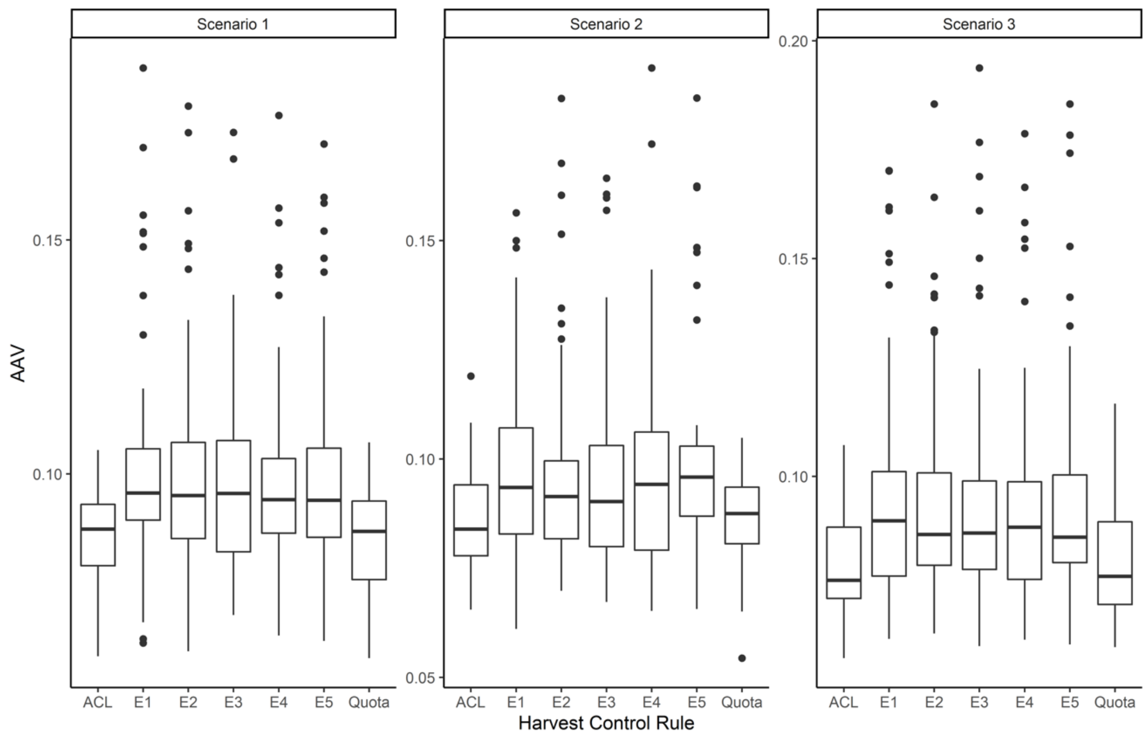

Figure 3.10 *Average Annual Variation of Recreational Landings*

Average annual variation of Recreational catch under each HCR and Scenario.

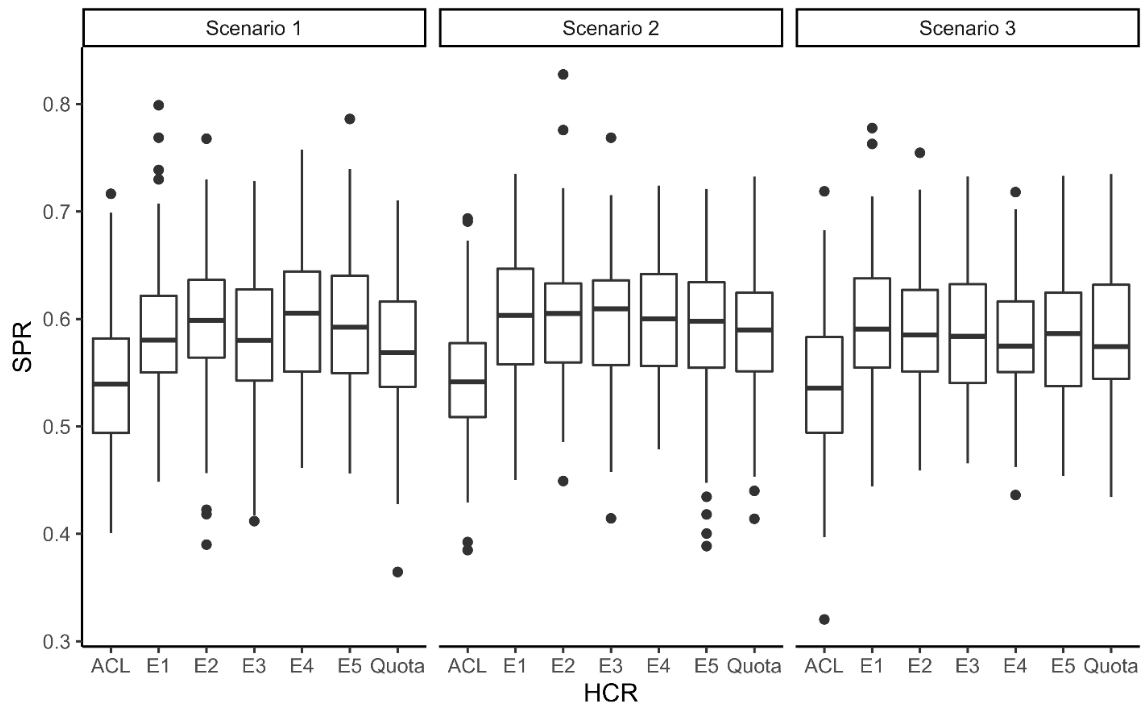

Figure 3.11 *Terminal SPRs*

Terminal spawning potential ratio (SPR) for each HCR and Scenario. All terminal values were above the 0.3 limit reference point.

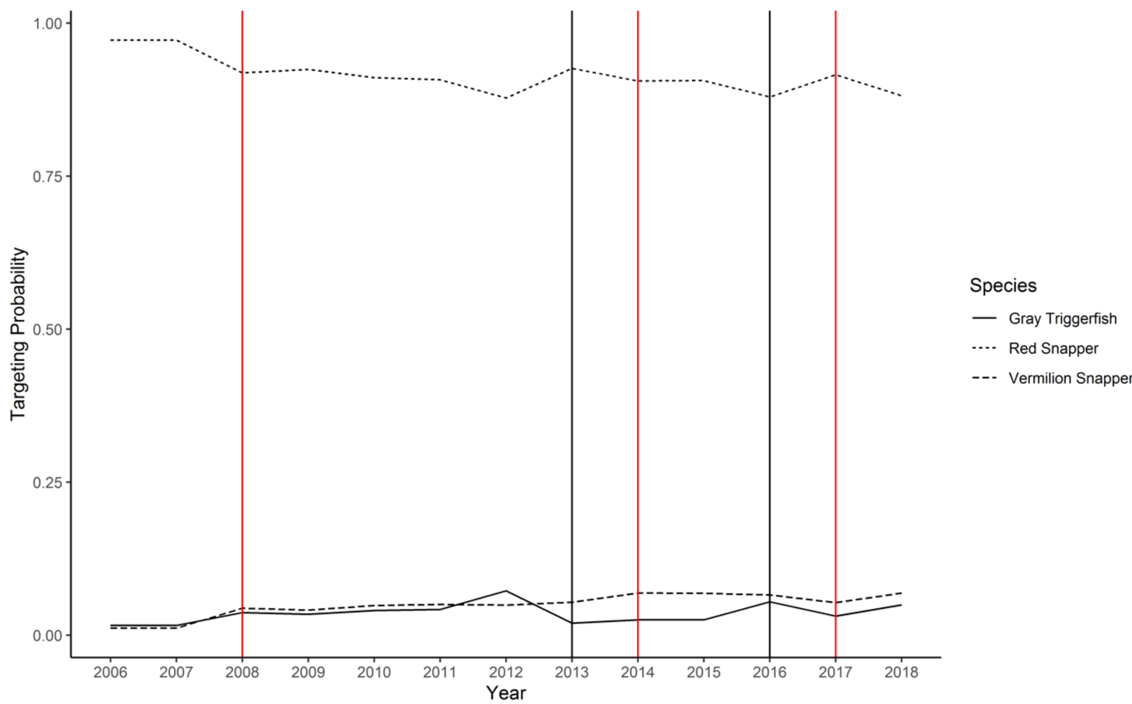

Figure 3.12 *Relative Targeting Probability*

Relative targeting probability as estimated by the random utility model for Vermilion Snapper, Gray Triggerfish, and Red Snapper. The vertical lines indicate years where drastic regulation changes for Red Snapper (red line) or Gray Triggerfish (black line) were implemented.

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