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Parameterization of an Ecosystem Model and Application for Assessing the Utility of Gulf of Mexico Pelagic Longline Spatial Closures

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PARAMETERIZATION OF AN ECOSYSTEM MODEL AND APPLICATION FOR ASSESSING THE UTILITY OF GULF OF MEXICO PELAGIC LONGLINE SPATIAL CLOSURES

By

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PARAMETERIZATION OF AN ECOSYSTEM MODEL AND APPLICATION FOR ASSESSING THE UTILITY OF GULF OF MEXICO PELAGIC LONGLINE SPATIAL CLOSURES

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Many highly migratory predator stocks that occupy the Gulf of Mexico are at risk, and the collapse of stocks could harm fisheries and ecosystems. Two pelagic longline spatial closures within the pelagic waters of the Gulf of Mexico have been established to protect pelagic species. In 2000, a permanent closure was established around DeSoto Canyon, with the management objectives of reducing catch and rebuilding biomass of bycatch and incidental catch species while minimizing impact to catch of target species. In 2015, a seasonal closure was established off the Louisiana shelf (*Spring Closure*), with the management objectives of reducing catch and rebuilding biomass of bluefin tuna (*Thunnus thynnus*). Pelagic spatial closures are relatively untested management tools. Science-driven analysis, including the investigation of ecosystem impacts through mathematical modeling, is necessary to address their utility. This dissertation presents research used to parameterize an ecosystem model, Atlantis, for the Gulf of Mexico marine ecosystem, followed by a study that used the Gulf of Mexico Atlantis model to conduct a policy exploration of the utility of Gulf of Mexico pelagic longline spatial closures.

Chapter 2 described the collection of Gulf of Mexico historical, species-specific landings data for the calibration of the Gulf of Mexico Atlantis model, and invest-

igated areas of uncertainty and bias, focusing on outputs from the Gulf of Mexico Atlantis model and landings-based indicators, due to unidentified landings and lack of data. U.S. landings not identified to species did not appear to bias landings-based indicators, nor does the aggregation of landings into Gulf of Mexico Atlantis functional groups. Chapter 3 described Gulf-wide spatial distributions of pelagic predatory functional groups. Distributions were estimated with generalized additive models fitted with U.S. bottom longline survey catch data (coastal models), and U.S. pelagic longline commercial catch data (pelagic models). This work advanced our knowledge on the correlations between the spatial distribution of pelagic predators within the Gulf of Mexico and the environment, and improved upon the spatial distributions previously used for the Gulf of Mexico Atlantis model. Finally, Chapter 4 described a policy exploration assessing if current pelagic longline spatial closures within the Gulf of Mexico, *DeSoto Canyon* and *Spring Closure*, could meet management objectives and evaluated possible ecosystem impacts. *DeSoto Canyon* was more successful at achieving management objectives and had more influence to ecosystem performance metrics than *Spring Closure*. Closures reduced Gulf-wide catches of bycatch and incidental groups with little reduction to catches of target groups. Rebuilding biomass of particular stocks may require additional reductions in fishing mortality.

The Atlantis framework allowed for the detailed, spatially-explicit representation of biota, fleets and spatial closures, and provided a means to explore broad-scale ecosystem impacts. This dissertation found that pelagic spatial closures could be viable means to achieve management objectives for protecting highly mobile pelagic predators from fishing pressure.

This work is dedicated to the pursuit to sustainable oceans.

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CHAPTER 1

Introduction

The Gulf of Mexico is a large marine ecosystem bordered by the United States, Mexico and Cuba. Due to the Gulf's complex network of habitats, the ecosystem supports a high level of biological diversity: from microbial communities to highly migratory predators (e.g., sharks, tunas, and billfish). Highly migratory predators are particularly common in the Gulf's pelagic environment with its highly complex physical dynamics consisting of strong currents and eddy networks.

As the Yucatán Current moves through the Yucatán Channel, features are constricted increasing surface water flow as it moves into the Gulf of Mexico to become the Loop Current (Badan et al., 2005). The Gulf's topology causes the current to loop clockwise before exiting through the Straits of Florida. The penetration of the Loop Current into the Gulf varies, but it eventually becomes great enough to produce large, anticyclonic rings known as Loop Current eddies (Leben, 2005). All of these physical forces generate a Gulf-wide network of fronts and eddies (Wiseman et al., 1999; Oey et al., 2005), which create favorable foraging and/or breeding environments for pelagic organisms by upwelling nutrients as well as retaining and concentrating particles (Olson et al., 1994; Bakun, 1996; Wiseman et al., 1999; Bakun and Broad, 2003).

Gulf fisheries contribute significantly to the economies of the surrounding countries. Coastal communities in particular depend heavily on the fisheries sector. Highly mobile predators are targeted with hook and line gears; either a vertical line consisting of no more than two hooks (handlines), or a horizontal mainline consisting of many hooks (longlines). U.S. commercial handliners harvest all across the Gulf shelf retaining reef fish (e.g., groupers and snappers) and pelagic fish (e.g., tunas and jacks). Longline operations consist of bottom longliners, which set hooks on or near the sea bottom, and pelagic longliners, which set hooks within the water column. U.S. commercial bottom longliners operate along the shelf and the start of the slope catching reef-based benthic species (e.g., groupers) and some highly migratory predators (i.e., sharks). U.S. commercial pelagic longliners operate in the open ocean targeting highly migratory species (e.g., tunas, swordfish and dolphinfish). Landings from U.S. commercial handline and U.S. commercial bottom longline are mostly reported in Florida, while landings from U.S. commercial pelagic longline are mostly reported in Louisiana (National Oceanic and Atmospheric Administration, 2012a). U.S. recreational handlines (i.e., tournaments, for-hire charters, and personal vessel activities) retain many different organisms but mostly target reef and pelagic fish (i.e., groupers and billfish). Recreational fishing plays an important role in the biological dynamics and coastal economy (National Oceanic and Atmospheric Administration, 2012b; Adams et al., 2004), because for some stocks recreational landings can match or surpass commercial landings.

Pelagic predators are particularly vulnerable to overfishing. Some pelagic organisms tend to be found in dense schools as they aggregate around patches of productivity in an otherwise oligotrophic environment. Advances in knowledge and technology have made it easier for fishers to locate fish schools. Thus, it is easier to locate and target large portions of the stock. Some pelagic predators tend to have slow-growing life history, meaning it can take several years for organisms to become sexually mature, which means juveniles can be subjected to fishing pressure before having an opportunity to reproduce. Because of these characteristics, and historically high fishing pressure which some species continue to experience, the sustainability of many highly migratory predator stocks are at risk. This includes some large sharks (Stevens et al., 2000; Baum et al., 2003b; Baum and Myers, 2004; Baum et al., 2005; Burgess et al., 2005; de Mutsert et al., 2008; Baum and Blanchard, 2010), Atlantic bluefin tuna, *Thunnus thynnus*, (Fromentin and Powers, 2005; ICCAT, 2014b), Atlantic marlins, *Makaira nigricans* and *Kajikia albidus*, (Peel et al., 2003; ICCAT, 2011, 2012), and sailfish, *Istiophorus albicans* (ICCAT, 2016c).

Shepherd and Myers (2005) found that large coastal sharks appear to cause strong top-down effects and their removal has lead to changes in community structure in the northern Gulf of Mexico. Thus, not only would the collapse of highly migratory stocks be devastating for local fisheries and economies, but research across terrestrial and marine ecosystems suggest that the removal of top predators could alter the structure and function of a marine ecosystem. This includes opening a niche which could be filled by organisms that are potentially harmful to the ecosystem (Parsons, 1992; Whitfield et al., 2007), reducing carbon flow to the benthic community (Parsons, 1992), or causing a trophic cascade (e.g., Parsons, 1992; Terborgh et al., 2001;

Heithaus et al., 2008; Baum and Worm, 2009; Casini et al., 2009; Bornatowski et al., 2014). A trophic cascade occurs when the removal of apex predators releases their prey groups (mesoconsumers) from predation, causing increased predation on the prey of mesoconsumers (resource species) (Heithaus et al., 2008). Trophic cascades may have negative impacts on an ecosystem, such as reduced fisheries due to the increase in natural mortality on resource species (Myers et al., 2007), a loss in goods and services due to shifts in underlining processes (Bakun and Weeks, 2006), and reducing ecosystem resistance and resilience (Britten et al., 2014).

Management of pelagic predatory stocks is both a domestic and international effort as these species are highly mobile. The International Commission for the Conservation of Atlantic Tunas (ICCAT) is an inter-governmental fishery organization responsible for the conservation of tunas and tuna-like species in the Atlantic Ocean and its adjacent seas. In the United States, the National Oceanic and Atmospheric Administration (NOAA) through the Highly Migratory Species Devision (HMSD) has primary authority for developing and implementing Fishery Management Plans (FMPs) for highly mobile species (HMS) in Atlantic federal waters, including the Gulf of Mexico. Such FMPs have enacted various input and output controls to ensure the ecological sustainability of pelagic predators (National Oceanic and Atmospheric Administration, 2016a). This includes establishing two pelagic longline spatial closures within the pelagic waters of the Gulf of Mexico. In 2000, a permanent pelagic longline spatial closure was established around the northern West Florida Slope (DeSoto Canyon) to reduce the interaction between non-targeted pelagic fish and longline fisheries. DeSoto Canyon is an area many pelagic predators frequent due to the increased productivity generated by oceanographic characteristics. In 2015, a seasonal pelagic longline spatial closure was established off the Louisiana shelf to reduce the interactions between bluefin tuna and longline fisheries. This area experiences an increase in bluefin tuna abundance during the spring because it is part of the spawning grounds of the western stock.

Fishery spatial closures are a type of marine protected area (MPA) within which fishing is limited and/or prohibited. MPAs are a tool for ocean conservation (Agardy, 1997). They can protect marine biodiversity by conserving habitat and landscape (Gray, 1997), as well as areas of connectivity (Almany et al., 2009). In addition, MPAs can provide protection to essential habitats and species of concern by protecting areas of aggregation, such as spawning areas, foraging areas, nurseries, and migration stopovers (Norse, 1993). Spatial closures can benefit fisheries by providing biomass through spillover (e.g., McClanahan and Mangi, 2000; Kelly et al., 2002; Guidetti, 2007; Januchowski-Hartley et al., 2013), and increase the size of individuals (e.g., Babcock et al., 1999; Lester et al., 2009).

Much of the current work on MPAs focuses on coastal environments and sedentary organisms because it was originally thought that MPAs would provide little benefit to pelagic predators due to their high mobility and weak site fidelity (Roberts, 1997; Boersma and Parrish, 1999). However, Hyrenbach et al. (2000) argued that pelagic closures could be feasible tools for protecting highly migratory predators since they tend to aggregate around predictable oceanographic features. The advancing knowledge in life histories of pelagic predators, oceanography, and fisheries science suggest that pelagic MPAs have the potential to be viable management tools for protecting pelagic organisms (Game et al., 2009). MPAs for the conservation of pelagic fish are now being recommended by management agencies and stakeholders (Musick et al., 2000a,b; ICCAT, 2007, 2009, 2010, 2014a; Highly Migratory Species Division, 2008). However, considering that there is a lack of empirical understanding of the direct and indirect impacts of pelagic MPAs, and that often MPAs can fail to meet management objectives (Jameson et al., 2002), it is imperative that science-driven analysis, including the investigation of ecosystem impacts through mathematical modeling, is done to address the utility of pelagic MPAs (Kaplan et al., 2010; Game et al., 2010; Grüss, 2014).

Ecosystem mathematical models are being developed for the Gulf of Mexico Integrated Ecosystem Assessment (IEA) program (Schirripa et al., 2013; Samhouri et al., 2014). An IEA is a framework to guide the process of synthesizing and analyzing relevant scientific information supporting Ecosystem-Based Fisheries Management (EBFM) (National Marine Fisheries Service, 1998, 2012; Levin et al., 2009; Foley et al., 2013). There has been a movement towards EBFM over the last few decades, under which scientists and managers aim to manage fisheries in an ecosystem context rather than a single-species context (Ecosystem Principles Advisory Panel, 1999; Pomeroy et al., 2010). One of the primary purposes of the Gulf of Mexico IEA is to manage the Gulf of Mexico from a broader perspective (e.g., Grüss et al., 2016b). A key component to an IEA is using ecosystem models to evaluate how different management strategies influence the status of indicators. One of the ecosystem models being developed for the Gulf IEA is Atlantis.

Atlantis is a biogeochemical and biophysical simulation framework (Fulton et al., 2004c,b; Fulton, 2010; Fulton et al., 2011). It models the turnover of chemical substances through the biotic and abiotic compartments of an ecosystem, and there are detailed routines for coupling the biological and physical components. Atlantis is an "end-to-end" model, meaning it represents biota from bacteria up to top predators. Biota can be represented as age-structured groups, or biomass pools. There is a detailed fisheries exploitation routine that allows the simulation of individual fleets, as well as routines for simulating a range of management measures, including fishery spatial closures. Interactions between species and fisheries are spatially explicit, and the spatial domain is composed of a 3-dimensional polygon network that reflects key geographic features, habitats, and essential management jurisdictions. The Atlantis framework has been used to investigate the spatial management of fisheries, including the use of spatial closures, e.g. Ainsworth et al. (2012); Kaplan and Leonard (2012); Morzaria-Luna et al. (2013). Although Atlantis is argued to be one of the best operating models for ecosystem simulation (Plagányi, 2007), one of the disadvantages is that Atlantis requires more data than other ecosystem models, including historical landings data, and seasonal spatial distributions of simulated functional groups (i.e., groups of species with similar life histories and ecosystem function).

One method for parameterizing an Atlantis model for forecasting involves first calibrating a historical Atlantis model with landings time series data. Values of dynamic parameters in the calibrated historical model are transferred to a present day model for forward simulations. A critical component of this methodology is the collection of historical, species-specific landings (organized by gear, season, and state if possible). Data need to be aggregated based on the Atlantis-defined functional groups, which could incorporate bias into the historical landings trends. This would impact the calibration of the Gulf of Mexico Atlantis model and forecasting simulation studies. Thus, Chapter 2 of this dissertation describes the collection of Gulf of Mexico historical, species-specific landings data for the calibration of the Gulf of Mexico Atlantis model, and investigates areas of uncertainty and bias due to unidentified landings and lack of data. This investigation provides a detailed picture of the historical development of fisheries in the Gulf, and is informative for the Gulf of Mexico Atlantis model, as well as other ecosystem models and metrics for the Gulf of Mexico.

To investigate the utility of pelagic fishery closures of the Gulf of Mexico, it is imperative that the forecasting Gulf of Mexico Atlantis model is parameterized with reasonable seasonal spatial distributions for pelagic functional groups. Spatial distributions can be inferred from predictive statistical models (Guisan and Zimmermann, 2000; Austin, 2002, 2007; Elith and Leathwick, 2009). Statistical models for predicting the spatial abundance of marine fishes depends on the fundamental relationship between catch rate (catch per unit effort) and density, and the shortcomings of using catch rate as an index of abundance have been long-studied in fisheries literature (e.g., Gulland, 1956; Beverton and Holt, 1957; Robson, 1966; Honma, 1973; Seber, 1982; Cooke and Beddington, 1984; Beddington and Cooke, 1984; Hilborn et al., 1992; Harley et al., 2001). However, advances in statistical methodologies (e.g., generalized linear modeling) address many of the shortcomings of fisheries data (Maunder and Punt, 2004).

In Chapter 3 of this dissertation, generalized additive models (GAMs) (Hastie and Tibshirani, 1986, 1990) were developed to describe the spatial distribution of pelagic functional groups within the Gulf of Mexico. Species-specific catch records were grouped according to pelagic functional groups identified for the Gulf of Mexico Atlantis model. Two types of GAMs were fitted: coastal (covering areas 0 - 200 m deep), and pelagic (covering areas greater than 200 m deep). Coastal models were fitted using NOAA's Bottom Longline Survey data, and pelagic models fitted using

NOAA's Pelagic Longline Observer Program data. A delta approach was followed to account for the zero-inflated catch data. This consisted of fitting a Bernoulli GAM with binomial data, and a Gamma GAM with zero-truncated catch rate data. Model descriptors (independent variables) considered for coastal models included year, sea bottom depth, altimetry, minimum distance from a front, as well as sea surface and sea bottom temperature, dissolved oxygen, oxygen saturation, and salinity. Descriptors considered for pelagic models included season, year, sea bottom depth, altimetry, minimum distance from a front, and sea surface temperature. Fitted models and data series describing seasonal environmental conditions were used to predict Gulf-wide seasonal, spatial distributions of pelagic predator groups.

With the Gulf of Mexico Atlantis forecasting model parameterized using historical landings data, and spatial distributions of pelagic predator functional groups generated from the statistical models, it was ready to be used to explore the utility of the Gulf of Mexico pelagic longline spatial closures. Chapter 4 describes a simulation test for investigating i) if Gulf of Mexico pelagic longline fishery spatial closures are likely to achieve management objectives, and ii) potential ecosystem impacts from pelagic longline closures. The Gulf of Mexico Atlantis model was used to simulate scenarios and calculate performance measures (indicators) corresponding to management objectives of the pelagic longline fishery spatial closures, as well as broader ecological objectives. Performance metrics were compared to examine potential long-term impacts of Gulf of Mexico pelagic longline spatial closures.

In summary, this dissertation consists of three components. First, Chapter 2 describes the collection of Gulf of Mexico historical, species-specific landings data for the calibration of the Gulf of Mexico Atlantis model, and investigates areas of uncertainty and bias due to unidentified landings and lack of data. Next, Chapter 3 describes the development of delta generalized additive models for estimating the Gulf-wide spatial distribution of pelagic predator functional groups as described for the Gulf of Mexico Atlantis model. Lastly, Chapter 4 describes a simulation test using the Gulf of Mexico Atlantis model for investigating whether Gulf of Mexico pelagic longline spatial closures could achieve management objectives, as well as their potential ecosystem impacts. This dissertation advanced our understanding regarding the strengths and weaknesses of some of the data currently available for the Gulf of Mexico IEA. In addition, it advanced our understanding of the drivers and patterns pertaining to spatial distributions of pelagic predators within the Gulf of Mexico. This work provided insight with respect to possible benefits from pelagic longline spatial closures, and improved our understanding and modeling of the Gulf of Mexico ecosystem.

CHAPTER 2

Landings Data for Ecosystem Fisheries Science: Lessons Learned from the Gulf of Mexico

2.1 Summary

Historical landings data are crucial for ecosystem based fisheries management in that they i) are needed for the calibration of ecosystem modeling tools, and ii) allow for the assessment of landings-based indicators. Such methodologies require landings data on species. Neglecting data not identified to species (ambiguous landings) could potentially bias results. This work considers Gulf of Mexico landings data to discuss potential uncertainties in the development of ecosystem based fisheries management tools, like the Gulf of Mexico Atlantis model, as well as landings-based indicators. Gulf of Mexico landings data (1980-2011) were described for the United States, Mexico, and Cuba. Landings were classified by species, then allocated into functional groups identified for the Gulf of Mexico Atlantis model. U.S. landings, both species-specific and functional group-specific, were used to compute qualitative landings-based indicators relating to stock assessment coverage, and quantitative landings-based indicators relating to system ecology (pelgic:demersal ration, and

mean trophic level). Commercial landings data have meaningful portions not identified to species, especially data from Mexico and Cuba (29.2% and 48.9%, respectively, are unidentified). U.S. recreational data have few ambiguous landings (0.4% are not identified to species), but there is a lot of variation in landings data from MRIP, at least some of which is estimation error. Ambiguous landings did not appear to be adding bias to investigated indicators pertaining to U.S. waters. In addition, the aggregation of landings into Gulf of Mexico Atlantis functional groups do not appear to biasing the computation of trends. Qualitative indicators show that a majority of U.S. commercial landings are of species that are not overfished, but the majority of U.S. recreational landings are of species of unknown overfished status. Although ecosystem based fisheries management of the Gulf of Mexico would benefit from more precise landings, current data is sufficient for the development of ecosystem models.

2.2 Motivation

Under ecosystem-based fisheries management (EBFM), scientists and managers aim to manage fisheries in an ecosystem context rather than a single-species context (Ecosystem Principles Advisory Panel, 1999; Link, 2002; Brodziak and Link, 2002; Pikitch et al., 2004; Link, 2010). There has been a shift towards EBFM (Pomeroy et al., 2010) due to the perception that fishing operations have the power to alter the structure and function of marine ecosystems (Marasco et al., 2007), and that healthy ecosystems are needed to sustain fished populations. Hilborn (2011) argues that even if single-species management was executed well, EBFM is still necessary because pure single-species management does not consider impacts on non-target species, trophic interactions among species, and habitat-destroying fishing practices.

Integrated Ecosystem Assessment (IEA) is an assessment methodology that supports EBFM (Foley et al., 2013). Originally described by Levin et al. (2008, 2009), an IEA is a cyclic process made up of five steps. First, ecosystem objectives and threats are identified. An important part of EBFM is the capability to monitor progress toward objectives, and this is achieved with indicators (Pikitch et al., 2004). Thus, the second step of an IEA is to identify and validate indicators for assessing the state of the ecosystem. EBFM requires a suite of indicators that provide insight into the state of the ecosystem, particularly in relation to the impact of fishing (Dale and Beyeler, 2001; Rochet and Trenkel, 2003; Fulton et al., 2005; Shin and Shannon, 2010; Powers and Monk, 2010; Link et al., 2010b). This includes indicators based on landings data, which can provide information regarding changes in the assessment and fisheries management coverage of the system (e.g., Piet et al., 2010; Gascuel et al., 2012; Karnauskas et al., 2013), as well as the system's fisheries ecology (e.g., Rochet and Trenkel, 2003; Fulton et al., 2005; Shin et al., 2010). Next, there is an evaluation of the risk posed by human activities and natural processes. This is followed by the use of ecosystem models to evaluate how different management strategies influence the status of indicators. This is a process referred to as a Management Strategy Evaluation (Smith, 1994; Sainsbury, 1998; Cooke, 1999; Sainsbury et al., 2000; Butterworth et al., 2010; Punt et al., 2016). Lastly, ecosystem indicators are monitored and assessed to determine the effectiveness of management strategies. Ideally, this process is repeated to support adaptive management (Dickey-Collas, 2014) and monitoring (Uychiaoco et al., 2005).

In the USA, the National Oceanic and Atmospheric Administration (NOAA) has been developing IEAs for marine ecosystems (Samhouri et al., 2014), including the

Gulf of Mexico (Karnauskas et al., 2013; Schirripa et al., 2013). The Gulf of Mexico is a large marine ecosystem that supports the livelihoods of people in coastal communities of the United States, Mexico, and Cuba (Adams et al., 2009; Yoskowitz, 2009), as well as the many populations of marine fauna (Giattina and Altsman, 1999; Landry Jr and Costa, 1999; Mullin and J, 1999). Some of the stressors facing the Gulf include habitat modification and unsustainable exploitation of living resources (Yáñez-Arancibia and Day, 2004), both of which threaten the sustainability of fisheries stocks (Coleman et al., 1996; Baum and Myers, 2004; Ault et al., 2005; Heithaus et al., 2007a; MacKenzie et al., 2009; Beck et al., 2011). The need for a holistic approach to meet these threats has influenced a movement towards an ecosystem approach to the management of the Gulf of Mexico ecosystem and fisheries (Yáñez-Arancibia and Day, 2004; Nugent and Cantral, 2005; Arreguín-Sánchez et al., 2008; Carollo and Reed, 2010; Day and Yáñez-Arancibia, 2013; Yáñez-Arancibia et al., 2013).

To support the Gulf of Mexico IEA, several ecosystem modeling frameworks are being developed (Schirripa et al., 2013), including Atlantis - a dynamic biogeochemical ecosystem model that simulates physical, chemical, biological, and fisheries components within a three-dimensional spatial domain (Fulton et al., 2004b,c, 2007). Atlantis has been used to investigate ecological indicators for detecting ecosystem impacts due to fisheries, investigate cumulative impacts, explore ecosystem dynamics, and test management approaches (Fulton et al., 2004a, 2005; Link et al., 2010a; Fulton et al., 2011; Kaplan et al., 2012; Ainsworth et al., 2012; Masi et al., 2017). To support the Gulf of Mexico IEA, a model for the entire Gulf of Mexico marine ecosystem was developed using the Atlantis framework (Ainsworth et al., 2015).

Initializing of the Gulf of Mexico Atlantis model for forecasting included calibrating a historical model to fit landings time series (Ainsworth et al., 2015). To do this, landings time series from 1980 to 2011 were collected and categorized into functional groups simulated in the Gulf of Mexico Atlantis model (Perryman et al., 2015). In addition, landings were partitioned across seasons and fishing fleets. Commercially important species often have complete landings profiles, however species that are not commercially important are often grouped into ambiguous categories. This includes records identified to a higher taxonomic classification (e.g., family), or no taxonomic classification (e.g., "unidentified"). Ambiguous landings may be negligible for some species, but other species can have significant portions of their landings not appropriately identified. Excluding ambiguous landings from EBFM tools could bias the computation of landings based indicators, as well as the calibration of ecosystem models (i.e., misrepresent the magnitude of fisheries on stocks).

Landings data pertaining to the Gulf of Mexico were presented and discussed in detail in the Gulf of Mexico Ecosystem Status Report (Karnauskas et al., 2013). Karnauskas et al. focused on identifying trends in Gulf-wide indicators. The following research builds on their findings. This study used Gulf of Mexico landings data that was somewhat different than data presented by Karnauskas et al. (2013) to discuss how data uncertainties, including landings not identified to species, aggregation of landings by Atlantis functional groups, and allocation of landings to season, state, and gear, could bias the Gulf of Mexico Atlantis model. Lastly, landings-based indicators were computed to discuss trends and possible bias on how data were grouped for the purposes of ecosystem modeling, including functional groups, recreational versus commercial fisheries, and seasonal and regional divisions. This study aims to gain insight into some of the uncertainties concerning landings data available for the Gulf of Mexico for use in ecosystem models.

2.3 Methods

2.3.1 Landings Data

Landings data from Gulf of Mexico waters are available for U.S. commercial, U.S. recreational, Mexico commercial, and Cuba commercial fleets. The National Oceanic and Atmospheric Administration (NOAA) Fisheries, Fisheries Statistics Division provides summaries of U.S. commercial fisheries landings, in weight (lbs), as annual landings, or annual landings itemized by state, season, or gear (National Oceanic and Atmospheric Administration, 2012a). These landings come from a cooperative State-Federal fishery data collection system that obtains landings data from state-mandated trip-tickets (which are filled out at the conclusion of every fishing trip), landing weigh-out reports provided by seafood dealers, federal logbooks of fishery catch and effort, and shipboard / portside interviews. Most states get their landings data from seafood dealers who submit monthly reports of the weight and value of landings by vessel; however, more states are switching to mandatory trip-tickets to gather landings data (National Oceanic and Atmospheric Administration, 2016b). U.S. commercial landings are dominated by menhaden, *Brevoortia* spp., (Figure 2.1). This analysis excludes U.S. commercial menhaden landings in order to identify underlying trends in the rest of the fisheries (de Mutsert et al., 2008; Karnauskas et al., 2013).

The NOAA Marine Recreational Information Program (MRIP) provided the bulk of the U.S. recreational data (National Oceanic and Atmospheric Administration, 2012b). MRIP is a compilation of regionally-based data collection programs that collects data from a subsample of anglers and captains, which is then expanded to all anglers based on a telephone survey to estimate effort (National Oceanic and Atmospheric Administration, 2014a). Texas is not part of MRIP surveys and instead the state conducts its own survey on recreational landings, which are then provided to NOAA (Gulf of Mexico Fishery Management Council, 2005). Lastly, NOAA's Southeast Fisheries Science Center (SEFSC) Recreational Billfish Survey System (RBS) provided data on recreational billfish tournaments within the Gulf of Mexico (A. Venizelos at NOAA, personal communication, May 8, 2013). The RBS has been collecting data on recreational billfish tournaments in the western North Atlantic, Gulf of Mexico and U.S. territories in the Caribbean since 1972, and is the primary source of U.S. recreational billfish catch and effort statistics (National Oceanic and Atmospheric Administration, 2014b). The Gulf of Mexico Ecosystem Status Report (Karnauskas et al., 2013) did not indicate if the RBS data were considered. Recreational data were extracted in numbers. Originally, MRIP data in weight were extracted but further analysis showed that MRIP data in weight had about half as many records as MRIP data in numbers. The Gulf of Mexico Ecosystem Status Report (Karnauskas et al., 2013) reports MRIP data in weight and does not discuss data in numbers.

Annual reports from the Secretaría de Agricultura, Ganadería, Desarrollo Rural, Pesca y Alimentación (SAGARPA) through the Comisión Nacional de Acuacultura y Pesca (CONAPESCA) provided landings data for Mexican commercial fisheries

(SAGARPA, 2016). Data provided in the reports were collected by the SAGARPA as well as the Órganos Centrales de la Secretaría from the various agencies active in the fisheries sector (SAGARPA, 1980 - 2011). Data, in weight (kgs), were extracted for the coastal Mexican states of Tamaulipas, Veracruz, Tabasco, Campeche, and Yucatán. Quintana Roo data were not included since landings from the Gulf of Mexico and landings from the Caribbean could not be separated, and all the major fishing ports of Quintana Roo are on the Caribbean coast. Data describing Mexican recreational landings from the Gulf of Mexico were not considered in this study (i.e., assumed to be zero) since information could not be found. These commercial landings are directly from Mexico. Landings considered in the Gulf of Mexico Ecosystem Status Report (Karnauskas et al., 2013) were from FAO.

The Food and Agriculture Organization of the United Nations (FAO) provided landings data for Cuban commercial fisheries (FAO, 2013a). Data from FAO describes total Cuban landings, in weight (tonnes). Claro et al. (2001) provided a regional breakdown (i.e., southeast, southwest, northwest and northeast) of common groups of species identified in Cuban commercial landings (1959 - 1998). It was assumed that the northwest region represents landings solely from the Gulf of Mexico. Thus, the data provided by Claro et al. (2001) was used to calculate average proportions of Cuban landings that were in the northwest region, which were applied to the FAO data on total Cuban landings to infer Gulf of Mexico landings. Data describing Cuban recreational landings from the Gulf of Mexico were not considered in this study (i.e., assumed to be zero) since information could not be found. The Gulf of Mexico Ecosystem Status Report (Karnauskas et al., 2013) did not discuss landings data from Cuba.

To evaluate the amount of landings associated to ambiguous groups for each region, landings data were categorized by species, genus, family+ (which includes landings identified to family or any higher Taxonomic Classification), or unidentified. This could be easily accomplished for U.S. and Cuban datasets, but many of the identifications used in Mexican data refer to general groups of organisms and not species. Thus, Mexico landings are instead categorized by "taxonomic classification", meaning that they were identified to some taxonomic group such as "snappers" or "large sharks", or "unidentified".

To evaluate whether uncertainties in species identification in the U.S. data varied over state, season, or gear, time series of total landings and fraction ambiguous were generated for each of these classifications. Both NOAA and MRIP provide landings itemized by state (i.e., the state of the port where catch was landed). Seasonal data from NOAA itemized commercial landings by month. Data were aggregated into the four seasons simulated in the Gulf of Mexico Atlantis model (winter, Jan. - Mar.; spring, Apr. - Jun.; summer, Jul. - Sep.; fall, Oct. - Dec). Seasonal data from MRIP itemized landings by six bimonthly intervals. Landings-by-gear data from NOAA were aggregated according to fleets described for the Gulf of Mexico Atlantis model (Appendix A) to simplify results while relating the analysis to EBFM tools. Three miscellaneous gear types could not be directly allocated into a fleet so each were left to stand alone for this analysis: "Combined Gears", "Not Coded", and "Unspecified Gear".

2.3.1.1 Functional Group-Specific Landings

Data described in section 2.3.1 were used to construct landings time series for the functional groups of the Gulf of Mexico Atlantis model. First, data were allocated into functional groups. To do this the taxonomic classification of landings were determined using the Integrated Taxonomic Information System (ITIS, 2012), FishBase (Froese and Pauly, 2016), SeaLifeBase (Palomares and Pauly, 2016), Salas et al. (2011), or the Universal Biological Indexer and Organizer (Norton et al., 2013). Species-specific data were directly allocated into functional groups, while ambiguous data were split amongst appropriate functional group(s). In some cases, a higher taxonomic level of identification, such as family, was sufficient to determine the appropriate functional group. In other cases, ambiguous landings were allocated to functional groups based on information from the literature, or assumptions made about the species composition. Second, data were converted to tonnes. Commercial landings were recorded by weight but recreational data (numbers) were converted to tonnes using length-weight relationships and the length information included in the datasets. This entire process was described in detail by Perryman et al. (2015).

2.3.2 Landings-based Indicators

This study considers two types of landings-based indicators: qualitative stock assessment coverage indicators, and quantitative community indicators. The computation of indicators were restricted to U.S. landings (section 2.3.1) because more data on species identification and status was available in the U.S. Landings-based indicators relating to ecological status were computed with i) landings itemized by season and state, as well as ii) functional group-specific landings constructed for the

Gulf of Mexico Atlantis model (section 2.3.1.1). The former allowed the assessment of indicator trends over finer temporal and spatial scales of the fisheries, and the latter allowed the analysis of impacts to indicators when data are aggregated into functional groups. Indicators are computed separately for commercial and recreational landings as to assess differences in trends between the two sectors. U.S. recreational species-specific landings data were in numbers, while the U.S. commercial species-specific landings data, and all functional group-specific landings data were in weight. For details on the species composition of recreational and commercial landings, see Appendix A.

2.3.2.1 Stock Assessment Indicators

Karnauskas et al. (2013) found that, for landings of federally managed stocks in the U.S. Gulf of Mexico, the ratio of overfished to not overfished stocks has decreased. To expand on this analysis, I included all landed species, not just those in federal fishery management plans, and evaluated overfished status and jurisdiction of i) number of landed species (combining commercial and recreational data), ii) U.S. commercial landings, and iii) U.S. recreational landings. Information on status was provided by annual Congressional Stock Status (CSS) Reports. Since 1997, NOAA has been submitting reports to Congress describing the state of the nation's marine fisheries and the effectiveness of fisheries management under the Magnuson-Stevens Fishery Conservation and Management Act as amended in 1996 by the Sustainable Fisheries Act (National Marine Fisheries Service, 1998 - 2012). These CSS Reports indicate the status of federally managed stocks. Species that are managed federally are identified under fishery management plans (FMPs) from the Gulf of Mexico Fishery Management Council (GMFMC). Stocks primarily retained within state waters (to 16.2 km from the coast in Texas and the west coast of Florida, to 5.6 km in the other Gulf of Mexico states) are generally managed by the individual states. The Interjurisdictional Fisheries Program of the Gulf States Marine Fisheries Commission (GSMFC) provides the Gulf States with information and recommendations for interstate FMPs.

First U.S. commercial and U.S. recreational landings data were categorized based on species-specific overfished status in each year's CSS report. A species landings were categorized as unknown if the overfished status was not reported. Then, for species of unknown overfished status, landings were classified according to FMP jurisdiction (i.e., GSMFC, GMFMC, or neither). Ambiguous landings were categorized as unknown overfished status with no FMP jurisdiction, because the overfished status and FMP jurisdiction cannot be determined. The same categorization was made for landings associated with species managed by individual states and not associated with the GSMFC. Spanish mackerel (*Scomberomorus maculatus*) which has FMPs under both GSMFC and GMFMC, were allocated to the GMFMC.

2.3.2.2 Pelagic:Demersal Ratio

Landings pelagic:demersal ratio is the ratio of landings of pelagic organisms to landings of demersal/benthic organisms. To calculate the ratio, information regarding the life history of adults organisms were used to classify landings as pelagic or demersal, then total landings of pelagic species were divided by total landings of demersal species. The pelagic:demersal ratio may be an informative for the ecosystem management of the Gulf of Mexico since the metric is primarily linked to the eutrophication (Caddy, 1993; Caddy and Bakun, 1994; Caddy et al., 1998a; Caddy and Garibaldi, 2000; Caddy, 2000; de Leiva Moreno et al., 2000), and the Gulf of Mexico experiences periodic large-scale eutrophication which has meaningful ecosystem impacts (Malakoff, 1998; Rabalais et al., 2002b,a). Karnauskas et al. (2013) discussed the pelagic:demersal ratio with respect to fishery independent trawl survey data, but do no discuss the metric in terms of landings data. These metrics have a different interpretation because the fishery-independent pelagic:demersal ratio is tracking changes in the ecosystem, while the pelagic:demersal ratio of landings can show shifts in fishery targets.

In this study, the pelagic:demersal ratio was computed with U.S. commercial, and U.S. recreational landings time series. This was done for both species-specific and functional group-specific datasets. Species and functional groups were classified as pelagic or demersal using life history information from FishBase (Froese and Pauly, 2016) and SeaLifeBase (Palomares and Pauly, 2016). Due to the configuration of functional groups for the Gulf of Mexico Atlantis model, most groups contained species that were either all pelagic or all demersal. The exceptions were the *skates and rays* functional group, which was assumed to be demersal, and the *large sharks* functional group, which was assumed to be pelagic, when calculating functional group specific pelagic:demersal ratio (Appendix A).

2.3.2.3 Mean Trophic Level

Landings mean trophic level is the sum of the product of species trophic level and species landings divided by landings summed across all species. This indicator has been proposed as evidence that there has been a gradual transition in landings from long-lived, high trophic level, piscivorous fish toward short-lived, low trophic level, invertebrates and planktivorous fish caused by sequential depletion of upper trophic level species to lower trophic level species - a phenomenon called "fishing down the foodweb" (Pauly et al., 1998; Pauly and Palomares, 2005; Pauly and Watson, 2005; Pauly et al., 2005). The Convention on Biological Diversity has identified landings mean trophic level as one of eight indicators to be tested to measure progress towards achieving a significant reduction in the current rate of biodiversity loss (Convention on Biological Diversity, 2004). Although, this indicator may be influenced by changes in fleet targeting, advancing harvesting technology, and fisheries management, rather than fisheries impact on an ecosystem (Caddy et al., 1998b; Caddy and Garibaldi, 2000; Essington et al., 2006; de Mutsert et al., 2008; Branch et al., 2010; Powers, 2010; Sethi et al., 2010), it can still be informative with respect to the targets and composition of fisheries (Shin et al., 2010).

Karnauskas et al. (2013) found the average trophic level of both Mexican and U.S. landings has increased since the 1950's. To evaluate whether this conclusion would change when the data were combined into functional groups, or with the additional datasets considered in this study, landings mean trophic level was calculated for U.S. commercial and U.S. recreational species-specific data and functional group-specific data. First, FishBase (Froese and Pauly, 2016) and SeaLifeBase (Palomares and Pauly, 2016) were used to get species-specific estimates of trophic level. If an estimate was not provided, then a value from a similar species of the same genus was assumed. Functional groups in the Gulf of Mexico Atlantis model were assigned trophic level by averaging the corresponding species-specific trophic levels.

2.4 Results

2.4.1 Landings Data

The amount of ambiguous landings varies across Gulf of Mexico countries (Figure 2.2). A majority of U.S. landings are identified to species. On average 94.8% of the commercial landings, excluding menhaden, (Figure 2.2a), and 95.2% of the recreational landings (Figure 2.2b). U.S. ambiguous landings mostly consist of records identified to a taxonomic classification higher than species. On average 68.6% of the commercial ambiguous landings, and 92.1% of the recreational ambiguous landings. Family is the most common taxonomic classification used other than species. Family is given for on average 57.1% of the commercial ambiguous landings, and 64.3% of the recreational ambiguous landings. Generally, the proportion of U.S landings that are of ambiguous groups fluctuates throughout the data series. After 1986, the proportion of U.S landings that are of ambiguous groups has decreased because the landings of ambiguous groups (e.g., miscellaneous finfish, and sharks) decreased while the landings of species-specific groups remained stable (Appendix A). The trend in proportion of U.S. recreational landings that are of ambiguous groups is generally decreasing due to a large decline in ambiguous landings early in the dataset.

Data from Mexico and Cuba have more landings associated to ambiguous groups. On average, 70.8% of the Mexican commercial landings are identified to taxonomic classifications while 29.2% are unidentified (Figure 2.2c). A majority of Cuban commercial landings (on average 66.8%) are of ambiguous groups (Figure 2.2d). Most of the Cuban ambiguous landings (on average 73.0%) are of unidentified groups. The proportion of Mexican commercial landings identified to a taxonomic classification increased over time due a gradual decline in unidentified landings (Appendix A). The proportion of Cuban commercial landings of miscellaneous/unidentified groups decreased over time, and the proportion of Cuban commercial landings of groups with a taxonomic classification other than species increased over time (Appendix A).

On average, more U.S. commercial and U.S. recreational landings occur in the summer months (Figure 2.3). Commercial ambiguous landings are more common during the spring, while recreational ambiguous landings are more common in the summer. The percent of commercial landings that are of ambiguous groups has decreased for every season except spring (Figure 2.3c). The percent of recreational landings that are of ambiguous groups has increased for summer months, and decreased for winter months (Figure 2.3d).

U.S. commercial landings (Figure 2.4a) are predominantly landed in Louisiana, Texas, and Florida. Over time, landings from Florida have decreased and landings from Louisiana have increased. U.S. recreational landings (Figure 2.4b) are predominantly from Florida. Over time, the proportion of landings from Florida and Texas have increased while the proportion of landings from Louisiana and Mississippi have decreased. On average, for both commercial and recreational data (Figure 2.4c, 2.4d), Mississippi has a higher fraction of landings that are of ambiguous groups, followed by Florida. However, the higher average of commercial landings from Mississippi is due to a large spike in ambiguous landings in the mid-90's. This was caused by a sudden reporting of unidentified shrimp (see Appendix A). In addition, the higher average of recreational landings from Mississippi is due to a large spike in ambiguous landings in 2010. This was caused by a sudden reporting of *Carcharhinidae* landings (see Appendix A). Not considering these sudden spikes, Florida has the higher fraction of landings that are of ambiguous groups for both commercial and recreational data.

U.S. commercial landings itemized by gear, which have been aggregated by Gulf of Mexico Atlantis fleets, are highly variable until the late 1990's (Figure 2.5). From 1980 to 2001, on average half of the commercial landings are not identified to a specific gear, thus could not be directly allocated to a fleet identified for the Gulf of Mexico Atlantis model (Figure 2.5a). From 1980 to 1996, over half of the ambiguous landings (55%) are from gear-types that could not be directly associated to an Atlantis fleet (Figure 2.5b). The percentage of landings that are of ambiguous groups varies amongst U.S. gear-types. Trends for hook-and-line gear-types stabilize and some are generally lower in recent years than in the 1980's and 1990's (Figure 2.5c). Trends for net gears, both those operated within estuaries (Figure 2.5d) and those operated within the shelf Figure 2.5e), vary, with some increasing over time. Trends for miscellaneous gear-types are highly variable (Figure 2.5f).

2.4.2 Landings-based Indicators

2.4.2.1 Stock Assessment Indicators

On average, about half of the federally managed species harvested by U.S. fleets are of an unknown overfished status (Figure 2.6a). In addition, on average 62.6% of the species harvested by U.S. fleets are not identified in a GMFMC or GSMFC FMP. The number of overfished species, and the number of species of unknown overfished status has decreased over time. Many of the landed species of unknown overfished status are from the U.S. recreational data, so it's possible that this trend is driven by improvements to the MRIP dataset (e.g., improved identification of landings).

The number of not overfished species landed has increased over time. This is possibly driven by improvements and expansion of stock assessments rather than improvements in fisheries sustainability.

On average, most (60.6%) of U.S. commercial landings (lbs) are of federally assessed stocks declared not overfished (Figure 2.6b), while most (84.0%) of U.S. recreational landings (numbers) are of species with unknown status (Figure 2.6c). Most of the U.S. commercial landings of unknown status (on average 67.7%) correspond to species associated to GSMFC FMPs. A majority of these landings are of blue crab (*Callinectes sapidus*), eastern oyster (*Crassostrea virginica*), and striped mullet (*Mugil cephalus*). Some of these species have been assessed by individual state agencies for part of the Gulf of Mexico, so U.S. commercial landings of species declared not overfished may be larger. U.S. recreational landings of unknown status are mostly (on average 59%) of species not associated to either GSMFC or GMFMC FMPs. A majority of these landings consist of scaled sardine (*Harengula jaguana*), pinfish (*Lagodon rhomboides*), white grunt (*Haemulon plumieri*), and Atlantic thread herring (*Opisthonema oglinum*). Many of these species are used in the bait industry and they may not be at much risk of being overfished because of their short lived and fast growing life history.

Trends from U.S. commercial data and U.S. recreational data should not be compared since commercial data were in weight and recreational data were in numbers. Since the U.S. recreational landings are in numbers, and the data are highly variable, it is difficult to discern the magnitudes of the resulting trends. For instance, U.S. recreational landings of unknown status are mostly smaller bait fish, while not overfished landings (mostly composed of Spanish mackerel) and overfished landings (mostly composed of red snapper , *Lutjanus campechanus*) consist of larger finfish.

2.4.2.2 Pelagic:Demersal Ratio

Landings pelagic:demersal ratio trends computed from U.S. commercial and U.S. recreational data are shown in Figure 2.7. There are no obvious seasonal trends of the pelagic:demersal ratio for U.S. commercial data (Figure 2.7a) or U.S. recreational data (Figure 2.7d). Seasonal pelagic:demersal ratio from U.S. recreational data are highly variable, so it is difficult to discern statistically meaningful trends. The commercial pelagic:demersal ratio trends decreased for all four seasons, while the recreational pelagic:demersal ratio increased for all six bimonthly intervals. The certainty of recreational trends is questionable since data are highly variable. Landings pelagic:demersal ratio trends differ amongst individual states for both U.S. commercial, and U.S. recreational data (Figure 2.7b and (Figure 2.7e), respectively). For both U.S. commercial, and U.S. recreational data, landings pelagic:demersal ratio is much larger for Florida landings. Florida landings had significant contributions from pelagic finfish groups (e.g., scaled sardine) while landings in the other states tend to be dominated by demersal groups (e.g., seatrout, shrimp, oysters) (Appendix A). Much of the U.S. commercial ambiguous landings consists of groups that are or have the potential to be demersal (e.g. shrimp, shellfish, flatfish, finfish), so ambiguous landings could influence U.S. trends from U.S. commercial data.

The pelagic:demersal ratio computed with functional group-specific landings tends to be similar to that computed with species-specific landings for both U.S. commercial (Figure 2.7c). The recreational pelagic:demersal ratio (Figure 2.7f) increased for both species-specific, and functional group-specific data up until 2000, after which while the trend from species-specific data continued to increase, the trend from functional group-specific data decreased. The divergence in trends is not due to the aggregation of data into functional groups as most species are assigned to functional groups with the appropriate pelagic/demersal classification. Species composition of recreational data suggests the divergence is due to the fact that species-specific data are in numbers while functional group-specific data are in weight - meaning the species-specific ratio does not account for weight differences between organisms. Landings of some small, pelagics (e.g., scaled sardine, *Harengula jaguana*) increased since 2000 influencing an increase in the species-specific ratio, while landings of several relatively larger demersal species (e.g., pigfish, *Orthopristis chrysoptera*, red porgy, *Pagrus pagrus*, and yellowtail snapper, *Ocyurus chrysurus*) have also increased influencing a decrease in the functional group-specific ratio.

There are more concerns regarding trends from U.S. recreational data then trends from U.S. commercial data. First, seasonal landings in pelagic:demersal ratio from U.S. recreational data are highly variable, so it is difficult to discern trends. Second, U.S. recreational data landed in Florida appear to be governing the overall trend for U.S. recreational pelagic:demersal ratio. Lastly, the U.S. recreational pelagic:demersal trend computed in numbers data has a different ecological meaning than trends computed with data in weight. Thus, caution should be used when interpreting and comparing the trend to others.

2.4.2.3 Mean Trophic Level

Landings mean trophic level trends computed from U.S. commercial and U.S. recreational data are shown in Figure 2.8. There are no obvious seasonal trends of landings mean trophic level for U.S. commercial data (Figure 2.8a) or U.S. recreational data (Figure 2.8d). For both commercial and recreational data, summer landings mean trophic level is the only significant trend and it is declining. In addition, there are no obvious differences in landings mean trophic level amongst States for U.S. commercial data (Figure 2.8b) or U.S. recreational data (Figure 2.8e). For both commercial and recreational data, Texas landings mean trophic level is the only significant trend and it is decreasing. Landings mean trophic level computed with functional group-specific data tends to be similar to that computed with species-specific data for both U.S. commercial (Figure 2.8c) and U.S. recreational (Figure 2.8f) data. Values from species-specific data tend to be smaller than values from functional group-specific data

Similar to the seasonal pelagic:demersal ratios from U.S. recreational data, seasonal landings mean trophic level from U.S. recreational data are highly variable, so it is difficult to discern trends. In addition, U.S. recreational data landed in Florida appear to be governing the overall trend for U.S. recreational landings mean trophic level. U.S. commercial ambiguous landings may have some influence on landings mean trophic level, especially since the computation of landings mean trophic level seems to be particularly sensitive to values used for trophic level (Appendix A). Ambiguous landings would likely reduce the U.S. commercial metric, especially in the late 80's to early 90's, since much of the U.S. commercial ambiguous landings are attributed to groups with lower trophic levels (e.g., miscellaneous shrimp, and unidentified bait finfish).

2.5 Discussion

Although a relatively small portion of the commercial landings from NOAA are of ambiguous groups, allocating ambiguous landings to the appropriate functional groups is important in order to i) maintain the magnitude of biomass extraction in ecosystem models, and ii) account for landings of organisms of concern that are not often identified to species. An important example of the latter is sharks. There have been improvements in the identification of shark species in the Gulf of Mexico U.S. commercial landings (Appendix A), but commercial landings of ambiguous shark groups may still represent significant amounts of biomass for some species, and ignoring these landings could bias the representation of harvesting pressure in ecosystem models like Atlantis. Mexico and Cuba landings have large portions that are of ambiguous groups, particularly miscellaneous, unidentified groups. Omitting these landings from EBFM tools (i.e., ecosystem models, indicators) would introduce bias and could lead to inappropriate management advice. Thus, it is essential to associate these ambiguous landings to taxonomic classifications.

Associating ambiguous landings to inappropriate taxonomic classifications could also introduce bias into EBFM tools. Considering Atlantis, it could shift fishing pressure and biomass loss from one group to another. This could create a situation where one group is being represented as more influenced by fishing than it is in reality, and representing another group to be less influenced by fishing than it is in reality. This, too, could lead to inappropriate management advice, like suggesting that increased fishing pressure is sustainable for one group (when it may not be), and/or that decreased fishing pressure is necessary for the sustainability of another group (when it may not be). This is less of a concern for ambiguous landings associated to a taxonomic classification higher than species (e.g., genus, family) because these landings are more likely to be associated to appropriate functional groups as functional groups often aggregate species of similar taxonomic classifications. Fortunately, much of the U.S. ambiguous landings are associated to a taxonomic classification so much of these landings are associated to appropriate functional group(s). However, distributing ambiguous landings from Cuba and Mexico across functional groups required making additional assumptions about the data as these landings were predominantly of miscellaneous/unidentified groups. Thus, there is more uncertainty concerning the Mexican and Cuban fisheries and ecosystem model outputs may not be accurate. The allocation of ambiguous catches to functional groups could be potentially be improved by incorporating knowledge of fish distributions, gear selectivity and seasonality, as the Sea Around Us Project has done in mapping global catches (Pauly, 2007).

Representing biomass loss due to recreational fishing is important for the development of EBFM tools for the Gulf of Mexico. Recreational activities are significant to the overall fishing pressure in the Gulf of Mexico (Coleman et al., 2004b), and changes in recreational information can impact management recommendations (Griffiths and Fay, 2015). MRIP, currently the best available data on U.S. recreational landings, is necessary when reconstructing historical landings profiles for the Gulf. Fortunately, most of the MRIP data are identified to species, so recreational ambiguous landings have little impact on the historical landings time series for the Atlantis Gulf of Mexico ecosystem model, and the computation of landings-based ecosystem indicators. However, MRIP data are highly uncertain as they are estimates based on surveys expanded across the whole fishery, unlike NOAA commercial data which are based on fishermen log books and trip tickets that cover the majority of the commercial fisheries. Thus, ecosystem model results concerning recreational fleets should be interpreted with caution. Specifically, the magnitude of landings of groups not commonly harvested by recreational activities as data from those groups tend to have more variability. Efforts are under way to improve MRIP estimates (Breidt et al., 2010), and EBFM tools would benefit from considering updated data as it becomes available. Unfortunately, information pertaining to recreational activities within the southern Gulf could not be found, and recreational activities are important sources of fishing mortality for Cuba (Claro et al., 2009), and Mexico (FAO, 2003). This is also true for illegal, unreported, and unregulated (IUU) fishing, which was also not considered in this study. Thus, landings data presented here from the southern Gulf are likely under-representing activities from Mexico and Cuba, and IUU catches could be taking place anywhere in the Gulf.

U.S. landings datasets itemized by season/state/gear are informative for EBFM, but need to be considered cautiously as they can introduce uncertainty into ecosystem model results. Small portions of the seasonal commercial landings are allocated to ambiguous groups so any uncertainty in the corresponding seasonal functional group composition or landings distribution is small. Data itemized by state were not used to calibrate the Gulf of Mexico Atlantis model, but data itemized by state are informative for other EBFM tools (i.e., indicators). Most of the ambiguous landings (both commercial and recreational) are from Florida, and the proportion of Florida landings allocated to ambiguous groups is increasing over time. This is an important area of uncertainty to be aware of for indicator assessment. Prior to 2000 a significant amount of the commercial landings could not be directly allocated to an Atlantis fleet because these data were not specified to a gear-type (e.g., combined gears, not coded). This does not bias the historical Gulf of Mexico Atlantis model because it simulates total harvest by functional group, space and time, but does not partition landings amongst fleets. However, this data will add uncertainty to the average proportions computed to distribute landings across fleets for forecast simulations.

Some U.S. commercial gears seem to be improving species identification of landings while others seem to be getting worse. Since 1997, gears targeting sharks show the most improvement towards identifying landings to species. By the end of the series, U.S. commercial ambiguous landings are dominated by the single identification used for hammerhead shark species (Appendix A), which is likely used because identifying hammerheads to species can be difficult (FAO, 2013b). However, gill netting gears show an increase in ambiguous landings, specifically of king/cero mackerel, and sharks. In terms of management, particularly for sharks, improved species identification of landings from these gears may be needed.

Trawl and purse seine gears are not associated to much of the ambiguous landings, which is not surprising as this analysis is restricted to landings and did not consider bycatch. Bycatch refers to unwanted catch that is often discarded at sea, and it is an important source of fishery induced mortality especially for trawl and seine gears (e.g., de Silva et al., 1996; Gallaway and Cole, 1999; Diamond et al., 2000; de Silva et al., 2001; Baum et al., 2003a; Harrington et al., 2005; Finkbeiner et al., 2011). The Gulf of Mexico trawl fisheries generate 19,000 tonnes of discards, generating a discard rate of 46.2 percent (Bojorquez, 1998). More recently, the U.S. National

Bycatch Report stated the Gulf of Mexico shrimp trawl had the highest ratio for trawl fisheries (0.75), and the HMS pelagic longline the smallest amongst longline fisheries (0.23) (National Marine Fisheries Service, 2013). Bycatch can impact assessment of stocks. For instance, Cortés (2002b) determined that the Atlantic blacknose shark stock was not overfished nor experiencing overfishing. Those results were influenced by catch series that did not include bycatch. When the stock was re-assessed by SEDAR (2007) which included estimates of bycatch, SEDAR concluded that the stock was overfished and experiencing overfishing. Although landings data are essential for the construction of EBFM tools and the assessment of ecosystem indicators, so are bycatch data. Neglecting bycatch can introduce bias into EBFM tools and the ecosystem indicators, particularly for species for which bycatch is an important source of mortality.

Landings-based indicator trends computed with functional group-specific data are similar to those computed with species-specific data. Thus, in the case of the Gulf of Mexico Atlantis model i) U.S. ambiguous landings have a negligible influence on landings-based indicators trends, and ii) the aggregation into functional groups has negligible influence on landings-based indicators trends. Indicator values from functional group-specific data tend to be slightly larger than indicator values from species-specific data. This is likely because of the aggregation of landings data into functional groups. Thus, landings-based indicator values from the Atlantis Gulf of Mexico model may not reflect values from raw data, but the differences observed here are relatively small. The largest difference observed was between the pelagic:demersal ratio values from U.S. recreational data, but this is due to functional group data being in weight and species-specific data being in numbers. Thus, the functional groups defined for the Gulf of Mexico Atlantis model seem to appropriately represent the hierarchy of species across the Gulf of Mexico. To fully investigate this would entail a study of different hierarchical species compositions of functional groups (e.g., Fulton, 2002).

Recreational indicators presented here should be interpreted with caution since data were in numbers, not weight, and trends from numbers data have a different meaning than trends in weight. The recreational landings pelagic:demersal ratio with species data (numbers) and functional group data (lbs) showed how number data and weight data can produce different trends. Weight data may be producing metrics with a more appropriate ecological interpretation of the ecosystem since the impact of a species on an ecosystem may be more related to the biomass of a stock than number of individuals. However, MRIP data collected in weight contains half as many records as MRIP data collected in numbers, thus the weight data do not represent as much of the U.S. recreational sector as the numbers data. For the Gulf of Mexico Atlantis model, data collected in numbers were converted to weight. Although this introduces uncertainty regarding the magnitude of functional group-specific landings in weight due to the simple assumptions made about average length-weight relationships of landed species (Hayes et al., 1995), it was the best estimate that could be made.

Quantitative community indicators reveal interesting trends and data considerations. Landings mean trophic level of U.S. recreational data are higher than landings mean trophic level of U.S. commercial data, and since 1980 both trends are relatively stable. This agrees with trends presented in the Gulf of Mexico Ecosystem Status Report (Karnauskas et al., 2013), except values in the report are somewhat larger than the values presented here. First, the U.S. commercial trend presented in the report is computed with finfish data only while this study excluded only menhaden landings.

Thus, popular demersal fisheries (e.g., shrimp, crabs, oysters) are driving down the trend computed in this study. In addition, the computation of landings mean trophic level seems to be sensitive with respect to the values of trophic levels assumed for each species, and this study and the Gulf of Mexico Ecosystem Status Report may have used somewhat different values for some species. Landings pelagic:demersal ratio was not presented by Karnauskas et al. (2013). The U.S. commercial (lbs) pelagic:demersal ratio quickly increased in the 1990's and has been slowing decreasing. The U.S. recreational pelagic:demersal ratio (functional-group trend) steadily increased until 2000. Indicators computed with data series itemized by season and state show that general trends from recreational data are dominated by data from Florida, and that trends in the western Gulf are different from trends in Florida. Computing indicators with landings datasets itemized by season and state revealed interesting trends within the ecosystem for both commercial and recreational data which may be reflecting differences in historical exploitation patterns and management (Blanchard et al., 2010).

Stock assessment indicators presented here support statements made in the Gulf of Mexico Ecosystem Status report (Karnauskas et al., 2013): a majority of landed stocks have an unknown overfished status, and are not identified under a FMP. This study found that there has been little change in the number of stocks not identified under a FMP as a decrease is likely due to the decrease in the overall number of landed stocks. Also, commercial landings are mostly of assessed stocks that are not overfished, and landings of overfished stocks decreased over time due to stocks being re-assessed and recovering from their overfished status. Commercial landings of stocks with unknown status are predominantly species under GSMFC's Interjurisdictional Fisheries Program, some of which have been assessed under the GSMFC or by individual states. For example, blue crabs (*Callinectes sapidus*) make up much of these landings, and blue crabs have a GSMFC regional management plan (Perry and VanderKooy, 2015) as well as a recent stock assessment that found the stock to be not overfished and not experiencing overfishing (VanderKooy, 2013). Lastly, recreational landings are predominantly stocks of unknown status - particularly stocks not identified under a GSMFC or GMFMC FMP. This is concerning, and there should be an effort to assess stocks of unknown status to determine species of concern. Assessment at the State level may be more appropriate for some species, in addition to low data stock assessment methods, such as Carruthers et al. (2014, 2016), and Southeast Data, Assessment, and Review (2016). In addition, the Atlantis model provides a means to qualitatively investigate fisheries impact on stocks in order to identify functional groups of concern.

Landings data are important for many aspects of fisheries science and management, and it would be advantageous of EBFM of the Gulf of Mexico if some of the landings data discussed here were improved. Historical landings from Gulf of Mexico waters off the coasts of Mexico and Cuba are uncertain due to the lack of recreational data, and large portions of landings allocated to ambiguous groups. To reduce uncertainty around Mexico and Cuba landings for the purposes of Gulf-wide EBFM tools like Atlantis, practitioners should continue working with management agencies from these regions to improve species-specific catch/landing information and develop estimates of recreational landings from Gulf waters. This could include using commercial data to indirectly estimate recreational catch series (Zeller et al., 2008). Although the MRIP dataset provides crucial information regarding recreational landings from the northern Gulf, EBFM tools of the Gulf would benefit from the incorporation of improved estimates of recreational landings. Until such efforts can be made, data discussed here are sufficient for the construction and calibration of EBFM tools like the Atlantis Gulf of Mexico model, and for calculating ecosystem indicators for the Gulf of Mexico IEA, keeping data uncertainties in mind.

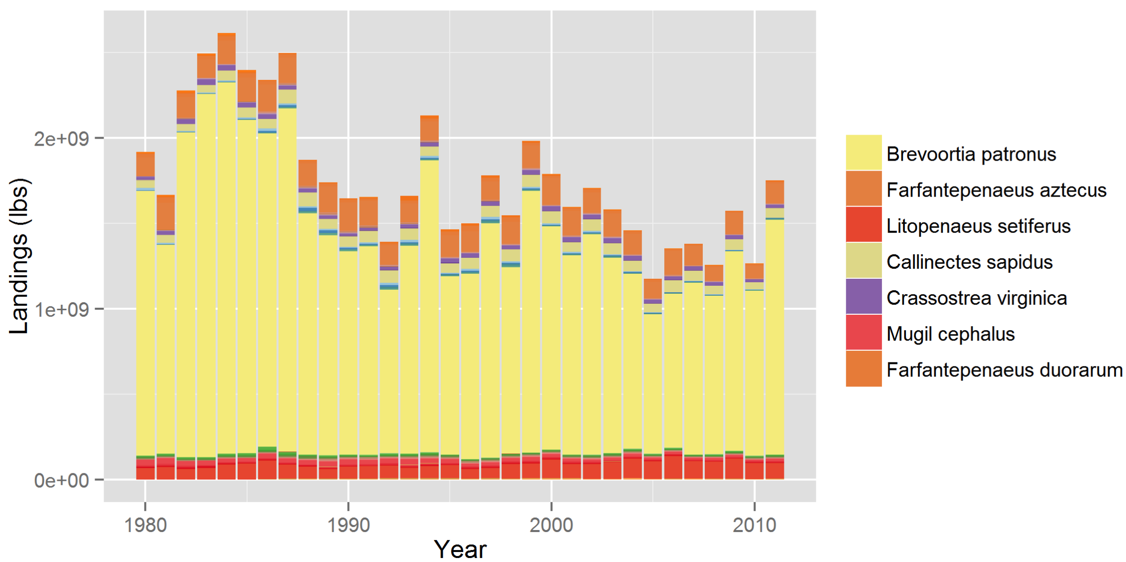
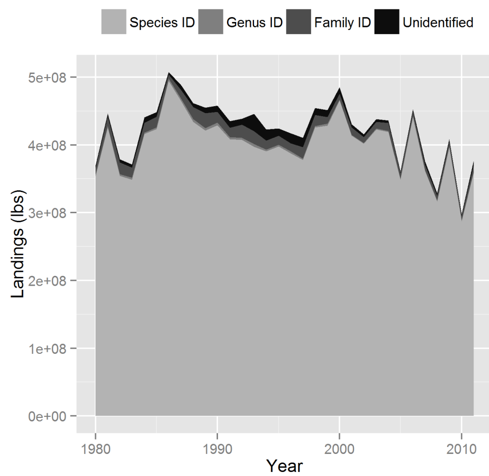
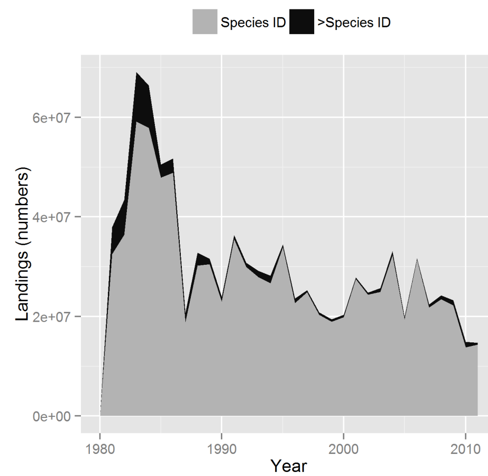


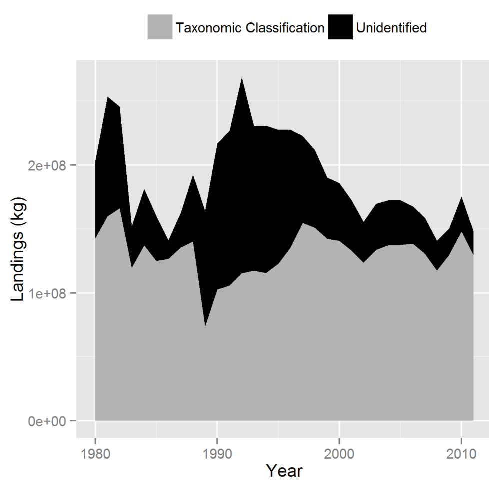
Figure 2.1: Species Composition of United States Commercial Landings Over Time. Legend shows only the seven most common species.



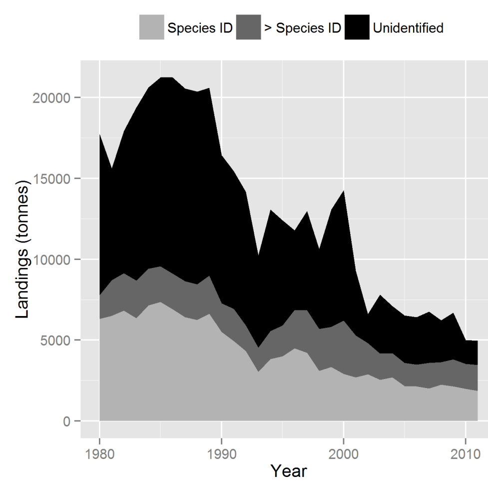
(a) U.S. Commercial (excluding menhaden)



(b) U.S. Recreational

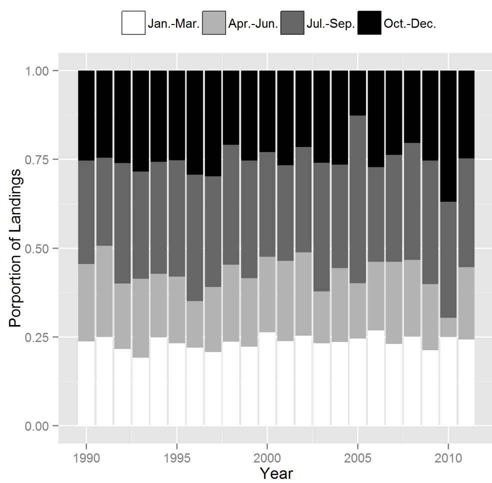


(c) Mexico Commercial

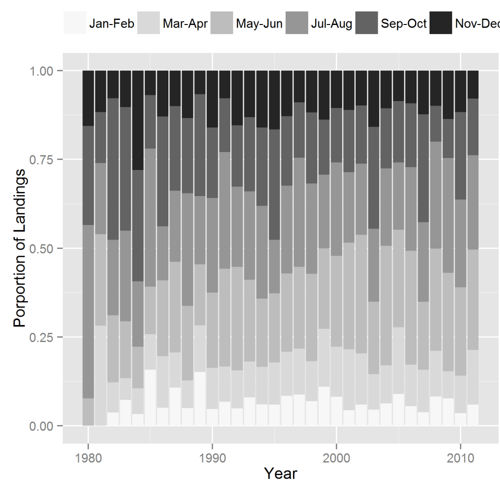


(d) Cuba Commercial

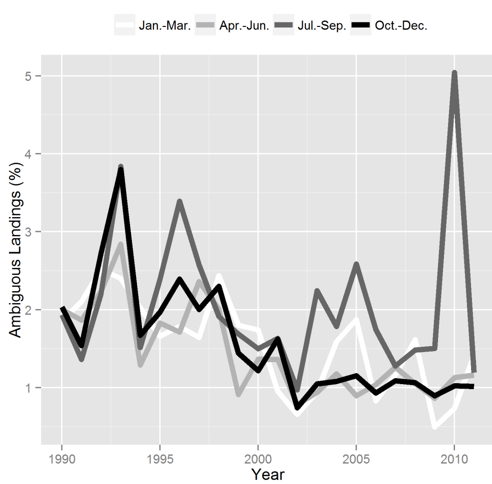
Figure 2.2: Regional Landings Categorized by Taxonomic Classification. Landing data are of United States commercial - excluding menhaden (a), United States recreational (b), Mexico commercial (c), and Cuban commercial (d) fleets.



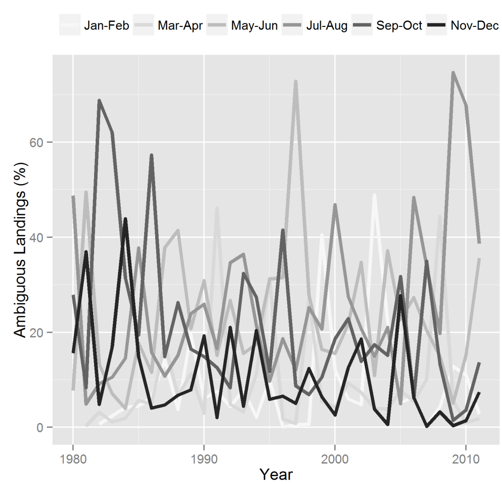
(a) U.S. Commercial



(b) U.S Recreational

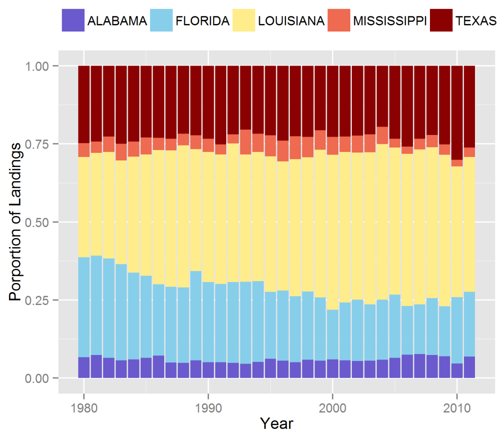


(c) U.S. Commercial

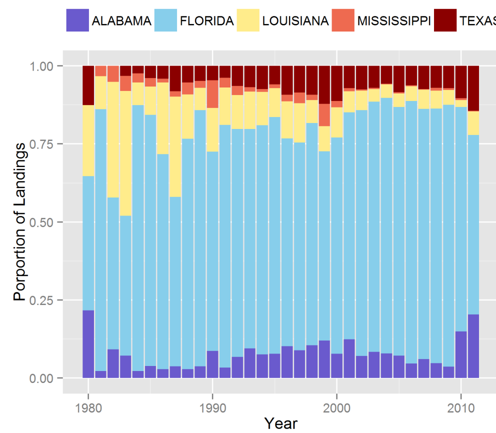


(d) U.S Recreational

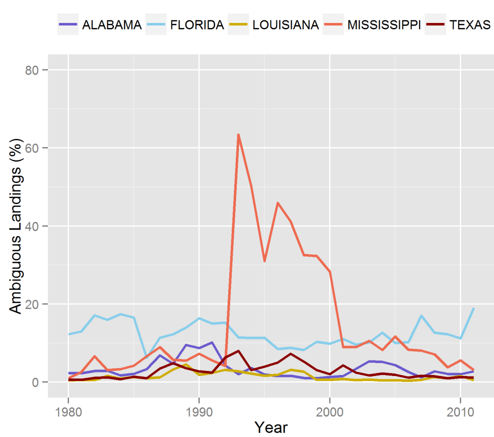
Figure 2.3: Seasonal Proportion of U.S. Landings and Percent of Seasonal U.S. Landings Allocated to Ambiguous Groups. U.S. commercial landings data from NOAA are itemized into four seasons, and U.S. recreational landings data from MRIP are itemized into six bimonthly intervals. Panels (a) and (b) show the seasonal proportions for U.S. commercial landings (excluding menhaden) and U.S. recreational landings, respectively. Panels (c) and (d) show the percentage of seasonal landings allocated to ambiguous groups for U.S. commercial data (excluding menhaden) and U.S. recreational data, respectively.



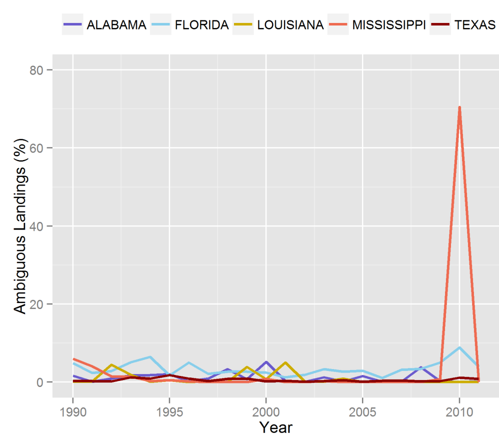
(a) U.S. Commercial



(b) U.S Recreational

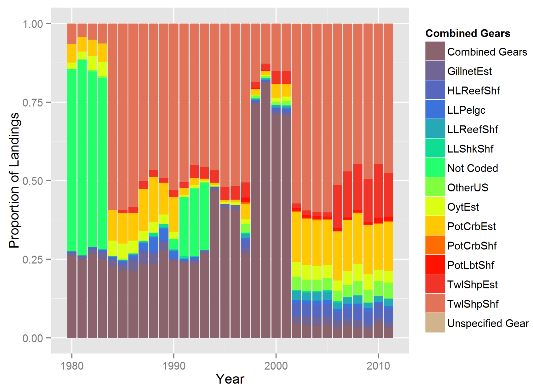


(c) U.S Commercial

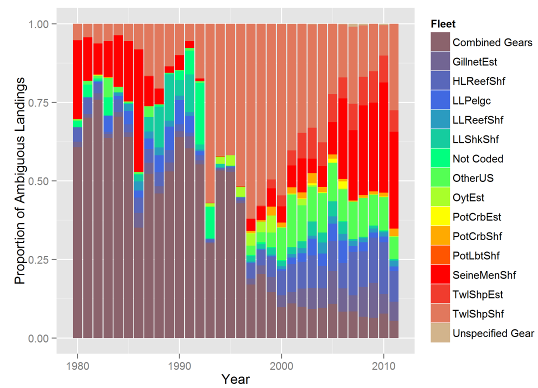


(d) U.S Recreational

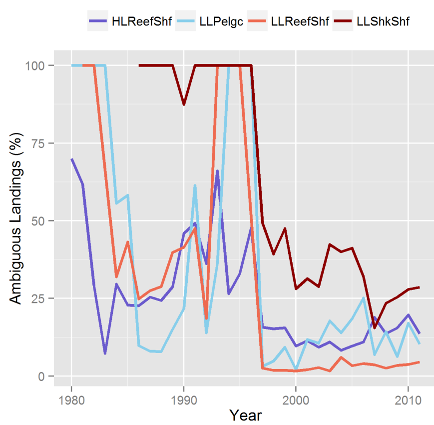
Figure 2.4: State Proportion of U.S. Landings and Percent of State U.S. Landings Allocated to Ambiguous Groups. Panels (a) and (b) show the state proportions for U.S. commercial (excluding menhaden), and U.S. recreational landings, respectively. Panels (c) and (d) show the percentage of state landings allocated to ambiguous groups for U.S. commercial (excluding menhaden), and U.S. recreational data, respectively.



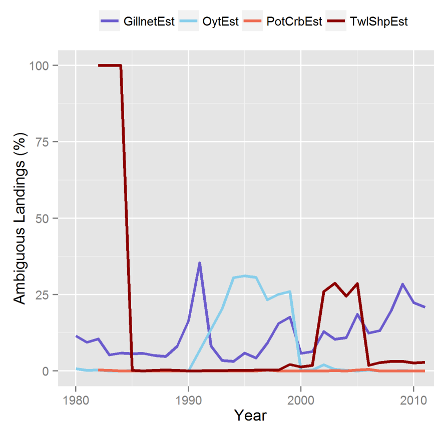
(a)



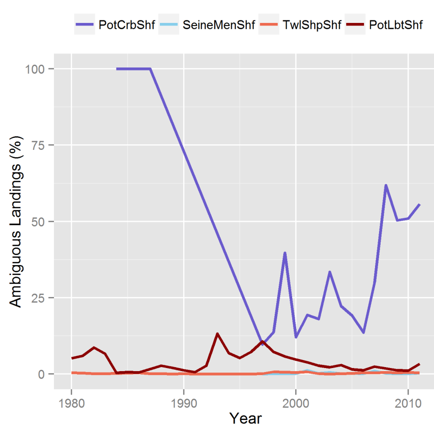
(b)



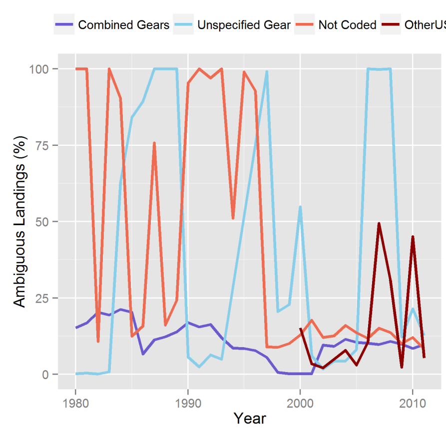
(c)



(d)



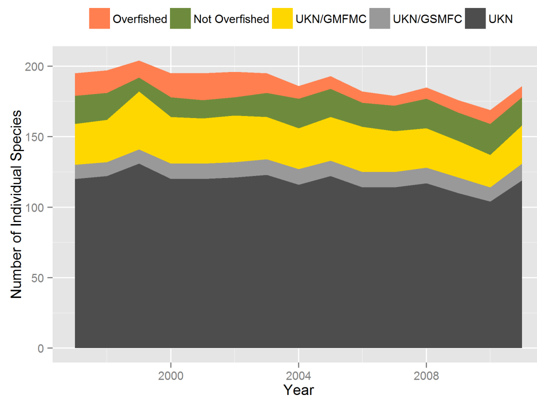
(e)



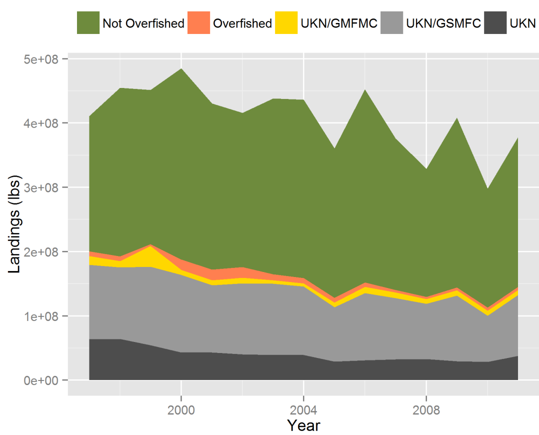
(f)

Figure 2.5: See following page for caption.

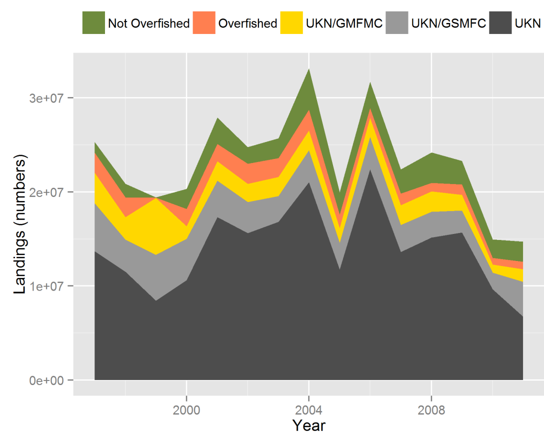
Figure 2.5: U.S. Commercial Landings and Ambiguous Landings Itemized by Gear. U.S. commercial gears are categorized by the fleets represented in the Gulf of Mexico Atlantis model. Panel (a) shows the proportion each fleet contributes to U.S. commercial landings (excluding the fleet targeting menhaden). Panel (b) shows the proportion each fleet contributes to U.S. commercial ambiguous landings. Panels (c - f) show the percentage of commercial landings allocated to ambiguous groups for hook-and-line fleets (c), estuary fleets (d), shelf fleets (e), and miscellaneous / unidentified gears (f).



(a) U.S. Commercial and Recreational Landings

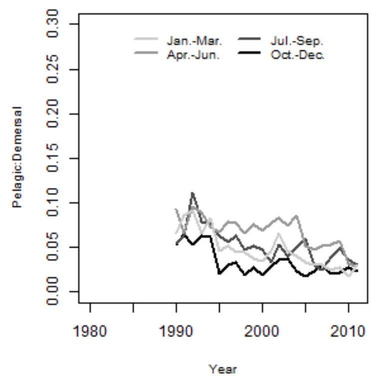


(b) U.S. Commercial Landings

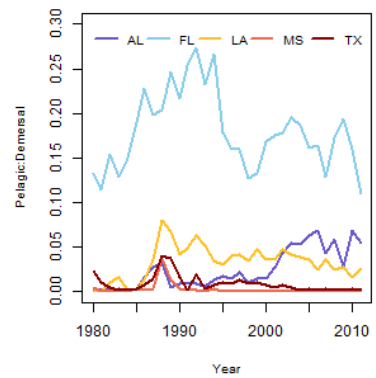


(c) U.S. Recreational Landings

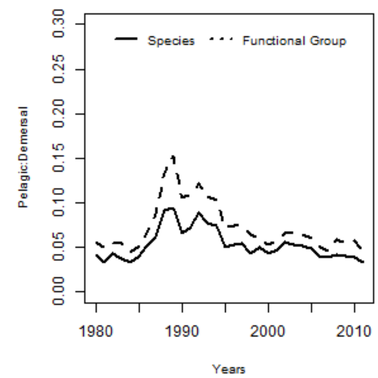
Figure 2.6: Number of Landed Species and U.S. Landings Classified by Overfished Status in Management Jurisdiction. Panel (a) shows the number of species indicated in U.S. landings categorized by overfished status described in the U.S. Congressional Stock Status Reports, and Fishery Management Plan jurisdiction. Panels (b, c) show the U.S commercial (excluding menhaden) and U.S. recreational landings, respectively, categorized by overfished status described in the U.S. Congressional Stock Status Reports, and Fishery Management Plan jurisdiction.



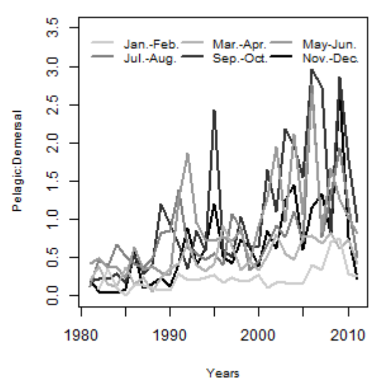
(a) U.S Commercial



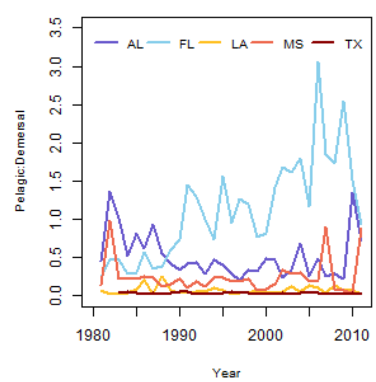
(b) U.S Commercial



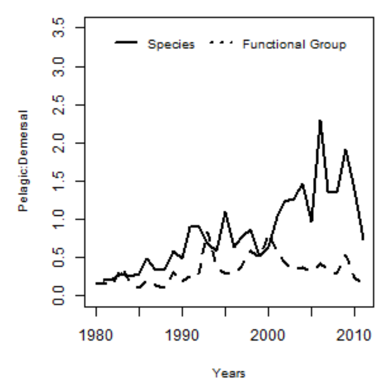
(c) U.S Commercial



(d) U.S Recreational

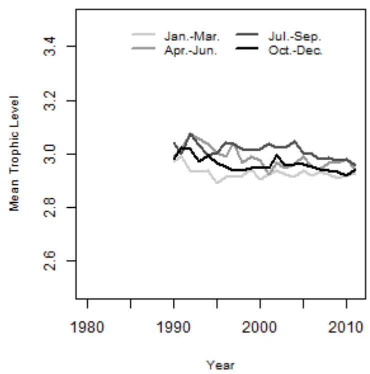


(e) U.S Recreational

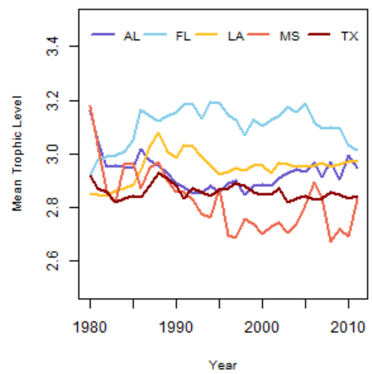


(f) U.S Recreational

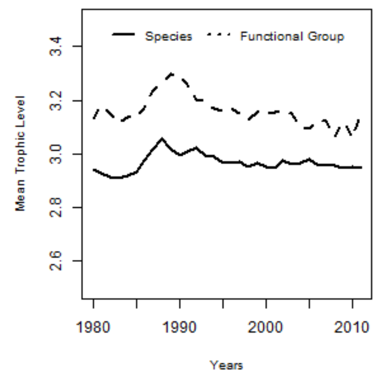
Figure 2.7: Trends in Landings-Based Indicator Pelagic:Demersal Ratio. Trends were computed from U.S. commercial data (a-c) and U.S. recreational data (d-f). Panels a and d show seasonal trends. NOAA's commercial data itemized by months were aggregated into four seasons, and MRIP's recreational data were itemized by bimonthly intervals. Panels b and e show trends for Gulf States. Panels c and f show trends from the annual summaries of species-specific data (solid line) and functional group-specific data (dashed line).



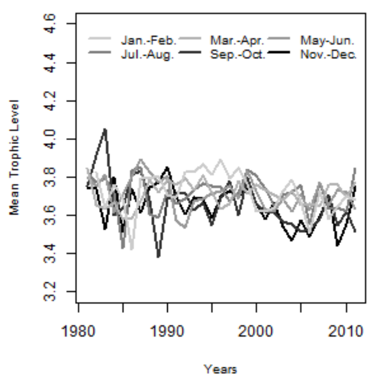
(a) U.S Commercial



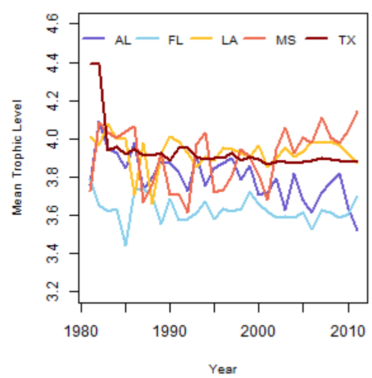
(b) U.S Commercial



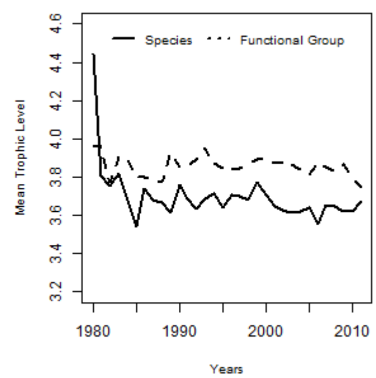
(c) U.S Commercial



(d) U.S Recreational



(e) U.S Recreational



(f) U.S Recreational

Figure 2.8: Trends in Landings-Based Indicator Mean Trophic Level. Trends were computed from U.S. commercial data (a-c) and U.S. recreational data (d-f). Panels a and d show seasonal trends. NOAA's commercial data itemized by months were aggregated into four seasons, and MRIP's recreational data were itemized by bimonthly intervals. Panels b and e show trends for Gulf States. Panels c and f show trends from the annual summaries of species-specific data (solid line) and functional group-specific data (dashed line).

CHAPTER 3

Predicting the Biomass Distributions of Pelagic Species Across the Gulf of Mexico Using Generalized Additive Models

3.1 Summary

Generalized Additive Models (GAMs) were fitted for 16 pelagic functional groups to predict spatial distributions within the Gulf of Mexico. Since data were zero-inflated a delta approach was followed, which consisted of fitting a Bernoulli GAM with binomial data and a Gamma GAM with zero-truncated catch rates [number of organisms per 100 hooks]. Delta GAMs were either coastal (covering areas 0 - 200 m deep) or pelagic (covering areas greater than 200 m deep). Species-specific catch records were collated based on the functional groups identified for the Gulf of Mexico Atlantis model. Coastal models were developed for 4 functional groups using NOAA's Bottom Longline Survey data, and pelagic models were developed for 15 functional groups using NOAA's Pelagic Longline Observer Program data. Descriptors considered for coastal models include year, sea bottom depth, altimetry, minimum distance from a front, as well as both sea surface and sea bottom measurements of temperature, dissolved oxygen, oxygen saturation, and salinity. Descriptors

considered for pelagic models include year, season, sea bottom depth, altimetry, sea surface temperature, and minimum distance from a front. Forward selection was used to select model descriptors. Basis dimensions of smoothing splines were iteratively adjusted based on smoother fits. Model residual diagnostics and performance were evaluated, which showed that many models seem to be underestimating catch rates. Models were used to develop seasonal distribution profiles by predicting across environmental data collected from Archiving, Validation and Interpretation of Satellite Oceanographic (AVISO) and the National Centers for Environmental Information (NCEI). Model fits and predictions for the large, predatory sharks group are discussed in detail. Fitted models for large, predatory sharks have some of the better fits, diagnostics, and performance. Fitted models are influenced by known environmental drivers as well as minimum distance from a front, and there is little research identifying the influence fronts have on the distribution of predatory sharks. Model prediction profiles successfully identify areas known to have higher catch rates of sharks within the Gulf of Mexico, thus predicted seasonal distribution profiles could help identify areas where stocks have increased vulnerability. This work advances our knowledge on the environmental cues and spatial distribution of pelagic groups within the Gulf of Mexico, suggests areas of future research, and could aid the investigation of spatial fisheries management within the Gulf of Mexico.

3.2 Motivation

In the Gulf of Mexico, the biomass levels of many pelagic predators are currently less than historic levels primarily due to overfishing (Pauly et al., 1998; Stevens et al., 2000; Baum et al., 2003b; Myers and Worm, 2003; Christensen et al., 2003; Peel et al., 2003; Baum and Myers, 2004; Baum et al., 2005; Safina and Klinger, 2008). Many of these stocks continue to be subjected to fishing pressure because they support economically important fisheries (e.g., Prince et al., 1989; Weidner et al., 2001; Fromentin and Powers, 2005; Barker and Schluessel, 2005; Arreguín-Sánchez and Arcos-Huitrón, 2011; Aguilar et al., 2014) or they are caught as bycatch (e.g., de Silva et al., 2001; Serafy et al., 2004; Mandelman et al., 2008). Because top predators are known to influence the structure and function of marine ecosystems (Paine, 1980; Duffy, 2002), and the decline of top predators may reduce ecosystem sustainability (Myers et al., 2007; Heithaus et al., 2008; Baum and Worm, 2009).

The 1996 Magnuson-Stevens Act includes requirements to identify essential fish habitats, i.e. waters and substrate necessary to fish for spawning, breeding, feeding or growth to maturity (U.S. Congress, 1996). The marine environment is heterogeneous, creating patchy fish populations driven by physical and biotic forcing. When marine fauna, like pelagic predators, aggregate within essential habits they are vulnerable to fisheries, so these areas should be targeted for conservation efforts. This is especially true for bycatch species as bycatch is not only harmful to affected marine fauna but also a waste of fisheries resources. Fisheries management regulations such as spatial fishery closures offer a means to protect essential habitats, but first these areas need to be defined for each species. This can be done by determining the spatial distribution of species.

Understanding the spatial distribution of fish stocks (one aspect of spatial fisheries ecology) can not only provide information regarding essential habitats, but can also lead to a better understanding of how species abundance changes over time (Ciannelli et al., 2008). The spatial distribution of an organism is often estimated using statistical methods relating abundance to measurable environmental conditions. Fishery independent catch data (i.e., survey data) are collected for statistical analysis, but sample sizes tend to be low. Fisheries dependent catch data are more abundant, but often have undesirable features that make them unsuitable to linear modeling (e.g., non-random sampling, lack of coverage of an organisms whole spatial range). However, the advancement of statistical methodologies (e.g., generalized linear modeling) provides a means to address such issues with fishery dependent catch data (Guisan et al., 2002; Venables and Dichmont, 2004; Ciannelli et al., 2008). Generalized Additive Models (GAMs) offer a particularly flexible form of statistical modeling. GAMs (Hastie and Tibshirani, 1986, 1990) can address non-linear relationships between the response and explanatory variables with smoothing splines. Such models can provide information on environmental drivers influencing stock abundance (e.g., Wall et al., 2009), and identify geographic areas of increased abundance (e.g., Saul et al., 2013).

Spatial distribution models support ecosystem based fisheries management, EBFM (Brodziak and Link, 2002; Pikitch et al., 2004) by identifying essential habitats, and provides a means to parameterize the spatial distribution of marine stocks for spatially explicit ecosystem models (e.g., Atlantis). There is a growing need to understand and predict the ecosystem effects of changing predator abundances as well as the interactions with intensifying anthropogenic stressors (Baum and Worm, 2009). This can be accomplished with spatially explicit ecosystem models, but it is important that these models are appropriately representing the temporal changes in spatial abundance.

Drexler and Ainsworth (2013) presented GAMs for predicting the spatial biomass distributions of organisms retained by Southeast Area Monitoring and Assessment Program (SEAMAP) trawls. SEAMAP trawls operate within the northern Gulf of

Mexico shelf, but models were used to predict the spatial distributions of organisms across the entire Gulf of Mexico shelf. The developed GAMs successfully predicted known areas of high abundance for some organisms (e.g., pink shrimp, *Farfantepenaeus duroarum*). Grüss et al. (2014) used survey data spanning the West Florida Shelf to fit delta GAMs, and found that predictions from fitted models for the different life-stage groups and seasons correctly predicted known qualitative differences between low- and high-abundance areas. Both these studies encouraged using fitted models for generating distribution maps for ecosystem models. Grüss et al. (2014) focused on the OSMOSE West Florida Shelf model, and Drexler and Ainsworth (2013) focused on the Atlantis Gulf of Mexico model. Grüss et al. did not discuss the distribution of pelagic predators, but Drexler and Ainsworth observed that models for groups less vulnerable to benthic trawling gear, such as pelagic fish, performed poorly. The authors suggested that their results for these groups may be unreliable and that the analysis of different data may be necessary.

The following presents a series of GAMs for describing the spatial biomass distributions of pelagic organisms across the Gulf of Mexico. Model fits were assessed using residual diagnostics and the performance of models were tested. Seasonal, Gulf-wide distribution profiles were developed using the fitted models to predict across grids of geographic coordinates representing seasonal averages of environmental conditions. While spatial distribution profiles are developed for several functional groups, the results for large, predatory sharks are presented and discussed in detail.

3.3 Materials and Methods

3.3.1 Data For Model Fitting

Datasets were provided by NOAA's Southeast Fisheries Science Center (SEFSC) Bottom Longline Survey, and Pelagic Observer Program (Table 3.1). The Bottom Longline Survey (Grace and Henwood, 1997; Ingram et al., 2005; Henwood et al., 2006) collects catch and environmental data along the U.S. continental shelf, operating in waters with a bottom depth between 9 - 366m. Baited hooks are suspended near the benthos, and the gear used is similar to commercial longlines. The Pelagic Observer Program (Beerkircher et al., 2002, 2004; Brooke, 2012) records catch data from observers aboard vessels in the U.S. commercial pelagic longline fleet. Vessels suspend longline gear mid-depth (approximately 33-66 m, but the actual fishing depth is unknown due to the influences by currents and environmental conditions (Beerkircher et al., 2004) throughout the Gulf's pelagic waters.

Data were collected from the Bottom Longline Survey between 2005 - 2012, and Pelagic Longline Observer Program between 2005 - 2010. Catch records were collated based on the functional groups identified for the Gulf of Mexico Atlantis model (Ainsworth et al., 2015). Tables 3.2 - 3.3 show the species identification and functional group classification for data from the Bottom Longline Survey and Pelagic Longline Observer Program, respectively. While some of the functional groups identified for the Gulf of Mexico Atlantis model consist of a single species (e.g. *yellowfin tuna*), others consist of many species (e.g., *large pelagic fish*). Thus, it is likely that longline catch data attributed to a multi-species functional group will not include all of the species identified in the functional group. This study does not consider longline catch data attributed to functional groups that i) are not associated to pelagic environments, or ii) lack sufficient data to fit a GAM.

Fishery-independent and fishery-dependent datasets can be combined to analyze spatial distributions of marine organisms if the datasets share similar spatial and temporal ranges (Pecquerie et al., 2004). Except for a small area off Louisiana, the Bottom Longline Survey and Pelagic Observer Program operate in different areas (Figure 3.1), so this study keeps the two datasets separate and constructs two series of statistical models: models fit with Bottom Longline Survey data (referred to as *coastal models*) and models fit with Pelagic Longline Observer data (referred to as *pelagic models*). Survey datasets, which are fishery-independent, are designed specifically for statistical analysis and are believed to provide more accurate information regarding catch rates, but Fox and Starr (1996) found that data from commercial operations, which are fishery-dependent, can be comparable.

In regards to large, predatory sharks, Grace and Henwood (1997) found that sharks caught by the Bottom Longline Survey tend to be a size similar to or larger than the minimum size at maturity, and that they are similar in age and size to sharks caught by commercial operations (like ones sampled by the Pelagic Longline Observer Program). Older juveniles and adults tend to spend their time in coastal/offshore waters (Hueter and Tyminski, 2007), making them more accessible to longline activities. Thus, models presented here for *large sharks* relate to older, likely sexually mature, organisms.

Environmental and temporal variables measured at the time of each catch observation in the datasets were used as model descriptors. Temporal variables included year and season. Season was broken down into four categories: 1 (Jan. - Mar.), 2

(Apr. - Jun.), 3 (Jul. - Sep.), or 4 (Oct. - Dec.). These seasonal categories may not line up exactly with the warming and cooling of the Gulf of Mexico, since temperatures tend to reach a minimum in early March and warm summer temperatures peak in October. However, these categories correspond to the seasonality represented in the Gulf of Mexico Atlantis model. Environmental variables required some reorganization in order to fit models, which included i) generating a single estimate for the environmental variables that have multiple measurements taken during a longline set, ii) generating estimates of key environmental variables for longline sets missing the information, and iii) associating longline sets in both datasets with additional environmental data directly related to the physical environment. Measurements of several variables (e.g., sea surface temperature, bottom depth, latitude, longitude, etc) were collected at various points during the setting and hauling of each longline. The mean of all observations in each set were used to characterize that set. Estimates of these variables were generated for all of the records in both catch datasets, however approximately 25% of the bottom longline records and 5% of the pelagic longline records were missing estimates of sea surface temperature. The *Interpolate PO.DAAC MODIS L3 SST at Points* tool from the Marine Geospatial Ecology Tools (MGET) toolbox in *ArcGIS* was used to get estimates of sea surface temperature for these records (see Appendix B). Approximately 0.05% of the bottom longline records and 9% of the pelagic longline records were dropped from this analysis because necessary information was missing and could not be recovered (e.g., date, species).

Commercial longlines often set gear based on the target species' expected position in the water column (Highly Migratory Species Division, 2000). Day sets tend to target yellowfin tuna (*Thunnus albacares*), when the fish tend to dive deeper into the water column (Weng et al., 2009). Night sets tend to target swordfish (*Xiphias gladius*), to take advantage of their nocturnal, near-surface feeding habits (Takahashi et al., 2003). Thus, time of day is an important temporal variable to consider when using commercial data. However, time of day relates less to the local stock horizontal density and more to the vertical distribution and foraging (i.e., the catchability of a functional group). Preliminary model fits were investigated using time of day, a binomial variable indicating if catch occurred at day or night, as a model descriptor (Appendix B). This work showed that spatial distribution profiles of pelagic model changed quantitatively (i.e., the magnitude of the predicted catch rates), but not qualitatively (i.e., observed trends in distribution profiles and resulting proportion maps). Since this work is more interested in horizontal (not vertical) distribution, time of day was excluded from further model fitting.

Descriptors corresponding to altimetry and ocean fronts were incorporated into the catch datasets because top marine predators are known to aggregate around oceanographic features (Olson et al., 1994; Kleisner, 2008; Kleisner et al., 2010). Altimetry data was provided by the Archiving, Validation and Interpretation of Satellite Oceanographic (AVISO) dataset (Ducet et al., 2000). Estimates of altimetry were derived by iteratively subsetting AVISO data by catch date and averaging the four AVISO records nearest to the catch location. The relationship between catch and fronts was represented by calculating the minimum distance between the catch location and a frontal feature. Frontal features were derived using the *Cayula-Cornillon Fronts in ArcGIS Raster MGET* tool from the MGET toolbox. This tool uses the Cayula and Cornillon (1992) edge detection algorithm for the identification and extraction of fronts. The Cayula and Cornillon edge detection algorithm is commonly used with sea surface temperature data, but the Gulf of Mexico is known to have weak sea surface temperature gradients (Legeckis, 1978). Features within the Gulf of Mexico are largely influenced by the physical oceanography, so AVISO altimetry data were used to derive frontal features (Appendix B). *ArcGIS*'s *Model Builder* was used to develop a routine that systematically estimates minimum distance from a front for catch records (Figure 3.2). For each date represented in the AVISO dataset, frontal features are derived based on the AVISO data subsetted by date, then the minimum distance between the features and catch records are calculated.

3.3.2 Model Description

Generalized additive models (GAMs) estimating the abundance index of individual functional groups in coastal waters (models fit with survey data) and pelagic waters (models fit with observer data) were developed using the statistical software *R* (R Core Team, 2014; Wood, 2006a, 2011; Wood and Wood, 2015). Catch-per-unit-effort (CPUE) is the metric commonly used as an abundance index in fisheries ecology (Hilborn et al., 1992). For this study, the calculation of longline CPUE followed an industry standard: the total numbers of individuals caught per 100 hooks. There was some debate in the literature on whether hook soak time impacts catch rates calculated from longline datasets. Ward et al. (2004) concluded that whether or not soak time effects catch rates will depend on the species, and that hook soak time does effect the catch rates of sharks and billfish. Watson et al. (2005) found soak time to have a meaningful effect on blue shark catch rates, but not on swordfish catch rates. However, recently Carruthers et al. (2011), who also studied swordfish and blue sharks, found that the method of calculating soak time will determine soak time impact on catch rates, and ended up concluding that although hook soak time effects mortality rates it does not effect catch rates. For this study, total numbers were calculated rather than total biomass because size data, which would be necessary to convert numbers to biomass, were not available for many of the records.

A Delta approach was followed to account for the zero-inflated nature of both longline datasets. The Delta method calls for fitting two statistical models: one predicting the probability of positive catch of binomial data (0,1), the other predicting the CPUE [number of organisms per 100 hooks] of zero truncated catch data. Determining an appropriate error structure for generalized models is an important aspect of model construction (Maunder and Punt, 2004). By convention, the Bernoulli distribution with a logit link function was used to model the error structure of the binomial data. Preliminary analyses suggested that the catch rate data were best supported by a gamma distribution with an inverse link function (Appendix B). Other studies fitting generalized linear models to estimate catch rates from longline data have achieved comparable, if not improved, model fits using the gamma distribution rather than the more commonly used lognormal (Punt et al., 2000; Ortiz and Arocha, 2004).

The construction of GAMs requires developing robust smoothing splines for each numerical descriptor. This study used penalized regression splines, which incorporate penalties to the least squares fitting objective based on the flexibility of a smoother (Wood and Augustin, 2002). Penalized regression splines have a smoothing parameter (λ), which controls the tradeoff between the model's fit and smoothness, and a basis dimension (k), which defines the maximum possible degrees of freedom (Guisan et al., 2002; Wood, 2006b). The *gam()* function in *R* calculates smoothing parameters using a smoothness selection criterion, either the generalized cross-validation (GCV) criterion or the Un-Biased Risk Estimator (UBRE) scores (Wood, 2006b). An additional penalty was incorporated to allow for the removal of a numerical descriptor if the smoothing parameter equals zero (i.e., if the smoother does not improve model fit).

Adjusting the basis dimension makes a spline more flexible (Ruppert, 2002; Li and Ruppert, 2008; Wood and Wood, 2015) but this is often not investigated (Kauermann and Opsomer, 2011; Pya and Wood, 2016). Pya and Wood (2016) concluded that the exact setting of the basis dimension is not crucial as long as it is large enough to avoid over-smoothing / under-fitting, and that the simple routine presented by Wood and Wood (2015) performs as well as complex, time expensive approaches. For this study, the routine described by Wood and Wood (2015), which follows a hypothesis testing approach, was used to check the adequacy of basis dimensions. The routine uses the k-index statistic to test if the basis dimension is large enough for the smoothing spline. The k-index is the ratio of the residual variance estimated by differencing residuals that are neighbors according to the covariates of the spline, and the residual variance estimate from the whole model fit (formulas described by Pya and Wood (2016)). The k-index should be close to one if the basis dimension is large enough. A k-index less than one indicates the possibility of a missed pattern in the residuals that could be addressed if the basis dimension is increased.

To adjust basis dimensions, first a GAM is fitted with each smoother's basis dimension set to three (the minimum accepted setting). The adequacy of basis dimensions are assessed individually for each numerical descriptor, in sequential order. If the computed k-index is less than one the basis dimension is adjusted, but if the sum of all basis dimensions in the GAM are less than three-fourths of the data's sample size the routine stops - this is to prevent overfitting. The GAM is re-fitted with the basis dimension set to a default value suggested by Kim and Gu (2004) ($10n^{2/9}$, where n is the sample size), which is typically much larger than three. Thus, if the resulting k-index remains less than one then adjusting the basis dimension will likely not assist reducing residual variance. In this situation, the routine sets the basis dimension to $max(3, \lceil edf \rceil + 1)$, where edf is the effective degrees of freedom. The latter value accounts for some improvement in smoother fit. If the resulting k-index is greater than one then the routine iteratively searches for the smallest basis dimension value that still produces a k-index greater than one. This is to find a balance between improved smoother fit and the preservation of degrees of freedom. The assessed basis dimension for each numerical descriptor is set to the determined value before assessment of the basis dimension of the next numerical descriptor commences.

The general form of the fitted GAMs is as follows:

$$g(\eta) = \sum_{i=1}^{n} s(d_i, k_i) + \sum_{j=1}^{m} f(d_j) \tag{3.1}$$

where η is either the probability of positive catch (η_B) or the abundance index (η_Z) according to the link function g, and d represents model descriptors. Models are the summation of functions of i numerical descriptors and j categorical descriptors. Numerical descriptors are processed with penalized regression splines (indicated by $s()$ with k being the spline's basis dimension, and categorical descriptors are treated as factors (indicated by $f()$). The bottom longline dataset contains measurements of environmental variables because a conductivity, temperature, and depth recorder (CTD) was deployed at each station. Although measurements were collected at incremental depths, this study only considers measurements recorded at the sea surface and sea bottom as they often represent the extremes. Environmental variables considered as potential descriptors for models fit with bottom longline data include: bottom depth (m), temperature (°C), dissolved oxygen (ppm), oxygen saturation (%), and salinity (ppt). Commercial longline observers record limited environmental information. Environmental variables considered as potential descriptors for models fit with pelagic longline data include: bottom depth (m) and sea surface temperature (°C). Year, altimetry (m), and minimum distance from a front (m) were considered as potential descriptors for all models.

Model integrity is jeopardized if a model overfits data, which can occur if the model contains an excessive number of model descriptors. Over-parameterization is particularly a concern for coastal models because fitting datasets have relatively small sample sizes and there are several variables being considered for model descriptors. Over-parameterization is less of a concern for pelagic models because fitting datasets tend to have larger sample sizes and only a few model descriptors were being considered. Forward model selection was followed to select model descriptors for all GAMs. Forward model selection was preferable over other methods (i.e., backward or stepwise) because it ensured that the most influential numerical descriptors had priority in the routine adjusting basis dimension. For coastal models, forward model selection ceased (i.e., descriptors were no longer added to a model) once no single variable improved a model's explained deviance by more than 5%. Forward selection for coastal models was conducted with the entire bottom longline dataset. For pelagic models, forward model selection ceased once no single variable provided any improvement to a model's deviance explained or AIC. Forward selection for pelagic models was conducted with data subsetted for cross validation (i.e., training datasets). Basis dimensions were not adjusted (remained set equal to three) during forward selection to ensure that a variable was selected as a model descriptor because the variable improved model fit and not because of the spline's flexibility. The presence of highly correlated descriptors can detract from a model's descriptive abilities and worsen its predictability, so forward selection ignored a variable if it was highly correlated (i.e. correlation greater than 0.80) with any of the selected model descriptors.

Model performance and fit was evaluated for logistic models, and delta models. The receiver operating characteristic area under the curve (AUC) metric is commonly used as a global indicator of performance for logistic models (Greiner et al., 2000). The AUC is equal to the probability that the model will correctly identify a randomly chosen pair of one positive event and one negative event (Hanley and McNeil, 1982). This study followed the arbitrary AUC guidelines suggested by Swets (1988) (i.e., 0.5 is non-informative, 0.5 - 0.7 are less accurate, 0.7 - 0.9 are moderately accurate, 0.9 - 1 are highly accurate, 1 is perfect). Cross validation was used to evaluate the performance of delta models. Functional group-specific catch records from both longline datasets were split into training and testing datasets. Training datasets contained three-fourths of a functional group's catch records and testing datasets received the remaining one-fourth. Because pelagic GAMs have factors for year and season, testing and training datasets from pelagic longline data were created based on each combination of year and season to ensure training datasets contained all of the sampled years and seasons. Results are presented by plotting observed catch rates from the testing dataset against predicted catch rates from the model fitted to the training dataset (Piñeiro et al., 2008). Model fits were assessed using Pearson residuals. Residual analysis for logistic regression is complicated because a model produces predicted probabilities for a binary response variable, however an adequate Bernoulli model should have residuals that produce a lowess curve centered along the horizontal line with a zero intercept.

3.3.3 Spatial Abundance Distribution Profiles

Seasonal, spatial abundance distribution profiles spanning the entire Gulf of Mexico were developed for each functional group based on predicted abundance indices generated by the fitted statistical models. First, grids describing hypothetical seasonal conditions in the Gulf of Mexico were developed. In *ArcGIS* a 0.1° latitude by 0.1° longitude grid of geographic coordinates spanning the entire Gulf of Mexico was created using the *Fishnet* tool. Four versions of the grid were generated, one for each season. Next, coordinates within the grids were assigned estimates for all model descriptors. Seasonal data collected from NOAA (Table 3.1) were interpolated into rasters using the *Kriging* tool. Then, the *Extract Values to Points* tool (set to bilinear interpolation) was used to assign seasonal estimates of the environmental data to each coordinate in the appropriate seasonal grid. A single bathymetry raster was used for all four seasons. Fitted models were restricted to only predict abundance at geographic coordinates having a depth estimate within the bathymetric range of the data used to fit the model. Thus, spatial grids were divided into two groups based on the 250m isobath - creating seperate seasonal grids for coastal waters and pelagic waters. Lastly, the abundance indices for each functional group were predicted at each geographic coordinate in the grids using the fitted GAMS (i.e., coastal models were used to predict across the coastal grids, and pelagic models were used to predict across pelagic grids).

Model predictions were used to estimate Gulf-wide abundance distribution profiles for the purpose of assigning proportion of biomass across the spatial map of the Gulf of Mexico Atlantis model. Many of the functional groups are represented in only one of the two longline datasets, thus general assumptions were made to extrapolate abundance indices into Gulf-wide abundance distribution profiles (see Appendix B). Although the *large pelagic fish* functional group has coastal and pelagic abundance index profiles, the two profiles could not be merged because the catchability could not be standardized. Thus, Gulf-wide abundance profiles for *large pelagic fish* were generated using general assumptions to extrapolate pelagic predictions across coastal waters (see Appendix B). For the *large sharks* and *skates and rays* functional groups, predictions from the coastal and pelagic models were merged by standardizing predictions to account for differences in functional group catchability between the two longline operations. Catch data from an area where the two longline datasets intersect, an area off the Louisiana coast (Figure 3.1), were used to fit simple statistical models for each of these two functional groups. Statistical models solving for CPUE were of the form shown in Equation 3.1. Model descriptors included bottom depth (m), sea surface temperature (°C), altimetry (m), minimum distance from a front (m), year (2005-2010), season (1-4), and longline type (bottom or pelagic). Standardization factors were calculated by dividing the median fitted pelagic CPUE by the median fitted coastal CPUE. The coastal and pelagic profiles of predicted abundance indices were averaged across the spatial map of the Gulf of Mexico Atlantis model, and averages corresponding the pelagic predictions were standardized with the computed factor. This calculation of coastal:pelagic ratios for catchability standardization assumes the ratios to be constant across space and time. Coastal and pelagic abundance averages were then merged to span the spatial map of the Gulf of Mexico Atlantis model. Standardization factors were used for all seasonal profiles. Additional details of the methods can be found in Appendix B.

3.4 Results

GAMs developed from the forward selection process are summarized in Table 3.4. The median model deviance explained by coastal Bernoulli models is 32.23% (ranging from 18.55% to 46.54%). Based on the AUC values, half of these Bernoulli models are classified as moderately accurate while other half are classified as highly accurate. The *large sharks* model produced one of the best fits (46.54% deviance explained; 0.91 AUC). Coastal gamma models described between 40.22% and 60.45% model deviance, with a median of 46.64%. The weakest fit belonged to the *large sharks* model. Generally, fits of the pelagic Bernoulli models are weaker than the coastal Bernouli models or the coastal or pelagic gamma models, describing on average 9.12% model deviance (ranging from 3.79% to 23.27%). Based on the AUC values, most of these Bernoulli models are classified as moderately accurate while the few remaining Bernoulli models are classified as less accurate. The *large sharks* model is one of the weaker fitting models (explaining 6.14% model deviance; 0.73 AUC). Fits of pelagic gamma models vary, describing between 8.33% and 71.03% model deviance with a median of 33.51%. The *large sharks* model is one of the better fitting models explaining 70.25% of the deviance.

Residuals from the Bernoulli models can be divided into a few general trends (Figure 3.3). Most of the Bernoulli models produce residuals that create lowess curves which are mostly or entirely within the negative region, and have positive residuals with heavier tails than the negative residuals. Thus, a majority of Bernoulli models are successful at estimating low probabilities of catch for non-catch events and unsuccessful at estimating high probabilities of catch for catch events. Some of these Bernoulli models have residuals that produce linear lowess curves and have heavy-tailed positive residuals (Figure 3.3a), while others have residuals that produce parabolic lowess curves and have light-tailed positive residuals (Figure 3.3b). The latter trend is from Bernoulli models which are more successful at estimating high probabilities of catch for catch events than Bernoulli models producing the former residual trend. The remaining Bernoulli models produce residuals with the opposite behavior (i.e., lowess curves mostly or entirely within the positive region, and negative residuals with heavier tails than positive residuals), indicating that these Bernoulli models are successful at estimating high probabilities of catch for catch events and are unsuccessful at estimating low probabilities of catch for non-catch events. Residuals from these Bernoulli models either produce a linear lowess curve with heavy-tailed positive residuals (Figure 3.3c), or a parabolic lowess curve with light-tailed positive residuals (Figure 3.3d). The latter trend is from Bernoulli models which are more successful at estimating low probabilities of catch for non-catch events than Bernoulli models producing the former residual trend. Residuals from the *spanish mackerel* and *large sharks* pelagic Bernoulli models produce lowess curves that have a tendency to be flat, featureless and more centered around the horizontal axis (Figure 3.3e), suggesting that there is no left-over pattern found in the residuals.

Residual diagnostic plots for gamma models are very similar to one another, so residuals for the *large sharks* pelagic gamma model are shown as a general example (Figure 3.4). The Q-Q plots often show deviance residuals in a U-shape (Figure 3.4a).

The weight of the tails differ among functional groups, ranging from light-tailed to heavy-tailed residuals. Error variances have a right skew (Figure 3.4b), with the severity of the skew differing among functional groups. Error variance is not constant and tends to decrease with an increasing linear predictor (Figure 3.4c). This is not immediately obvious for all functional groups, especially those with larger sample sizes, but the standardized residuals below the zero residual horizontal line tend to suggest the trend. There is no obvious trend in residuals over time (Figure 3.4d). Box-plots showed that all datasets have outliers (Figure 3.4b), some datasets with more severe outliers than others.

Cross validation results for *large sharks* are shown as a general example (Figure 3.5), results from the remaining models are presented in Appendix B. Many of the results resemble that of the coastal *large sharks* model (Figure 3.5a), however many of them have a poor r-squared value (e.g., *deep water fish* have a slope = 1.05 and an $r^2 = 0.02$, *filter feeding sharks*, *small sharks* have a slope = 0.5 and $r^2 = 0.6$). The *large sharks* pelagic model (Figure 3.5b) produced the best cross validation results out of all of the fitted models (slope = 0.82; $r^2 = 0.457$). Most of the models show a tendency to predict low catch rates for larger observed catch rates. The larger cross validation residuals from the coastal model tend to be off the Mississippi river outlet (Figure 3.5c). The same is true for larger cross validation residuals from the pelagic model, with the addition that larger residuals are closer to the slope (Figure 3.5d).

Bottom depth has a significant impact on the probability of catching *large sharks* for both the coastal ($p < 2.0E^{-16}$) and pelagic ($p < 2.0E^{-16}$) models. Descriptor Fits for coastal and pelagic GAMs are shown in Figure (3.6) and Figure (3.7), respectively. The probability of catching *large sharks* increases moving away from the shoreline until approximately 40m, beyond which the probability of catching *large sharks* decreases (Figure 3.6a). Depths greater than 1200m influence an increase in the probability of catching *large sharks* (Figure 3.7b). Both bottom depth smoother fits become unreliable in the deeper ranges (exceeding approximately 200m for the coastal model and 1700m for the pelagic model) due to sparse data.

The binomial pelagic model for *large sharks* is also significantly influenced by minimum distance from a front, season, and year. Minimum distance from a front significantly influenced the probability of catching *large sharks* in pelagic waters ($p = 4.6E^{-5}$). The probability of catching *large sharks* decreases as minimum distance from a front increases, then the probability of catching *large sharks* increases (Figure 3.7a). The smoother fit throughout farther distances reflect increasing uncertainty due to sparse data. The probability of catching *large sharks* in pelagic waters has significant differences among seasons. Figure 3.7e shows a decrease in the probability of catching *large sharks* in pelagic waters, which is significantly different from winter months for summer months ($p = 0.002$) and fall months ($p = 4.56E^{-6}$). Figure 3.7f shows a decrease in the probability of catching *large sharks* in pelagic waters, which is significantly different from the value in 2005 for all years (2006, $p = 0.000516$; 2007, $p = 3.96E^{-5}$; 2008, $p = 0.012$; 2009, $p = 8.74E^{-6}$; 2010, $p = 1.6E^{-11}$).

The numerical descriptors driving the *large sharks* coastal gamma model are sea bottom temperature ($p = 1.24E^{-13}$) and altimetry ($p = 2.56E^{-15}$). Higher levels of abundance of *large sharks* in coastal waters are encouraged by lower sea bottom temperatures (Figure 3.6b) and altimetry between 0.20 and 0.35 (Figure 3.6c). Smoother fits become less certain in sparse data ranges. Estimates of the yearly contributions to mean catch rates tend to increase over time (Figure3.6d), but only 2012 is significantly different than the reference year ($p = 0.023$). There is a decrease in *large sharks* abundance within coastal waters for 2011. This may be a response to changes in environmental influences or fishing effort (e.g., the 2010 *Deepwater Horizon* oil spill, and/or the shifting of effort due to the dynamic network of fishing closures that followed the oil spill). The abundance of *large sharks* in pelagic waters does not dramatically increase or decrease over time, but in 2007 their abundance was significantly larger than the reference year ($p = 0.0009$). Seasonal changes in the abundance of *large sharks* in pelagic waters are significant: spring ($p = 9.29E^{-5}$), summer ($p = 0.0005$), and fall ($p = 0.0036$). The numerical descriptors in the *large sharks* pelagic gamma model are sea surface temperature ($p = 0.01$), bottom depth ($p < 2.0E^{-16}$), altimetry ($p = 2.43E^{-10}$), and minimum distance from front ($p < 2.0E^{-16}$).

Before predicting with fitted GAMs, densities of data used to fit GAMs were compared to densities of data used to make seasonal predictions with GAMs. Data densities pertaining to environmental data of *large sharks* GAMs are shown in Figure 3.8. For much of the environmental data for all functional group GAMs, data densities are similar to Figure 3.8a. This is an good because i) prediction data are within the range of fitting data, ii) there is seasonality in the prediction data, and iii) the prediction data are within plausible ranges. However, data densities for bottom oxygen saturation and sea bottom dissolved oxygen indicate no seasonality in the prediction data, and that the prediction data doesn't span the entire range of the fitting data (e.g., see Figure 3.8b). In addition, data densities indicate that for coastal models some of the environmental data used for fitting doesn't span the seasonality represented in the prediction grids (e.g., see Figure 3.8c). This is caused by the lack of seasonal coverage of the bottom longline survey, discussed earlier.

Predictions across seasonal grids for both coastal and pelagic *large sharks* GAMs are shown in Figure 3.9. The abundance of *large sharks* within coastal waters is relatively low during the winter (Figure 3.9a), increases during the spring (Figure 3.9b) and summer (Figure 3.9c), and is the highest during the fall (Figure 3.9d). The abundance of *large sharks* within pelagic waters does not have a strong seasonal signal (Figure 3.9e - 3.9h). The borders of the pelagic maps often indicate higher levels of abundance, which seems to be an indication that *large sharks* abundance increases moving into shallower waters. The maps reveals several areas where *large sharks* may be aggregating (i.e., hotspots). Coastal predictions indicate hotspots in the southwest Florida shelf, the Mississippi River outlet, the Texas coast, and Campeche Bank. Pelagic predictions indicate hotspots off the northwest Florida slope, and in the area connecting De Soto Canyon, Mississippi Canyon, and Mississippi Fan. Predictions across seasonal grids for all fitted GAMs are shown in Appendix B.

Standard errors of spring predictions for both coastal and pelagic *large sharks* GAMs are shown in Figure (3.10). The coastal Bernoulli model is often the most uncertain along the edge of the grid - areas that are the shallowest or deepest (Figure 3.10a). The spring predictions from the coastal Gamma model have much error (Figure 3.10b). This is because the altimetry estimates for spring are below the range of the altimetry data used for model fitting (Figure 3.8c), and smaller altimetry values are highly uncertain (Figure 3.6c). Thus, this error is largely due to the lack of seasonal coverage of the data used for fitting. The pelagic Bernoulli model has more error around the deep-edge of the slope (Figure 3.10c). The same can be said for the pelagic gamma model, with the addition that there is commonly more error in areas within the eastern Gulf basin (Figure 3.10d). Sea bottom depth data used for fitting does not span the greater depths represented in the seasonal grids (e.g., Figure 3.8c), which is likely contributing to the error in the two GAMs. Predictions associated to areas with high standard error should be interpreted with caution. Standard errors of seasonal predictions for all fitted GAMs are shown in Appendix B.

The coastal:pelagic ratios produced by the catchability standardization (10:5.22 for *large sharks*, and 100:6.1 for *skates and rays*) allowed merging coastal and pelagic predictions to estimate the seasonal proportion of *large sharks* across the spatial map of the Gulf of Mexico Atlantis (Figure 3.11). Proportions were not corrected by polygon area. For instance, the relatively large proportion of *large sharks* in the polygon corresponding to Campeche Bank is influenced by the large size of the polygon.

3.5 Discussion

3.5.1 Model Findings

Models fitted with bottom longline survey data (coastal models) and models fitted with pelagic longline observer data (pelagic models) range in their capabilities to adequately represent data. The AUC values ranked coastal Bernoulli models between moderately and highly accurate and pelagic Bernoulli models between moderately and less accurate. Pearson residuals for coastal Bernoulli models tended to span a smaller range than Pearson residuals from pelagic Bernoulli models (i.e., pelagic Bernoulli models have more extreme residuals than coastal Bernoulli models). Thus, coastal Bernoulli models tend to be more adequate than pelagic Bernoulli models. Considering all of the Bernoulli models fitted here, most fail to produce residuals evenly scattered around the horizontal axis when residuals are plotted against fitted values. Instead, residuals show that the Bernoulli models can be divided into two general groups: models better at predicting low probabilities of catch for non-catch events, and models better at predicting high probabilities of catch for catch events. Most Bernoulli models fitted in this study are in the former group, which may be causing the underestimation of delta-model catch rates observed in the cross validation results.

Residuals from coastal gamma models are often less extreme compared to residuals from pelagic gamma models, however residuals from all of the fitted gamma models have similar trends. Gamma models residuals appear to be independent, but they are often not normal nor are they evenly distributed across the linear predictors. The magnitude of the skew differs between gamma models so, to various degrees, many of the gamma models do not adequately represent the data. Transforming the response variable may improve these diagnostics. Log-transforming the response variable was investigated in preliminary modeling, but was not pursued as it often failed to normalize the data (Appendix B). Gamma model diagnostics may improve with the consideration of other transformations like the Basic or Box-Cox, which were suggested by Mateu (1997) in reference to normalizing environmental data. All gamma models appear to have extreme residuals which may be leverage points (i.e., extreme predictor values), and outliers (i.e., extreme response values). Removing outliers could improve the diagnostics and fits for gamma models and possibly smoothing splines as well. However, because extreme values may be correct measurements representing important variations in the system, an analysis of the extreme values might be informative.

Cross validation results showed that all delta models have less than ideal prediction performance, and some have very poor performance (e.g., *large pelagic fish*, *filter feeding sharks*, *small sharks*, and *other turtles*). Models for *large sharks* produced the best performance results out of all models. Cross validation results showed all models have a tendency to underestimate higher observed catch rates. This suggests a systematic bias. This may be driven by the Bernoulli models which tend to have weaker fits than Gamma models with residuals often being negative. Pelagic Bernoulli models are particularly poor. This is likely happening since pelagic models are fitted with fishery dependent data, which doesn't appropriately represent where fish are, or are not, since fishers operate in areas where fish tend to be found. This may also influencing stronger fits for the pelagic Gamma models. When assessing model predictions to detect population hotspots (i.e., areas of increased catch rates), it is important to remember that predictions may be under-representing or missing aggregations considering that many of these models seem to be underestimating higher catch rates. This may be especially true if aggregations are occurring at time-scales smaller than season.

This work executed various recommendations from the literature in order to ensure improved model fits while not violating statistical assumptions. This includes verifying the appropriate error distribution for catch rate data, determining the link functions that improves model fits, checking for correlated descriptors, buffering against overfitting, and adjusting of a spline's basis dimension of to improve model fits. Spline basis dimensions ended up being adjusted for many of the fitted models, and a couple of interesting observations emerged. First, basis dimensions were adjusted more often for splines in coastal models than for splines in pelagic models. This may be related to the fact that coastal models have fewer descriptors than pelagic models, because the forward modeling process restricted what variables could be used as descriptors in coastal models. Also, some descriptors became statistically important after the basis dimension was adjusted. This point is important to consider when using a model selection routine along with adjusting spline basis dimensions, because selected models may be different after adjustment of a spline's basis dimension.

Extrapolating estimates for altimetry and minimum distance from a front into catch datasets helped improve model fits, especially for pelagic models. This is understandable as frontal features offer crucial zones of productivity in the open ocean because the open ocean is oligotrophic compared to nearshore waters. Minimum distance from a front improved fits for a few of the fitted models. Similarly, Podestá et al. (1993) found an association between swordfish catch rates and distance to the nearest front, as did Kleisner et al. (2010), who modeled spatial autocorrelation of fish species and temperatures at an appropriate range of depths. In addition, minimum distance from a front explained more model deviance for pelagic models of *large sharks* than the other numerical descriptors. There is growing evidence that filter feeding sharks orient to fronts (Sims and Quayle, 1998; Sims et al., 2000; Priede and Miller, 2009; Miller et al., 2015), also the pelagic models presented here for *filter feeding sharks* are largely driven by minimum distance from a front, but there is little information on predatory sharks aggregating near/around frontal boundaries (Queiroz et al., 2012). Queiroz et al. (2012) found that blue sharks (*Prionace glauca*) in the northeast Atlantic ocean displayed site fidelity correlating with local frontal areas, and that the temporal and spatial pattern overlapped that of pelagic longlining activities. Queiroz et al. (2016), used movement modeling to find that sharks (i.e., blue shark, shortfin mako; *Isurus oxyrinchus*, longfin mako; *Isurus paucus*, tiger; *Galeocerdo cuvier*, great hammerhead; *Sphyrna mokarran*, and scalloped hammerhead; *Sphyrna lewini*) across the Atlantic ocean prefer habitats characterized by strong sea surface-temperature gradients (fronts). Large, predatory sharks could be drawn to frontal zones as these areas could be concentrating food sources. Thus, metrics relating to the oceans physical dynamics, like minimum distance from a front, have the potential to be critical model descriptors when estimating the distribution of pelagic organisms.

3.5.2 Limitations

Coastal models tend to have more adequate diagnostics and tend to explain more model deviance than pelagic models, and this could be because coastal models are fitted with fishery independent data while pelagic models are fitted with fishery dependent data. Fishery dependent data (e.g., the Pelagic Longline Observer data) represent skilled fishers sampling areas known to have increased abundance of targeted organisms. Thus, the catchability represented in the dataset is higher and can lead to a overestimate of populations. Also, fishery dependent data have limited information regarding environmental conditions during catches. Fishery independent surveys often measure a variety of environmental variables at each site with devices like a CTD. Descriptors explaining the most deviance for coastal models often are variables measured by the CTD (e.g., oxygen saturation and salinity). Similar environmental information is not present in fishery dependent datasets. Thus, fishery independent data may offer more contrast of environmental conditions for target species - allowing the flexibility to capture more environmental drivers in the model.

Many pelagic stocks have seasonal migrations that cover large areas of the Atlantic Ocean and include moving into and out of the Gulf of Mexico. Some examples include *Prionace glauca* (Matsunaga, 2009), *Thunnus thynnus* (Block et al., 2001), and *Xiphias gladius* (Abascal et al., 2015). Thus, it is no surprise that season often explained more deviance in pelagic models than other descriptors as season relates directly to stock density. For the coastal models, season could not be included as a predictor because data were not available in winter. The lack of a season predictor may be biasing predictions from some of the coastal models. A seasonal bias is not easily detected with predictions of *large sharks* or *blacktip sharks* because shark populations are less abundant in the Gulf of Mexico during the winter months due to their southward migration (Hueter and Tyminski, 2007; Carlson et al., 2010b). A seasonal bias is obvious in the predictions form the *large pelagic fish* coastal model. Coastal predictions reflect much higher catch rates in the summer than other seasons (Appendix B), suggesting that large pelagic fish are either more abundant or have higher catchability in summer. There is a seasonal signal in pelagic predictions suggesting increased abundance in summer months, but not as extreme as the coastal predictions (Appendix B). Seasonal catch records developed in Chapter 2 show that the magnitude of *large pelagic fish* catches do not change seasonally. This suggests that *large pelagic fish* species are present and can be caught in the Gulf of Mexico all year. Incorporating additional datasets so that coastal models are fitted with data covering the entire seasonal range could reduce the bias observed in coastal predictions.

Incorporating other catch datasets into model fitting could improve the taxonomic coverage of this study. First, models for other important pelagic groups could not be fitted in this study due to insufficient catch data (e.g., *king mackerel*, *small sharks*, and *small pelagic fish*). Also, some of the models for multi-species functional groups were not fitted with catch information pertaining to all of the species categorized into the functional group. For example, *large pelagic fish* catches from the bottom longline survey primarily consist of *Remora* and *Sphyraena* spp., but the group consists of many other genera (Ainsworth et al., 2015). Also, for functional groups with a coastal, and pelagic model, there is often different taxa represented between the two catch datasets. Thus, the fitted models are missing the behavior of the other species in the group. This is important to be aware of when using these results for the parameterization of the Gulf of Mexico Atlantis ecosystem model. These issues could relate to the fact that the two operations considered in this study do not select all pelagic predators throughout the water column, so considering additional catch datasets with different harvesting strategies could be informative.

Foraging behavior of pelagic piscivores governs how they are exposed to gear like baited hooks. Humphries et al. (2010) found that many open-ocean predators (e.g., sharks, tunas, billfish and ocean sunfish) exhibit vertical movement through the water column to detect food (bait) via sound, movement, and/or oder plumes. Some of these predators feed at various depth levels throughout the entire water column - exposing them to both bottom and pelagic longline activities. Medved and Marshall (1981) investigated the feeding behavior of young sandbar sharks (*Carcharhinus plumbeus*) and were able to catch individuals at surface, mid-depth, and bottom depth. Lowe et al. (1996) found that larger tiger sharks (*Galeocerdo cuvier*) move through the water column to feed at the bottom during the night and near the surface during the day. However, other pelagic predators like Bluefin tuna (*Thunnus thynnus*) (Lawson et al., 2009), dolphinfish (*Coryphaena hippurus*) (Oxenford and Hunte, 1999), and blue marlin (*Makaira nigricans*) (Goodyear et al., 2008) traverse the near-surface layer of the water column, so they are only exposed to shallow-set pelagic longline operations. If species like these are retained in bottom longline operations it is likely incidental catch occurring during the setting/hauling process while the hooks are moving through the water column.

Gear design and bait can impact an organism's susceptibility to harvesting activities. Hook size, shape, and offset all have species-specific effects on catch rates. Larger hooks have resulted in decreased catch rates of the pelagic stingray (*Pteroplatytrygon violacea*) (Piovano et al., 2010; Coelho et al., 2012). Circle hooks, compared to J-hooks, can increase the catch rates of yellowfin tuna (*Thunnus albacares*) (Falterman and Graves, 2002; Kerstetter and Graves, 2006), bigeye tuna (*Thunnus obseus*) (Pacheco et al., 2011), and blue sharks (*Prionace glauca*) (Amorim et al., 2015), and decrease the catch rates of swordfish (*Xiphias gladius*) (Coelho et al., 2012; Amorim et al., 2015), sailfish (*Istiophorus platypterus*) (Pacheco et al., 2011), as well as loggerheads (*Caretta caretta*) and leatherbacks (*Dermochelys coriacea*) (Foster et al., 2012). Increasing the circle hook offset can reduce the catch rates of swordfish (Rice et al., 2012). Mackerel bait, compared to squid bait, can result in decreased catch rates of tuna (i.e., *Thunnus obesus* and *Thunnus alalunga*) (Foster et al., 2012) and swordfish (Coelho et al., 2012; Amorim et al., 2015), in addition to increased catch rates of some mackerel sharks (i.e., *Lamna nasus* and *Isurus oxyrinchus*) (Foster et al., 2012) and blue sharks (Coelho et al., 2012; Amorim et al., 2015).

A comprehensive list of fishery independent and fishery dependent surveys conducted within U.S. Gulf of Mexico waters was presented at the 2016 Gulf of Mexico Ecosystem Modeling Workshop, GOMEMOw (Grüss et al., 2016a), and highlights additional catch datasets possibly worth integrating with the datasets considered in this study for future model fitting efforts. Like the NMFS Expanded Annual Stock Assessment (EASA) Survey, which sampled with both vertical line and longline gear from April to October in 2011 (Fitzhugh et al., 2012; Campbell et al., 2012), or the the NMFS Small Pelagics Survey, which samples the northern Gulf of Mexico from the fall through the winter using a trawl (Ingram Jr., 2008; Pollack and Ingram Jr., 2014). These two examples are fishery independent surveys but there are also fishery dependent surveys worth considering, like the NMFS Southeast Region Headboat Observer Program (O'Hop and Sauls, 2012), the Marine Recreational Fisheries Statistics Survey (MRFSS) At-Sea Observer Program (O'Hop and Sauls, 2012), and the NMFS Shark Bottom Longline Observer Program (Hale and Carlson, 2007). All of these examples are conducted within the northern Gulf of Mexico. Considering similar catch datasets from the southern Gulf of Mexico, if they exist, would greatly benefit model fits.

Minimum distance from a front was selected for several models fitted in this study. This metric depends on adequately estimating frontal zones. Estimating frontal zones by processing altimetry data with the *Cayula-Cornillon Fronts in ArcGIS Raster MGET* tool in *ArcGIS* seems to sufficiently capture macroscale and large-mesoscale eddies, but struggles to represent sub-mesoscale eddies. These features are also known to also support pelagic fish (Godø et al., 2012). Thus, some of the catch records considered in this study may be closer to a frontal edge than estimated. To capture these features and potentially improve estimates of the minimum distance from a front - which may improve model fits and predictions - future work should investigate incorporating methods that are capable of estimating finer-scaled fronts (e.g., Luo et al., 2015).

There are descriptors that were not considered in this study that have the potential to improve fitted models. Chlorophyll-A has been found to influence the movement of pelagic predators Brill and Lutcavage (2001); Drymon et al. (2013), but this is likely species specific as some studies found chlorophyll-A did not improve model fits (Su et al., 2008; Grémillet et al., 2008). Prey dynamics could also inform distribution models. Schick and Lutcavage (2009) and Benoit-Bird et al. (2013) found that including data pertaining to prey groups improved predictions of bluefin tuna distributions. Drymon et al. (2013) found the CPUE of blacktip sharks was related positively with crustacean biomass. Also, some studies standardizing the catch rates of sharks found bait type to be a significant descriptor for models (Carlson et al., 2010a; Carlson and Gulak, 2013). When interpreting variables to use to model catch rates it is important to consider not only the ability to explain model deviance but also determining if the descriptor relates to local density and/or catchability. Variables relating to local density directly describe changes in stock density, while variables relating to catchability describe how susceptible an organism is to harvesting gear and methods. It is important to know an organism's life history and to make this distinction because a variable that influences catchability and varies randomly may help explain model deviance without improving the accuracy of predicting stock density. On the other hand, if a variable influencing catchability changes over time or space, it may be necessary to include this variable in the model to avoid bias in the estimates of density.

Predictions of spatial abundance using model forecasts have some limitations. First, models were fit with *in situ* environmental observations, which represent instantaneous conditions, but models were forecasted with data representing time- and space-integrated means. This assumes that models trained with data representing short-term behavioral responses can predict long-term habitat suitability. Thus, results may not detect acclimation, or estimate a quick population response within a functional group's range of environmental tolerance. Second, for some model descriptors, data used to forecast with fitted models do not to properly represent the seasonality of the ecosystem. This may be driving some of the differences between model predictions and information presented in literature and other data sources. Some variables could not be considered as descriptors because seasonal Gulf-wide estimates could not be developed. For instance, preliminary model fits showed beam transmission (%), a measurement of the penetration of light through the water column, to be a statistically important descriptor (Appendix B). However, beam transmission depends on dynamic environmental processes (e.g., cloud cover, sediment, etc), so averages spanning large temporal and spatial scales would not be meaningful.

Predictions within the southern Gulf of Mexico should be interpreted with caution as they are extrapolated (i.e., there are no data from Mexican nor Cuban waters in the datasets used for model fitting). Thus, these predictions assume that the relationship between environmental drivers and functional groups densities in the southern Gulf are the same as those in the northern Gulf, which may or may not be valid. To produce more robust predictions within the southern Gulf of Mexico models should be re-fitted with datasets that include hook and line catch data from these waters.

3.5.3 *Large Sharks* Models

Temperature and depth are driving both the coastal, and pelagic *larges sharks* models. Water temperature is the most influential on abundance (catch rates), and bottom depth influences where sharks are (probability of positive catch) as well as abundance. Movement of shark species often corresponds with changing sea temperatures (Morrissey and Gruber, 1993; Bigelow et al., 1999; Parsons et al., 2005; Hueter and Tyminski, 2007; Ortega et al., 2009; Carlson et al., 2010b; Baum and Blanchard, 2010), and depth influences habitat selection (Morrissey and Gruber, 1993; Heithaus et al., 2007b; Carlson et al., 2010b; Hoffmayer et al., 2014) and catch rates (Carlson et al., 2010a; Baum and Blanchard, 2010; Drymon et al., 2010; Carlson et al., 2012). Factors time and season were also significant for *larges sharks* pelagic models, which has been observed in studies standardizing catch rates of sharks (Carlson et al., 2010a, 2012; Carlson and Osborne, 2013; Carlson and Gulak, 2013). Sea bottom habitat could also drive the distribution of some shark species (Hannan et al., 2012). Salinity can also influence the habitat selection for sharks (Heupel and Simpfendorfer, 2008; Ubeda et al., 2009; Bethea et al., 2015), but models fitted with salinity (*large sharks* coastal models) did not select salinity as a model descriptor. This is because studies relating to salinity tend to focus on young, juvenile sharks and localized inshore systems, but this research aimed to describe the distribution of older juveniles and adults, which often spend most of their time in coastal/offshore waters (Hueter and Tyminski, 2007). Constructing models to describe the distribution profiles for younger organisms would be beneficial, but would require catch data that retains those individuals and should focus more on small scale, inshore studies.

Major features of predictions made with the fitted *large sharks* coastal model seem to be supported by observations from the literature. First, predictions indicate a seasonal signal. Catch rates are very low in the winter, but increase in the spring, summer, and fall. This corresponds to the theory of a general southward migration of sharks (Hueter and Tyminski, 2007; Carlson et al., 2010b). Second, areas of increased catch rates in the northern Gulf are predicted off the coasts of Texas, Louisiana, Mississippi and south Florida. Hotspots off of Texas, Louisiana, and south Florida appear in the spring while the hotspot off of Mississippi appears in the summer. Hueter and Tyminski (2007) concluded that 16 different species of sharks use areas off of Florida and Texas as primary and/or secondary nurseries. Their results for Texas show more older individuals were observed off Corpus Christi, and their results for Florida indicate that many older individuals were observed off the Florida Keys. These areas are approximately where the corresponding hotspots are occurring in the results presented here. Bethea et al. (2015) determined some areas in the northeast Gulf to be important nursery grounds. Results presented here did not show increased abundance in these areas, but Bethea et al. (2015) studied young of the year and juveniles while this study only studied adults.

Results presented in this study suggest a connection between large, predatory sharks and the Mississippi River outlet, particularly the dead zone. First, for both the coastal and pelagic *large sharks* models, extreme outliers from the cross validation tend to be located off the Mississippi River outlet. Although removing extreme outliers could improve model fits, it appears these outliers represent important instances of variation in the ecosystem - specifically how variable shark catches are in this area. Second, the predictions from the *large sharks* coastal model show increased abundance of sharks along the Gulf's northeastern shelf in the summer months. This temporal and spatial domain matches that of the Gulf of Mexico hypoxic zone (a.k.a., dead zone). Studies of hypoxic conditions within the Gulf of Mexico have observed fish aggregating along the edge, and/or immediately above, the hypoxic areas since many marine teleost can not inhabit hypoxic waters (Stanley and Wilson, 2004; Zhang et al., 2009). However, experimental studies have found that some sharks are capable of altering their physiology and swimming behavior to tolerate hypoxic conditions (Metcalfe and Butler, 1984; Wise et al., 1998; Carlson and Parsons, 2001). Also, Heithaus et al. (2009) found dissolved oxygen to drive the distribution of bull sharks (*Carcharhinus leucas*) within Everglades National Park even in the absence of hypoxia. Thus some species of sharks might take advantage of the Gulf of Mexico hypoxic zone to forage for benthic organisms (e.g., crabs) and/or locate aggregations of fish occurring around the zone-edge. Prince and Goodyear (2006) analyzed tag data from individuals exposed to the eastern tropical Pacific hypoxic zone and suggested that the larger sizes of sailfish observed may be due to the enhanced foraging opportunities afforded by the closer proximity of predator and prey in compressed habitat.

Predictions of *large sharks* across the pelagic environment do not have noticeable seasonality, but there are two distinct features of these results that stand out. First, the continental slope has higher catch rates than deep, pelagic waters. Many studies have found sharks in the Gulf to have an affinity for the shelf and coast, but there have been individuals observed making trips into the deep, pelagic waters. For instance, Hoffmayer et al. (2014) tagged several dusky sharks (*Carcharhinus obscurus*) in the northern Gulf, and observed sharks spending most of their time along the shallow edges of the slope. However, in the fall one shark swam south to spend time at depths greater than 300m. Second, the slope has areas of increased catch rates. Higher catch rates are estimated around DeSoto Canyon, Mississippi Canyon, and Mississippi Fan. These increased estimates are consistent through winter to summer but decrease in the fall. Coincidentally, this spatial range and temporal pattern is similar to that of the intrusion and eddy shedding of the Loop Current (Leben, 2005). Considering the influence minimum distance from a front and altimetry have on the delta model, it is possible that these features may be connected to the physical dynamics generated from the Loop Current. Some research have suggested these areas to be important for various shark species. For instance, Etnoyer and Warrenchuk (2007) suggested the Mississippi Canyon may be a nursery for catsharks (*Scyliorhinidae* spp.). Also, Hueter and Tyminski (2007) found offshore coastal nurseries off Texas, Louisiana, and Mississippi through longline surveys in the months of July and August. The importance of these areas for predatory shark populations should be an topic of future research in order to improve our understanding of shark habitats in the Gulf of Mexico.

Predictions show that sharks may appregate in areas of the southern Gulf of Mexico - primarily within Campeche Bank, some coastal estuaries, and the continental slope. These results should be interpreted with caution since forecasts across the southern Gulf of Mexico were extrapolated, but some of these trends are supported by the literature. In Cuba, sharks are commonly caught as bycatch in the pelagic longline fisheries (Guitart, 1975; Aguilar et al., 2014). In Mexico, some of the indicated areas correspond to shark fisheries Castillo-Géniz et al. (1998); Pérez-Jiménez and Mendez-Loeza (2015), and possible nurseries (Montiel, 1988; Bonfil, 1997).

3.5.4 Moving Forward

Spatial distributions of pelagic fish within the Gulf of Mexico can be quite different from one another. Some of the species investigated here are not properly represented by longline datasets alone, and more catch and environmental information is needed to get a better understanding of their Gulf-wide distribution. Models for *large sharks* produced some of the best fits with few diagnostic issues which resulted in good performance, thus these models could aid conservation efforts for large, predatory sharks inhabiting Gulf of Mexico waters. However, The *large sharks* functional group consists of twenty-six different shark species, all of which have slightly different life histories, behaviors, and habitat preferences. As our knowledge and data-banks grow, species-specific investigations should be pursued so conservation plans can aim at species of concern in addition to the large sharks complex. Seasonal predictions from all of the models presented here can provide some improvement to the representation of pelagic functional groups in the Gulf of Mexico Atlantis ecosystem model, which will aid ecosystem based fisheries management efforts in the Gulf of Mexico. Considering that many of these highly migratory stocks inhabit waters far beyond the Gulf, ecosystem models like Atlantis are critical in gaining insight on how conservation efforts covering very small areas of their spatial range impact the overall status of these stocks.

Table 3.1: Data Used For Model Fitting and Predicting. Catch and effort data were provided by the Southeast Fisheries Science Center (SEFSC), and were supplemented with sea surface temperature and altimetry data from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Archiving, Validation and Interpretation of Satellite Oceanographic (AVISO) datasets, respectively. AVISO data were collected from NOAA's Easier Access To Scientific Data database, while MODIS data were assigned to catch records using the *Interpolate PO.DAAC MODIS L3 SST at Points* tool from the Marine Geospatial Ecology Tools toolbox in *ArcGIS*. Data used to forecast with fitted models all came from NOAA. The National Centers for Environmental Information (NCEI) provided bathymetry data, and the NOAA's National Centers for Environmental Information (NCEI) provided climatological seasonal averages of sea temperature, dissolved oxygen, oxygen saturation, and salinity.

Data	**Source**	**Spatial/Temporal Resolution**	**Use**
Coastal catch and effort	SEFSC	Northern Gulf of Mexico (9 - 366m isobaths)	Fitting
Pelagic catch and effort	SEFSC	Northern Gulf of Mexico (200m isobath - EEZ)	Fitting
Sea surface temperature	MODIS	grid (4km/9km) / (Daily/8Day/Monthly)‡	Fitting
Altimetry	AVISO	0.25° x 0.25° grid / weekly averages	Both
Bathymetry	NCEI	Gulf-wide (5 - 4000 m isobaths)	Forecast
Sea temperature†	NCEI	0.25° x 0.25° grid / seasonal averages	Forecast
Dissolved oxygen†	NCEI	1° x 1° grid / seasonal averages	Forecast
Oxygen saturation†	NCEI	1° x 1° grid / seasonal averages	Forecast
Salinity†	NCEI	0.25° x 0.25° grid / seasonal averages	Forecast

† Averages for both sea surface and sea bottom

‡ See Appendix B for details

Table 3.2: Species identified in NOAA's Bottom Longline Survey dataset collated by functional groups defined for the Gulf of Mexico Atlantis Model (Ainsworth et al., 2015).

***Greater amberjack* (AMB)***
Seriola dumerili

***Black drum* (BDR)**†
Pogonias cromis

***Benthic feeding sharks* (BEN)***
Heptranchias perlo
Hexanchus vitulus

***Deep serranidae* (DSR)**†
Centropristis striata
Epinephelus drummondhayi
Epinephelus flavolimbatus
Epinephelus nigritus
Epinephelus niveatus

***Flatfish* (FLT)**†
Syacium papillosum

***Gag grouper* (GAG)**†
Mycteroperca microlepis

***Jacks* (JCK)***
Carangidae
Seriola zonata

***King mackerel* (KMK)***
Scomberomorus cavalla

***Large sharks* (LGS)**
Carcharhinidae
Carcharhinus
Carcharhinus acronotus
Carcharhinus altimus
Carcharhinus brevipinna
Carcharhinus falciformis
Carcharhinus isodon
Carcharhinus leucas
Carcharhinus plumbeus
Carcharhinus signatus
Galeocerdo cuvier
Ginglymostoma cirratum
Negaprion brevirostris
Rhizoprionodon terraenovae
Sphyrna
Sphyrna lewini
Sphyrna mokarran
Sphyrna tiburo
Sphyrnidae

***Loggerhead* (LOG)***
Caretta caretta

***Large pelagic fish* (LPL)**
Acanthocybium solandri
Coryphaena hippurus
Echeneis naucrates
Echeneis neucratoides
Remora remora
Sphyraena barracuda

***Large reef fish* (LRF)**†
Brotula barbata
Conger oceanicus
Echiophis punctifer
Rhynchoconger flavus
Ophichthidae
Ophichthus Gulf of Mexicoesi
Ophichthus puncticeps
Ophichthus rex
Trichiurus lepturus

***Little tunny* (LTN)***
Euthynnus alletteratus

***Lutjanidae* (LUT)**†
Etelis oculatus
Lutjanus analis
Lutjanus griseus
Pristipomoides aquilonaris

***Other demersal fish* (ODF)**†
Arius felis
Bagre marinus
Gymnothorax kolpos
Gymnothorax nigromarginatus
Haemulon plumieri
Muraena retifera
Opsanus pardus
Pagrus pagrus
Prionotus tribulus
Urophycis
Urophycis cirrata
Urophycis floridana

***Skates and Rays* (RAY)**
Dasyatidae
Dasyatis
Dasyatis americana
Dasyatis centroura
Dasyatis sabina
Mustelus
Mustelus canis
Mustelus norrisi
Mustelus sinusmexicanus
Raja eglanteria
Raja garricki
Rhinoptera bonasus
Scyliorhinus retifer
Triakidae

***Red drum* (RDR)**†
Sciaenops ocellatus

***Red grouper* (RGR)**†
Epinephelus morio

***Red snapper* (RSN)**†
Lutjanus campechanus

***Sciaenidae* (SCI)**†
Menticirrhus americanus
Micropogonias undulatus

***Scamp* (SCM)**†
Mycteroperca phenax

***Small demersal fish* (SDF)**†
Scorpaena agassizii

***Seatrout* (SEA)**†
Cynoscion arenarius
Cynoscion nothus

***Small sharks* (SMS)***
Centrophorus granulosus
Squalus
Squalus cubensis

***Small pelagic fish* (SPL)***
Merluccius bilinearis

***Small reef fish* (SRF)**†
Caulolatilus microps
Lopholatilus chamaeleonticeps
Rachycentron canadum
Synodus foetens
Trachinocephalus myops

***Swordfish* (SWD)***
Xiphias gladius

***Blacktip sharks* (TIP)**
Carcharhinus limbatus

***Vermilion snapper* (VSN)**†
Rhomboplites aurorubens

Not Assigned†
Gadidae
Unidentified

† Functional group is not considered pelagic-based fish
* Functional group does not have enough data to fit a statistical model

Table 3.3: Species identified in the NOAA's Pelagic Longline Observer dataset collated by functional groups defined for the Gulf of Mexico Atlantis Model (Ainsworth et al., 2015).

Code	Species
***Benthic feeding sharks* (BEN)⋆**	
SSG	Heptranchias perlo
***Other billfish* (BIL)**	
BIL	Istiophoridae
SAI	Istiophorus albicans
WHX	Tetrapturus
SPX	Tetrapturus
SPG	Tetrapturus georgii
SPF	Tetrapturus pfluegeri
***Blue marlin* (BMR)**	
BUM	Makaira nigricans
***Bluefin tuna* (BTN)**	
BFT	Thunnus thynnus
***Diving birds* (DBR)†**	
SWC	Calonectris diomedea
GUX	Laridae
GHE	Larus argentatus
GBB	Larus marinus
GLA	Leucophaeus atricilla
GAN	Morus bassanus
SPW	Oceanites oceanicus
PBR	Pelecanus occidentalis
SWX	Puffinus
SWG	Puffinus gravis
***Deep diving odontocetae* (DDO)†**	
PSW	Kogia breviceps
WSP	Physeter macrocephalus
***Dolphins and porpoises* (DOL)†**	
MDO	Delphinidae
MCO	Delphinus delphis
MPW	Globicephala
PWL	Globicephala macrorhynchus
PWS	Globicephala melas
MRD	Grampus griseus
WNB	Hyperoodon ampullatus
WHA	Cetacea
MKW	Orcinus orca
MPD	Stenella attenuata
MCL	Stenella clymene
MSD	Stenella coeruleoalba
MAD	Stenella frontalis
MBD	Tursiops truncatus
WBK	Ziphiidae
***Deep water fish* (DWF)**	
CUB	Cubiceps
DEA	Trachipterus arcticus
***Filter feeding sharks* (FIL)**	
MAN	Mobulidae
***Jacks* (JCK)⋆**	
JAC	Caranx
RUN	Elagatis bipinnulata
AMJ	Seriola
***King mackerel* (KMK)⋆**	
KGM	Scomberomorus cavalla
***Kemps ridley* (KMP)⋆**	
TKR	Lepidochelys kempii
***Large sharks* (LGS)**	
XTH	Alopias
BTH	Alopias superciliosus
PTH	Alopias vulpinus
SRQ	Carcharhinidae
SBN	Carcharhinus acronotus
SSP	Carcharhinus brevipinna
FAL	Carcharhinus falciformis
SFT	Carcharhinus isodon
SBU	Carcharhinus leucas
OCS	Carcharhinus longimanus
DUS	Carcharhinus obscurus
SRF	Carcharhinus perezi
SSB	Carcharhinus plumbeus
SNI	Carcharhinus signatus
SBG	Carcharhinus ultima
SST	Carcharias taurus
TIG	Galeocerdo cuvier
XMA	Isurus
SMA	Isurus oxyrinchus
LMA	Isurus paucus
SMK	Lamnidae
POR	Lamna nasus
BSH	Prionace glauca
SCR	Pseudocarcharias kamoharai
SAS	Rhizoprionodon terraenovae
XHH	Sphyrna
SPL	Sphyrna lewini
GHH	Sphyrna mokarran
SHH	Sphyrna zygaena
***Loggerhead* (LOG)⋆**	
TTL	Caretta caretta
***Large pelagic fish* (LPL)**	
WAH	Acanthocybium solandri
LAX	Alepisaurus
DOL	Coryphaena
REM	Echeneidae
SKJ	Katsuwonus pelamis
OPA	Lampris guttatus
MST	Masturus lanceolatus
MOX	Mola
MOC	Mola mola
BLU	Pomatomus saltatrix
BON	Sarda sarda
CHM	Scomber japonicus
MAC	Scomber scombrus
BAR	Sphyraena
TUN	Thunnus
ALB	Thunnus alalunga
BLK	Thunnus atlanticus
BET	Thunnus obesus
***Large reef fish* (LRF)†**	
CNG	Conger
TPL	Lobotes surinamensis
TRX	Trichiuridae
ACT	Trichiurus lepturus
***Little tunny* (LTN)**	
LTA	Euthynnus alletteratus
***Medium pelagic fish* (MPL)**	
POA	Brama
TAR	Megalops atlanticus
***Other demersal fish* (ODF)†**	
PUX	Tetraodontidae
***Other tuna* (OTN)⋆**	
FRM	Auxis thazard
***Skates and Rays* (RAY)**	
SRX	Elasmobranchii
DGS	Mustelus canis
PEL	Pteroplatytrygon violacea
***Red snapper* (RSN)†**	
RSN	Lutjanus campechanus
***Surface feeding birds* (SBR)†**	
FRB	Fregata magnificens
***Spanish mackerel* (SMK)**	
GEM	Lepidocybium flavobrunneum
OIL	Ruvettus pretiosus
***Small sharks* (SMS)**	
SCO	Isistius brasiliensis
SHX	Elasmobranchii
SGR	Somniosus microcephalus
SDG	Squalidae
DGY	Squalus acanthias
DGV	Zameus squamulosus
***Squid* (SQU)†**	
SQX	Teuthida
***Small reef fish* (SRF)†**	
CBA	Rachycentron canadum
***Swordfish* (SWD)**	
SWO	Xiphias gladius
***Blacktip sharks* (TIP)⋆**	
SBK	Carcharhinus limbatus
***Other turtles* (TUR)**	
TTG	Chelonia mydas
TLB	Dermochelys coriacea
THB	Eretmochelys imbricata
TTX	Chelonioidea
***White marlin* (WMR)**	
WHM	Tetrapturus albidus
***Yellowfin tuna* (YTN)**	
YFT	Thunnus albacares
***Not Assigned*†**	
BRD	Aves
MAM	Mammel
UNC	Unknown
UNK	Unknown

† Functional group is not considered pelagic-based fish
⋆ Functional group does not have enough data to fit a statistical model

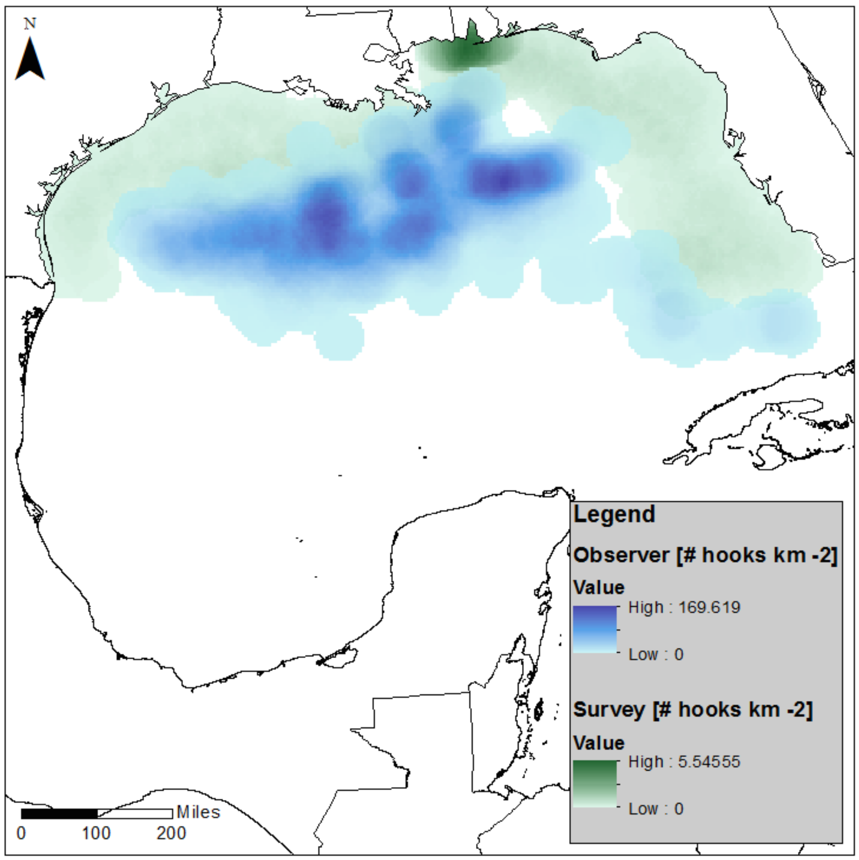


Figure 3.1: Geographic Distribution of Effort from NOAA's Bottom Longline Survey and NOAA's Pelagic Longline Observer Program. Effort [# of hooks per km^2] from NOAA's Bottom Longline Survey is shown in green, and effort from NOAA's Pelagic Longline Observer Program is shown in blue. This map was calculated and created in *ArcGIS* via the *Point Density* tool.

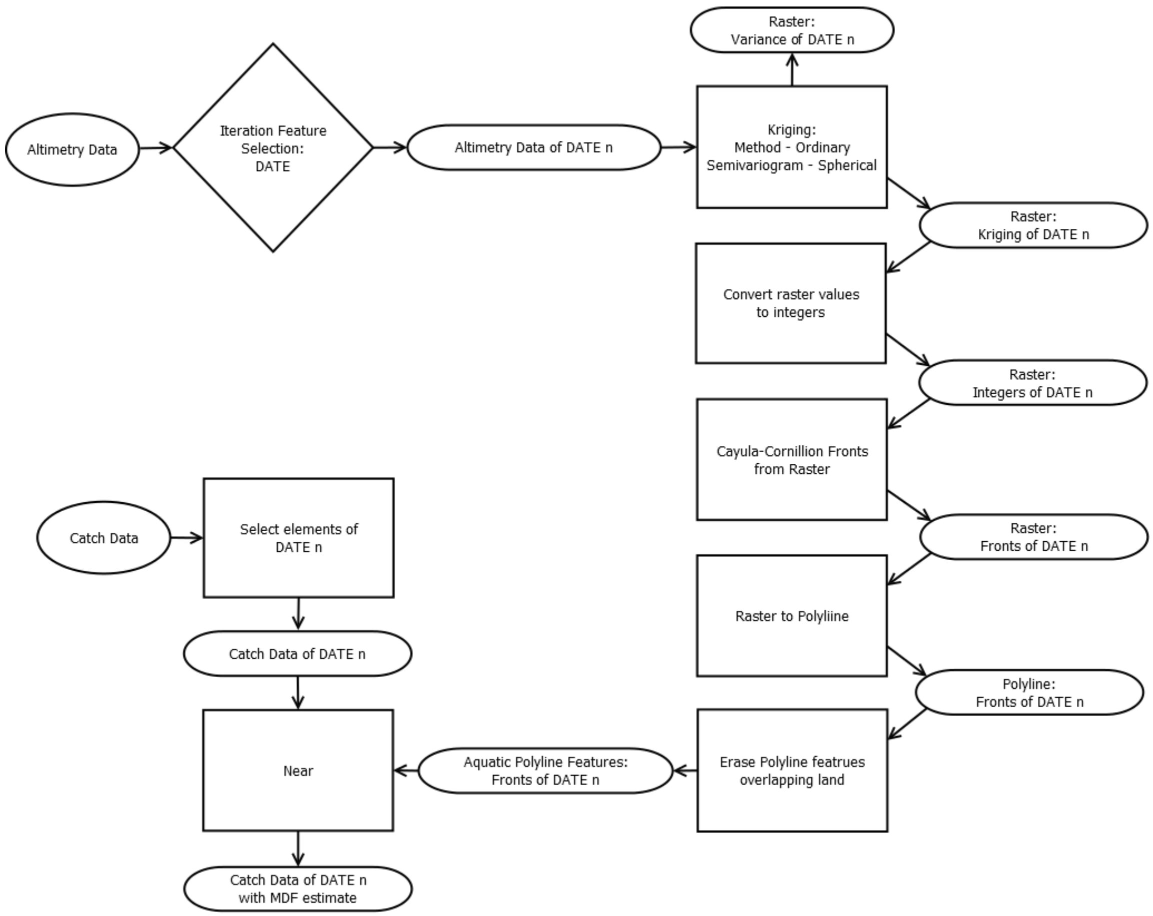
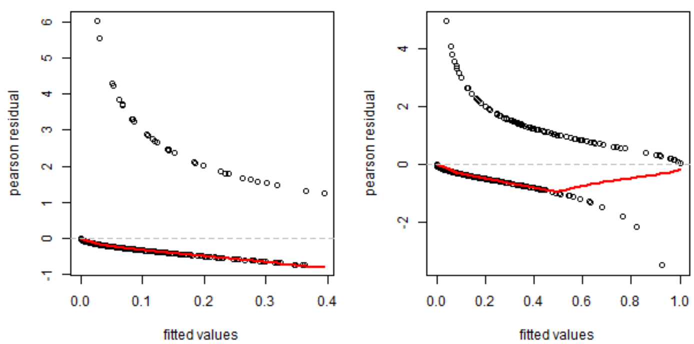


Figure 3.2: Conceptual Routine for Calculating Minimum Distance from A Front. The routine to calculate minimum distance from front (MDF) was constructed in *ArcGIS*'s *Model Builder*. Oval boxes indicate data files, square boxes indicate *ArcGIS* tools, and oblong boxes indicate tool outputs. The diamond box indicates a feature for iterating through unique dates identified in the altimetry dataset. A front profile is constructed for an individual date (n), which is used to calculate the minimum distance from a front for catch records associated to longline sets that occurred on date n.

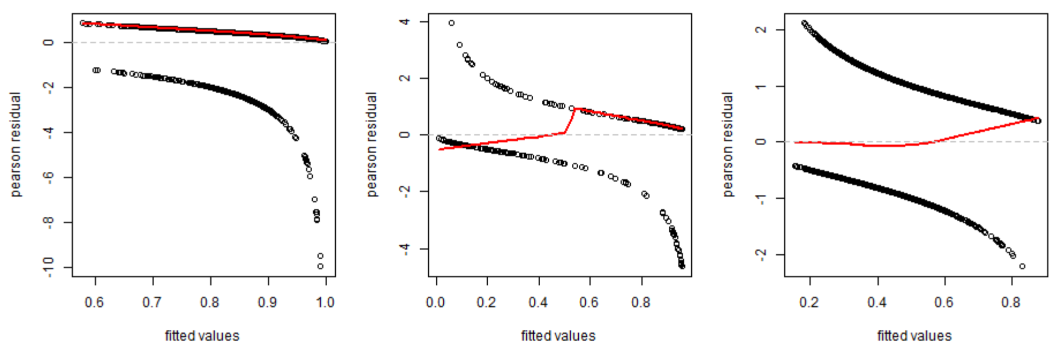
Table 3.4: Generalized Additive Models Fitted for Seasonal Predictions. Results from the forward model selection procedure for all fitted models. Models were determined for both parts of the delta model predicting CPUE: the probability of positive catch (η_B) and the abundance index (η_Z). Numerical descriptors include bottom depth (BD), sea surface temperature (SST), sea bottom temperature (SBT), sea surface height (SSH), oxygen saturation (OS), dissolved oxygen (DO), salinity (SAL), and minimum distance from front (MDF) - subscripts indicate whether the descriptor is measured from the sea surface (S) or sea bottom (B). All of which were fitted with penalized regression splines ($s()$). Year (yr) and season (sn) are treated as factors ($f()$). Deviance explained ($D.E.$, %) is displayed for each model, and the receiver operating characteristic area under the curve (AUC) is displayed for Bernoulli models.

Table 3.4: Continued.

Functional Group		Model	D.E.	AUC
		Models Fit with NOAA's Bottom Longline Survey Data		
Functional Group		Model	D.E.	AUC
large sharks	η_B	$s(BD, 7)$	46.5	0.91
	η_Z	$s(SBT, 13) + s(SSH, 12) + f(yr)$	40.2	
large pelagic fish	η_B	$s(OS_B, 4) + s(SST, 7) + s(DO_S, 4) + s(BD, 9) + s(SAL_B, 7)$	22.9	0.86
	η_Z	$s(DO_S, 3) + s(SSH, 3) + f(yr) + s(OS_B, 3)$	60.4	
skates and rays	η_B	$s(SBT, 11) + s(OS_B, 3)$	18.5	0.79
	η_Z	$s(SBT, 5) + s(SST, 10) + s(SAL_S, 4)$	50.9	
blacktip sharks	η_B	$s(SBT, 6) + s(SAL_S, 3) + s(SSH, 3) + s(OS_B, 3)$	41.6	0.91
	η_Z	$s(SAL_B, 3) + s(DO_B, 15) + s(BD, 3)$	42.4	
		Models Fit with Pelagic Longline Data		
Functional Group		Model	D.E.	AUC
other billfish	η_B	$s(SST, 3) + f(yr) + f(sn) + s(MDF, 3) + s(BD, 3) + s(SSH, 3)$	13.6	0.75
	η_Z	$f(yr) + s(BD, 22) + s(SST, 28) + s(MDF, 3) + s(SSH, 3)$	37.5	
blue marlin	η_B	$s(SST, 3) + f(sn) + f(yr) + s(SSH, 3) + s(MDF, 3) + s(BD, 3)$	9.5	0.71
	η_Z	$s(SST, 3) + s(SSH, 3) + f(yr) + s(BD, 3) + s(MDF, 21) + f(sn)$	31.8	
bluefin tuna	η_B	$f(sn) + s(SST, 3) + f(yr) + s(SSH, 3) + s(MDF, 3) + s(BD, 3)$	18.2	0.78
	η_Z	$f(yr) + s(SSH, 3) + f(sn) + s(MDF, 3) + s(BD, 3)$	8.3	
deep water fish	η_B	$f(sn) + s(SST, 3) + s(MDF, 3) + s(BD, 3) + s(SSH, 3)$	11.1	0.77
	η_Z	$f(sn) + s(SST, 3) + s(MDF, 3) + f(yr) + s(SSH, 3) + s(BD, 3)$	55.0	
filter feeding sharks	η_B	$f(sn) + f(yr) + s(MDF, 3) + s(BD, 3) + s(SSH, 3)$	7.0	0.72
	η_Z	$f(yr) + s(BD, 5) + s(SSH, 3) + s(MDF, 3) + s(SST, 3)$	33.4	
large sharks	η_B	$f(sn) + f(yr) + s(MDF, 3) + s(BD, 3) + s(SST, 3) + s(SSH, 3)$	6.14	0.73
	η_Z	$s(SST, 3) + s(BD, 3) + f(yr) + f(sn) + s(SSH, 29) + s(MDF, 33)$	70.3	
large pelagic fish	η_B	$f(sn) + f(yr) + s(SSH, 3) + s(BD, 3) + s(SST, 3)$	8.7	0.65
	η_Z	$f(yr) + s(BD, 46) + s(SST, 12) + s(SSH, 37) + f(sn) + s(MDF, 8)$	33.6	
medium pelagic fish	η_B	$s(SSH, 3) + f(yr) + f(sn) + s(SST, 3) + s(BD, 3) + s(MDF, 11)$	6.5	0.68
	η_Z	$f(sn) + f(yr) + s(SSH, 3) + s(SST, 3) + s(MDF, 3) + s(BD, 3)$	16.6	
skates and rays	η_B	$f(yr) + f(sn) + s(SST, 3) + s(MDF, 3) + s(BD, 3)$	16.1	0.76
	η_Z	$f(sn) + f(yr) + s(SST, 3) + s(SSH, 3) + s(BD, 3) + s(MDF, 13)$	36.5	
spanish mackerel	η_B	$s(SST, 3) + f(yr) + f(sn) + s(MDF, 3) + s(SSH, 8)$	3.8	0.63
	η_Z	$f(sn) + s(BD, 41) + f(yr) + s(SST, 19) + s(SSH, 9) + s(MDF, 43)$	25.5	
small sharks	η_B	$f(sn) + f(yr) + s(SST, 3) + s(BD, 3) + s(MDF, 3) + s(SSH, 3)$	4.3	0.65
	η_Z	$s(BD, 35) + s(MDF, 3) + s(SSH, 19) + s(SST, 3) + f(yr) + f(sn)$	58.5	
swordfish	η_B	$f(sn) + f(yr) + s(SSH, 3) + s(SST, 9) + s(MDF, 3) + s(BD, 3)$	14.9	0.76
	η_Z	$s(BD, 49) + s(MDF, 3) + s(SST, 3) + s(SSH, 3) + f(yr) + f(sn)$	48.7	
other turtles	η_B	$f(sn) + f(yr) + s(BD, 3) + s(SSH, 3) + s(SST, 3) + s(MDF, 11)$	4.7	0.67
	η_Z	$f(yr) + s(MDF, 4) + s(SST, 3) + s(SSH, 3) + s(BD, 4)$	71.0	
white marlin	η_B	$s(SST, 3) + f(yr) + s(SSH, 3) + f(sn) + s(BD, 3) + s(MDF, 10)$	18.7	0.82
	η_Z	$f(yr) + s(SST, 3) + s(SSH, 3) + s(MDF, 3) + s(BD, 3)$	25.1	
yellowfin tuna	η_B	$f(sn) + f(yr) + s(SSH, 3) + s(MDF, 3) + s(SST, 3) + s(BD, 3)$	23.3	0.80
	η_Z	$s(SST, 3) + s(BD, 3) + f(yr) + f(sn) + s(SSH, 28) + s(MDF, 4)$	14.7	



(a) coastal *large pelagic fish* (b) coastal *blacktip shark*



(c) pelagic *large pelagic fish* (d) coastal *large sharks* (e) pelagic *large sharks*

Figure 3.3: General Trends of Residual Diagnostics for Fitted Bernoulli Models. Examples of the general trends of residuals from fitted Bernoulli models are shown for indicated functional groups. Red lines indicate the lowess smooth.

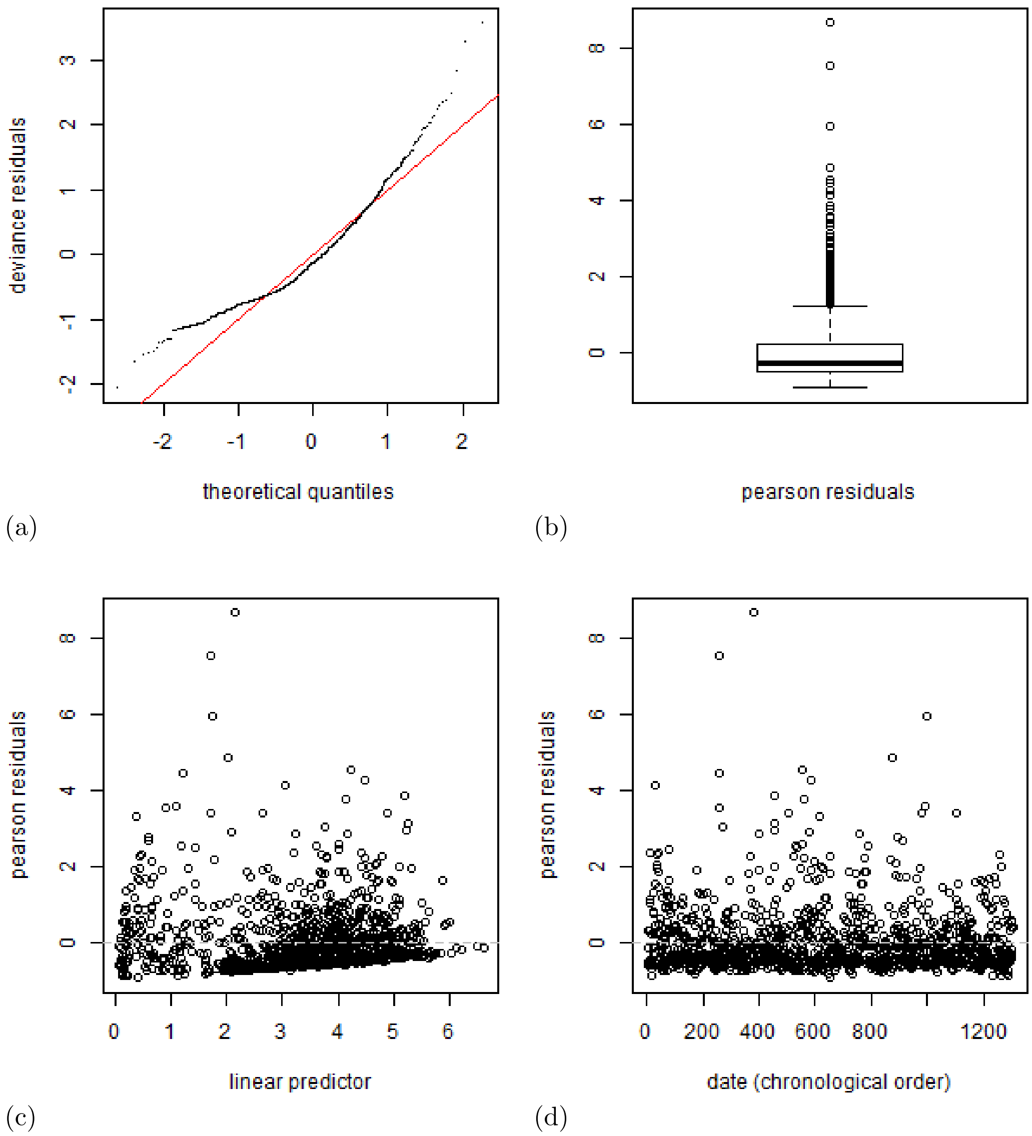
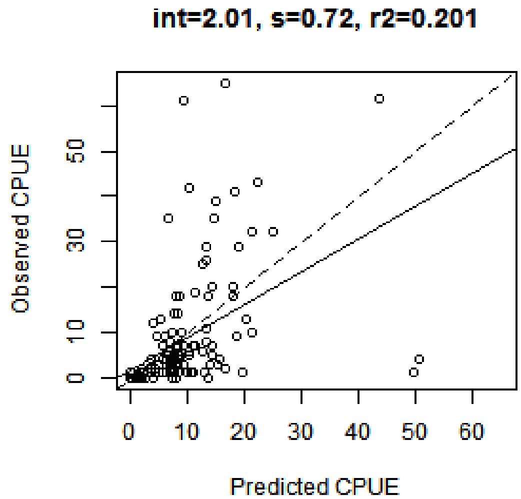
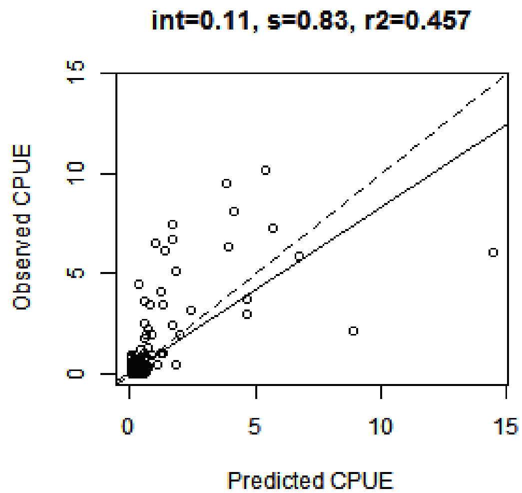


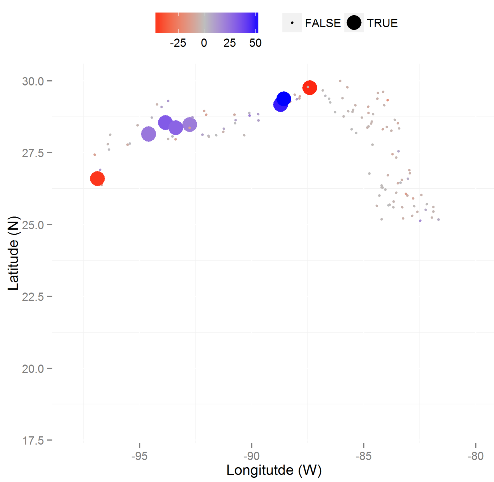
Figure 3.4: Residual Diagnostics from the *Large Sharks* Gamma Model Fitted with Pelagic Longline Observer Data. Residual diagnostics include: the Q-Q plot (a), box plot (b), residuals against linear predictor (c), which is the predicted value for each data point in the scale of the link function, and residuals against time (d).



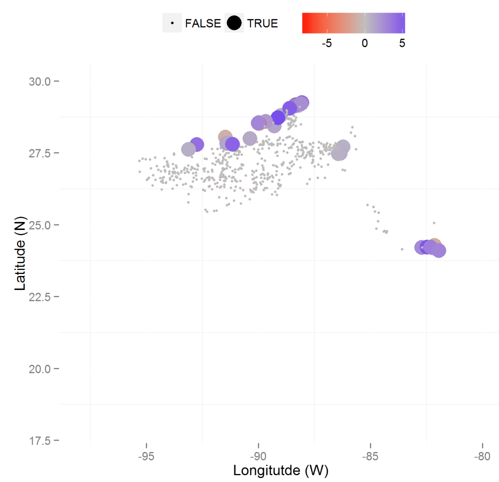
(a)



(b)

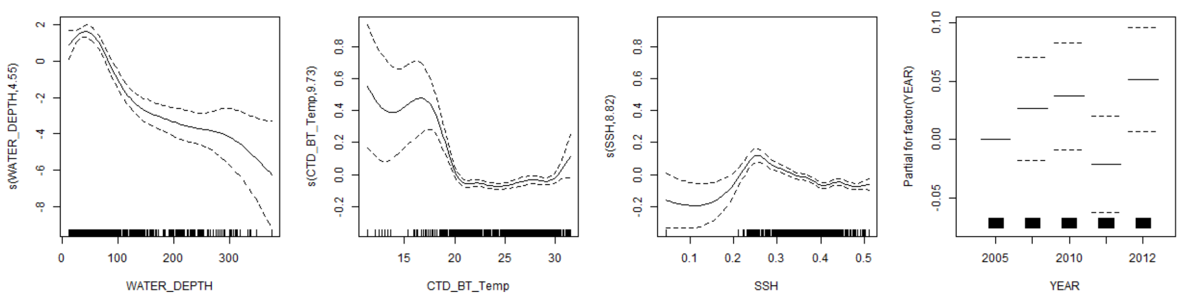


(c)



(d)

Figure 3.5: Cross Validation Results from the *Large Sharks* Delta Generalized Additive Models. Results are presented as observed against predicted catch rates for the coastal model (a) and pelagic model (b). Results from a linear regression on the points (solid line) are shown: intercept (int), slope (s), and adjusted r-squared value (r2). The dashed line indicates the 1:1 ratio between observed and predicted values. Cross validation residuals are presented based on the corresponding geographic coordinates for the coastal model (c) and pelagic model (d). Point size indicates if the residual is larger than the 95% quantile.



(a) (b) (c) (d)

Figure 3.6: Model Descriptor Fits from the *Large Sharks* Generalized Additive Model Fitted with Bottom Longline Survey Data. Panel (a) displays the model descriptor fit for the binomial data model, and panels (b) - (d) display the model descriptor fits for the zero-truncated data model. Solid lines indicate the fit, dashed lines indicate the 95% confidence interval, and the black dashes along the horizontal axis display the rug plot. The estimated degrees of freedom for smooth fits are included in the vertical axis label.

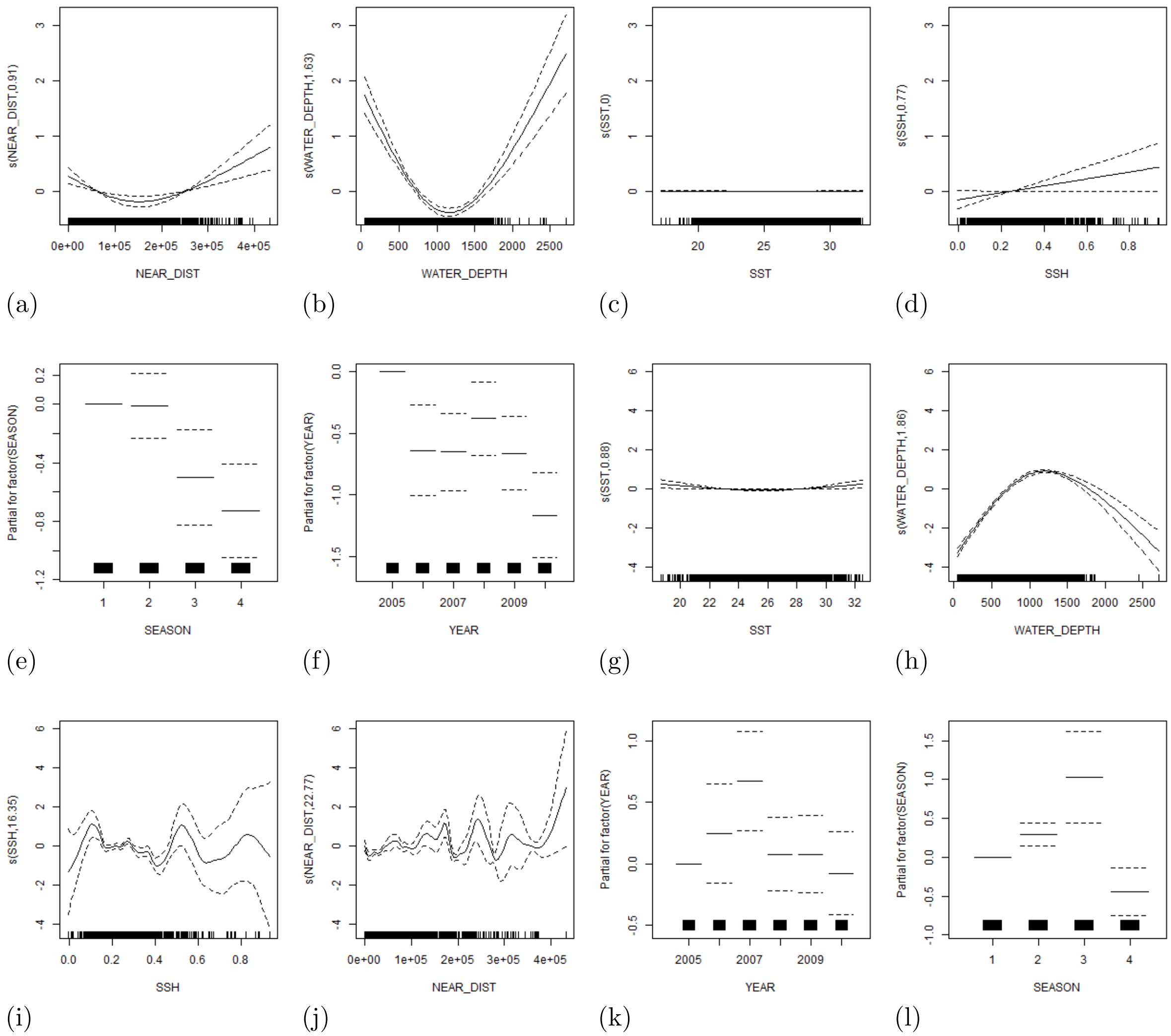
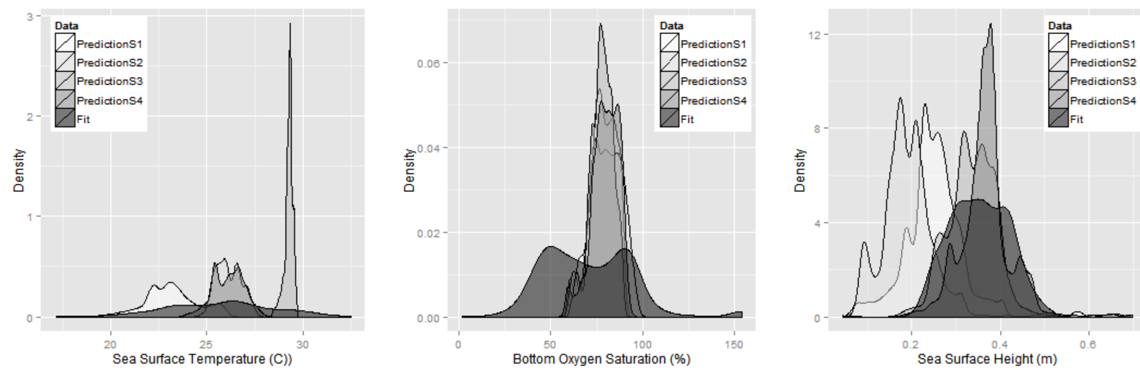


Figure 3.7: Model Descriptor Fits from the *Large Sharks* Generalized Additive Model Fitted with Pelagic Longline Data. Panels (a) - (f) display descriptor fits for the binomial data model, and panels (g) - (l) display descriptor fits for the zero-truncated data model. Solid line indicates the fit, dashed lines indicate the 95% confidence interval, and black dashes along the horizontal axis display the rug plot. The estimated degrees of freedom for smooth fits are included in the vertical axis label.



(a) *large sharks* pelagic model (b) *blacktip sharks* coastal model (c) *large sharks* coastal model

Figure 3.8: Examples of Density Plots Comparing Fitting and Predicting Data. The density curve for data used for model fitting is plotted in black, and the density curves for data used for seasonal predictions are plotted individually in the indicated shades of grey. Panel (a) displays an ideal situation: prediction data within the range of fitting data, and seasonality amongst prediction data. Panel (b) displays a less ideal situation: prediction data failing to span the range of fitting data, and no seasonality amongst prediction data. Panel (c) displays a less ideal situation: fitting data failing to span the range of prediction data.

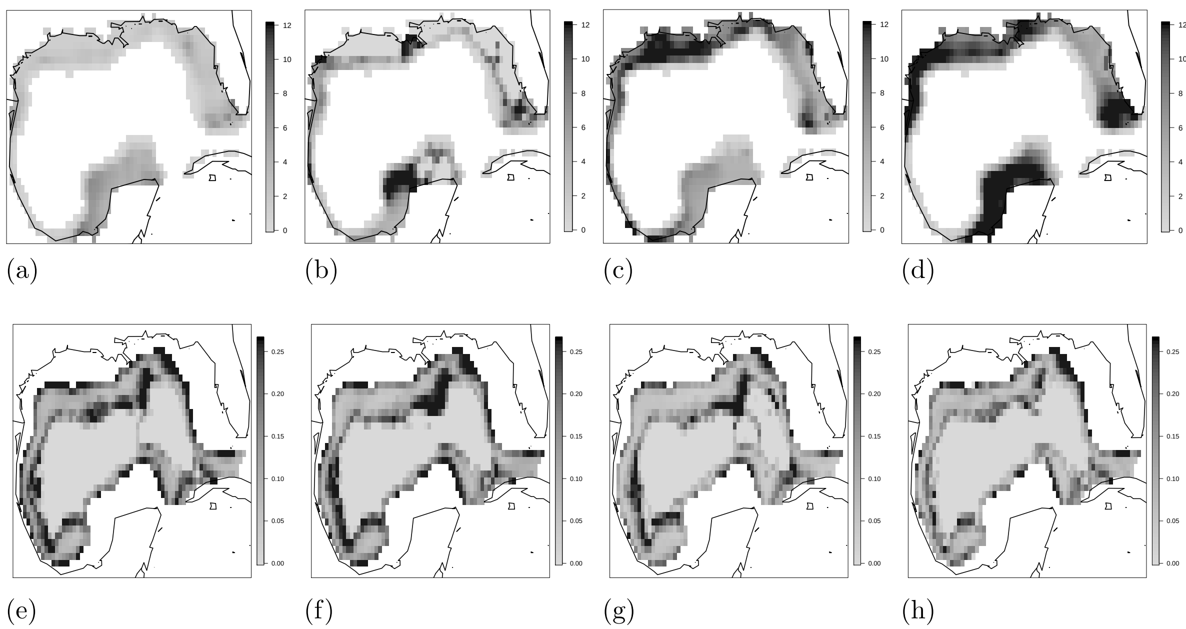


Figure 3.9: Seasonal Predictions of *Large Sharks* Catch Rates. Panels (a) - (d) display the catch rates predicted from the *large shark* GAM fit with bottom longline survey data for season 1 (a), season 2 (b), season 3 (c), and season 4 (d). Panels (e) - (h) display the catch rates estimated when predicting the *large shark* GAM fit with pelagic longline observer data across for season 1 (e), season 2 (f), season 3 (g), and season 4 (h).

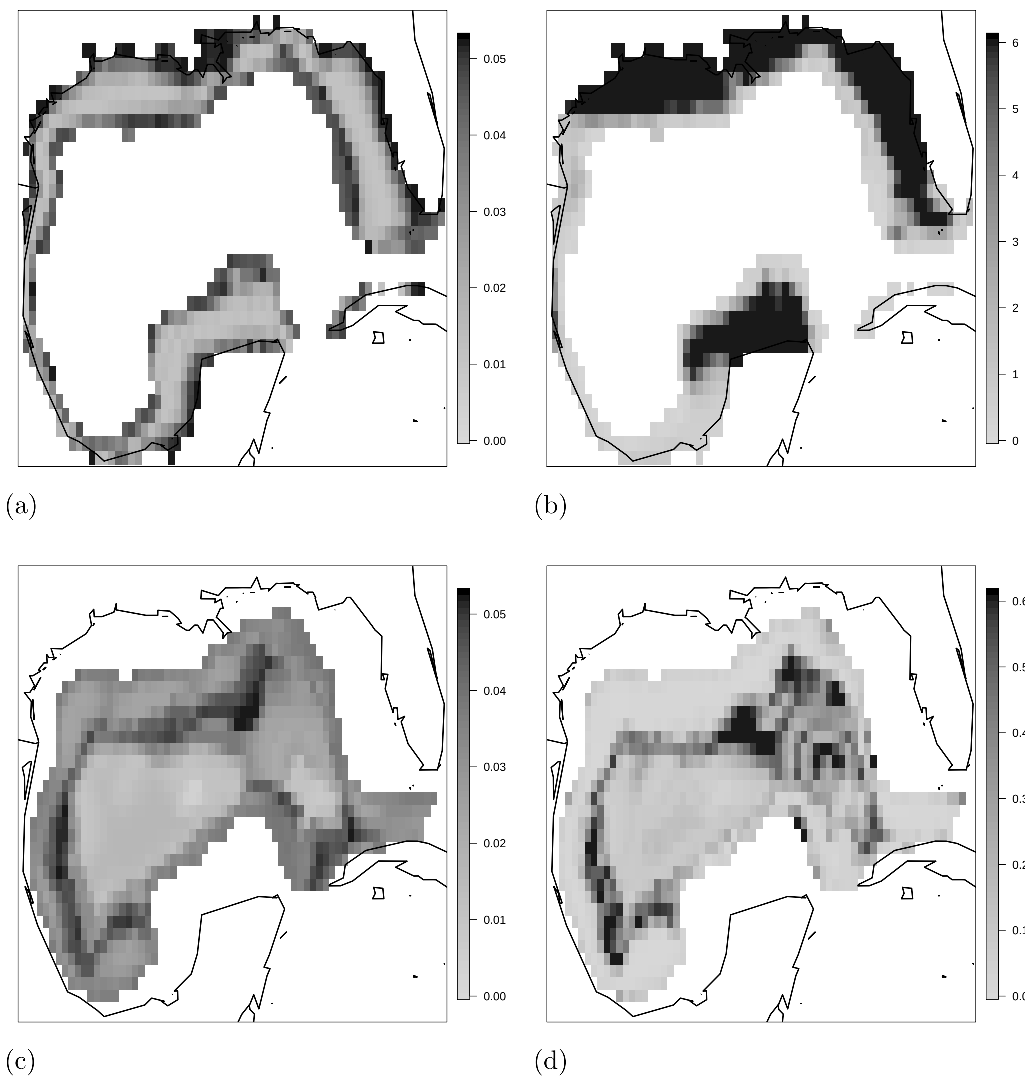


Figure 3.10: Example of Standard Errors of Predictions from *Large Sharks* Generalized Additive Models. Standard error of season 2 predictions for the *large sharks* coastal Bernoulli model (a), coastal Gamma model (b), pelagic Bernoulli model (c), and pelagic Gamma model (d).

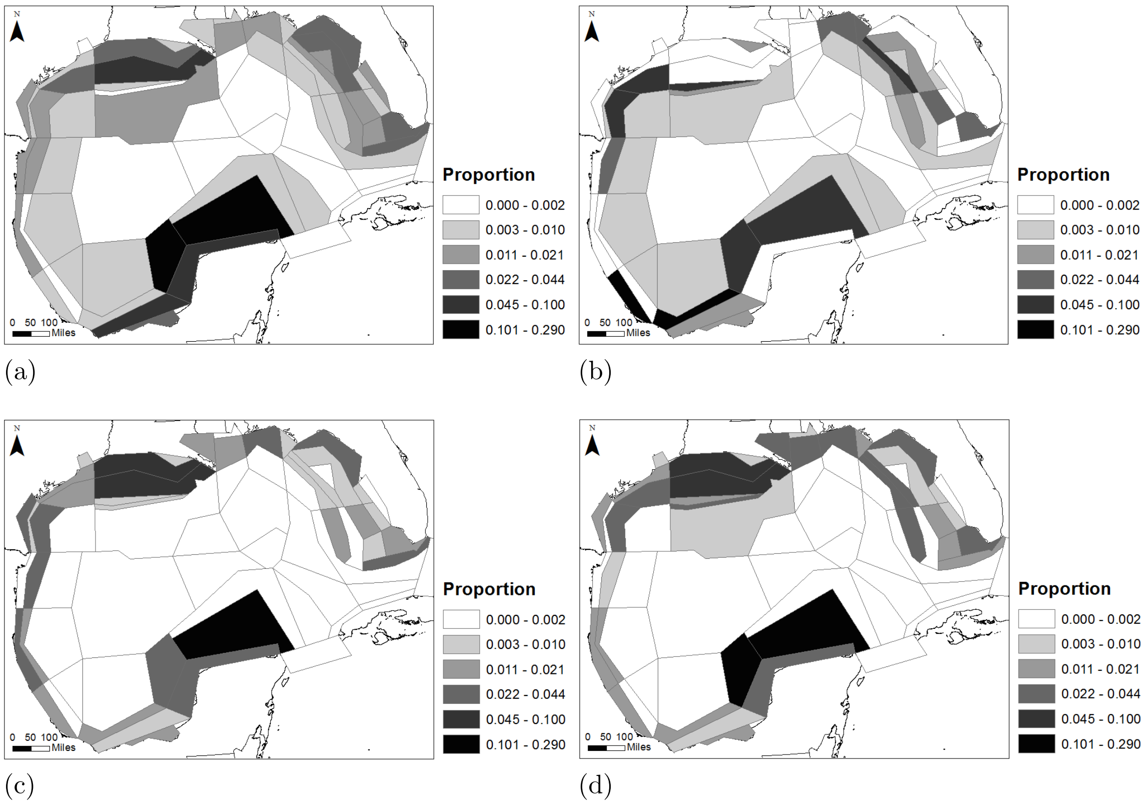


Figure 3.11: Proportion of *Large Sharks* Abundance Aggregated by Gulf of Mexico Atlantis Polygon Map. Seasonal predictions for the coastal and pelagic *large sharks* models were merged using a standardized relative catchability coastal:pelagic ratio (10:5.22), which was computed with data collected from an area where the two longline catch datasets overlapped. Figures are partitioned seasonally: season 1 (a), season 2 (b), season 3 (c), and season 4 (d).

CHAPTER 4

Can Gulf of Mexico Pelagic Longline Fishery Closures Meet Management Objectives?

4.1 Summary

The Gulf of Mexico has two pelagic longline closures, a permanent closure (*DeSoto Canyon*), and a seasonal closure (*Spring Closure*), which span pelagic waters where highly migratory predators aggregate to spawn and/or forage. Management objectives of these closures include reducing the catch and rebuilding the biomass of bycatch groups (i.e., Atlantic billfish, bigeye tuna, some pelagic sharks, prohibited sharks, and sea turtles) and incidental species (i.e., bluefin tuna), without impacting catch of target species (i.e., swordfish, yellowfin tuna, bigeye tuna, skipjack tuna, albacore, dolphin fish, wahoo, and some coastal sharks). Ecosystem modeling tools like Atlantis can be used to address the utility of pelagic MPAs for mitigating fishing pressure experienced by highly migratory predators, as well as broader ecosystem impacts. A policy exploration was conducted with the Gulf of Mexico Atlantis model to investigate if Gulf of Mexico pelagic longline spatial closures could achieve management objectives, as well as potential ecosystem impacts. Performance measures

corresponding to management objectives were monitored, as well as the ecosystem performance measures average individual weight, proportion mature, pelagic:demersal ratio (for catch and the ecosystem), and ecosystem biodiversity. *DeSoto Canyon* was more successful at achieving management objectives than *Spring Closure*. Both closures reduced Gulf-wide catches of some bycatch and incidental groups (especially green turtles and miscellaneous tunas) with little reduction to total catch of target groups. Gulf-wide catch of targeted yellowfin tuna actually increased. Neither closure caused meaningful increases in biomass of bycatch or incidental groups, but there were meaningful increases in biomass of some targeted groups (especially yellowfin tuna). *DeSoto Canyon* changed ecosystem performance metrics while *Spring Closure* did not. In particular, *DeSoto Canyon* reduced catch pelagic:demersal ratio which increased ecosystem pelagic:demersal ratio. This study suggests that *DeSoto Canyon* could be meeting most of the management objectives, and that *Spring Closure* may not meet long-term management objectives.

4.2 Motivation

Many pelagic predators around the globe have historically low biomass (Pauly et al., 1998; Myers and Worm, 2003; Christensen et al., 2003; Baum and Worm, 2009). Reduction in top-down pressures can restructure marine communities (Parsons, 1992; Heithaus et al., 2008; Baum and Worm, 2009) and initiate impacts, including shifting mortality to stocks that cannot sustain such pressure (Myers et al., 2007), shifting ecosystem functionality (Casini et al., 2009), and reducing ecosystem resistance and resilience (Britten et al., 2014). Although there are stocks of Atlantic of pelagic predators (e.g., billfish and tuna) that are not overfished nor suffering overfishing (Die, 2006; Collette et al., 2011; Juan-Jordá et al., 2011), there are other stocks that are of concern. Some species of large sharks are particularly depleted (Stevens et al., 2000; Baum et al., 2003b; Baum and Myers, 2004; Baum et al., 2005; Burgess et al., 2005; de Mutsert et al., 2008; Baum and Blanchard, 2010). Around the world sharks are targeted by large-scale, artisanal, and sport fisheries (Castillo-Géniz et al., 1998; Smale, 2008; Morgan et al., 2009; Pérez-Jiménez and Mendez-Loeza, 2015; Fahmi and Dharmadi, 2015), in addition to being caught as bycatch (McKinnell and Seki, 1998; de Silva et al., 2001; Beerkircher et al., 2002; Rogan and Mackey, 2007; Mandelman et al., 2008; Petersen et al., 2009; Belcher and Jennings, 2011). The intense fishing pressure combined with their slow growing life history makes sharks particularly vulnerable to overfishing and extinction (Monte-Luna et al., 2007; Dulvy et al., 2008; García et al., 2008; Field et al., 2009; Worm et al., 2013; Ceccarelli et al., 2014). Atlantic yellowfin tuna (*Thunnus albacares*) are overfished but not experiencing overfishing (ICCAT, 2016b). Recently, the western stock of Atlantic bluefin tuna (*Thunnus thynnus*) were declared to not be experiencing overfishing and may no longer be overfished (ICCAT, 2016a). Previously, the stock was considered overfished and experiencing overfishing (Fromentin and Powers, 2005; ICCAT, 2014b), and possibly at risk of collapsing (Bjørndal and Brasão, 2006; Safina and Klinger, 2008; MacKenzie et al., 2009). Atlantic marlin (*Makaira nigricans*, and *Kajikia albidus*) are considered overfished, and possibly risk extinction, due to mortality experienced from recreational fisheries, which target marlin, pelagic longline commercial fisheries, which incidentally catch marlin, and artisanal fleets, which target marlin (Peel et al., 2003; ICCAT, 2011, 2012).

Management of pelagic predatory stocks is both a domestic and international effort as these species are highly mobile. In the United States, the National Oceanic and Atmospheric Administration (NOAA) Fisheries Program, known as the National Marine Fisheries Service (NMFS), has primary authority for developing and implementing a Fishery Management Plan (FMP) for highly mobile species (HMS) in federal waters of the Atlantic. Such FMPs have enacted input and output controls (National Oceanic and Atmospheric Administration, 2016a), including fishery area closures. Fishery time and area closures, a type of marine protected area (MPA) within which fishing is limited and/or prohibited, have been recommended by management agencies and stakeholders as a viable management option for protecting pelagic predators. The American Fisheries Society (AFS) and the International Commission for the Conservation of Atlantic Tunas (ICCAT) recommend the development, use, and evaluation of large time and area closures to protect and rebuild shark populations (Musick et al., 2000a,b; ICCAT, 2007, 2009, 2010). In 2008 NMFS implemented time/area closures proposed by the South Atlantic Fishery Management Council (SAFMC) to protect and rebuild shark stocks (Highly Migratory Species Division, 2008). ICCAT recommends the consideration of area and/or time restrictions to prevent directed fishing on the bluefin tuna spawning stock within the western Atlantic spawning grounds (i.e., the Gulf of Mexico) (ICCAT, 2014a). Peel et al. (2003) concluded that coupling time and area closures with some restraint on targeted effort may help rebuild some billfish stocks.

The Gulf of Mexico is a key area in which to consider fishery closures because the physical dynamics and topology make for a productive system for Atlantic pelagic predators. The pelagic waters consist of a dynamic network of cyclonic and anticyclonic features (both filaments and eddies) primarily due to the physical forcing of the Loop Current and the episodic shedding of a warm-core, anti-cyclonic Loop Current eddy (Wiseman et al., 1999; Oey et al., 2005). Cyclonic features, which create patches of nutrient upwelling, retention, and concentration, are intensified by these dynamics (Schmitz, 2005), enhancing favorable environments for foraging planktonic larvae (Bakun, 1996). Bluefin tuna migrate into the northwest Gulf of Mexico between April and June to spawn (Dicenta et al., 1980; Richards, 1990; Mather et al., 1995; Block et al., 2005). Yellowfin tuna (*Thunnus albacares*) spawn in the northern Gulf of Mexico between July and August (Lang et al., 1994). Billfish, particularly sailfish (*Istiophorus albicans*) and blue marlin (*Makaira nigricans*), are believed to use the northern Gulf of Mexico as spawning grounds and early life habitat (Rooker et al., 2012). Spawning season can vary amongst billfish species (de Sylva and Breder, 1997). Although some shark species are more common within the Gulf's expansive shelf, which is used for migration (Branstetter, 1981, 1987), foraging (Hoffmayer and Parsons, 2003; Hammerschlag et al., 2012), and to access nurseries and pupping grounds (Bethea et al., 2006; Hueter and Tyminski, 2007), shark species are also encountered in the Gulf's pelagic environment (Branstetter, 1981; Beerkircher et al., 2002; Cortés, 2002a), and it is possible that these species aggregate around fronts (Queiroz et al., 2012, Chapter 3 of this dissertation).

The Gulf of Mexico's U.S. pelagic longline fleet targets swordfish, yellowfin tuna, skipjack tuna, albacore, dolphin fish, wahoo, and some coastal sharks, while incidentally catching bluefin tuna, billfish, miscellaneous tunas (e.g., some bigeye tuna), some pelagic sharks (e.g., blue sharks), prohibited sharks (e.g., hammerheads), sea turtles, seabirds, and mammals (Highly Migratory Species Division, 2000). To mitigate the incidental catch of non-targeted species (a.k.a, bycatch), two pelagic longline fishery closures are currently established in the Gulf of Mexico. The first is a permanent closure around DeSoto Canyon with the primary management objectives to reduce the catch and rebuild the biomass of groups caught incidentally while having little impact on the catch of targeted species (Highly Migratory Species Division, 2000). The second is a seasonal closure off the Louisiana shelf with the primary management objectives to reduce the catch and rebuild the biomass of bluefin tuna (Highly Migratory Species Division, 2014). Although it was originally thought that MPAs would provide little benefit to pelagics due to their high mobility and weak site fidelity (Roberts, 1997; Boersma and Parrish, 1999), more recent research supports spatial closures as viable tools for mitigating bycatch, including bycatch of pelagic species (Goodyear, 1998; Grantham et al., 2008; Dunn et al., 2011), but there is uncertainty regarding the success of pelagic spatial closures.

Hyrenbach et al. (2000) suggested pelagic spatial closures may be feasible tools for pelagic conservation since the physical habitats highly mobile predators aggregate around tend to be spatially and temporally predictable. More recent research supports this and argues that pelagic MPAs are defensible tools for pelagic conservation due to the advances in conservation, oceanography, and fisheries science (Game et al., 2009, 2010). However, there are still concerns regarding the utility and feasibility of pelagic MPAs. First, areas must be identified within which pelagics of concern have high site fidelity, and practical enforcement plans must be developed (Kaplan et al., 2010). Second, it is not known if pelagic spatial closures will provide the same benefits as some coastal spatial closures, like providing biomass to the fisheries through spillover (e.g., McClanahan and Mangi, 2000; Kelly et al., 2002; Guidetti, 2007; Januchowski-

Hartley et al., 2013) or increasing the size of individuals (e.g., Babcock et al., 1999; Lester et al., 2009). Lastly, MPAs often fail to meet management objectives (Jameson et al., 2002). Thus, science-driven analysis, including the investigation of ecosystem impacts through mathematical modeling, should be done to address the utility and feasibility of pelagic MPAs (Kaplan et al., 2010; Game et al., 2010; Grüss, 2014).

For this study, a policy exploration was conducted to investigate i) if Gulf of Mexico pelagic longline fishery spatial closures are likely to achieve management objectives, and ii) potential ecosystem impacts from pelagic longline closures. An ecosystem model of the Gulf of Mexico was used to simulate scenarios and calculate performance measures (indicators) corresponding to management objectives of the pelagic longline fishery spatial closures, as well as broader ecological objectives. Performance metrics were then compared to evaluate potential long-term impacts of Gulf of Mexico pelagic longline spatial closures.

4.3 Methods

4.3.1 The Simulation Framework

Atlantis is a biogeochemical and biophysical modeling framework (Fulton et al., 2004c,b, 2011). It models the turnover of chemical substances through the biotic and abiotic compartments of an ecosystem, in addition to the biological and physical components. The Atlantis framework is appropriate for this study in many ways. First, Atlantis was developed with the intention to evaluate performance measures (i.e., indicators) for use in ecosystem-based fisheries management (Fulton et al., 2004a; Plagányi, 2007; Fulton et al., 2011). Second, Atlantis is an 'end-to-end' model (Fulton, 2010), meaning it represents biota from bacteria up to top predators in addition to human activities (e.g., fisheries). Third, species and fisheries interactions are spatially explicit. Fourth, the spatial domain is represented by a network of polygons that reflect the ecosystems geographic features, habitats, and essential management jurisdictions. Lastly, Atlantis contains a detailed exploitation routine which allows for the simulation of individual fleets, as well as a management routine to simulate a range of fishery management measures, including spatial closures.

The Gulf of Mexico Atlantis Model (GoMAM) is described in detail by Ainsworth et al. (2015), so the following will be a summary of the model. The spatial domain of GoMAM consists of a polygon network spanning the entire Gulf of Mexico marine ecosystem (Figure 4.2), which was developed based on bathymetry, habitat, physical oceanography, and management boundaries. The simulated biology consists of 91 functional groups of finfish, invertebrates, seabirds, mammals, plankton, and bacteria/detritus. Vertebrate functional groups have 10 age classes and all remaining groups are represented as biomass pools. The flux of nitrogen for primary producers, biomass pools, and age-structured groups are modeled differently.

Spawning and recruitment are only explicitly modeled for age-structured groups. Reproduction of simple biomass pools is included in the growth terms. For age-structured groups, nitrogen produced as spawn is temporarily removed from the system and returned as recruits after a defined larval period. In GoMAM, for tuna, billfish, and sharks this period is about a month. The stock recruitment curve assumed is the Beverton-Holt with recruitment based only on species biomass. This is for all functional groups except mammals, birds, and large sharks, which are assumed to have a constant recruit production per adult. The assumed vertical distribution of recruits is the same as the daytime vertical distribution of juveniles. The assumed horizontal distribution of recruits is the same as the horizontal distribution of adults in the first season.

GoMAM was parameterized for forecasting based on the parameterization of a historical version of GoMAM, which was driven by historical landings time series (summarized in Chapter 1 of this dissertation, and discussed in detail by Perryman et al. (2015)), calibrated to fit historical abundance trends from 1980 to 2010. Allocating the biomass of functional groups across space is important for spatially explicit models like Atlantis (Grüss et al., 2016a). Biomass of demersal functional groups were spatially allocated using statistical models presented by Drexler and Ainsworth (2013). Statistical models presented in Chapter 2 of this dissertation were used to refine the spatial allocation of pelagic fish groups as they were originally based on somewhat homogenous assumptions.

Sedentary functional groups in GoMAM do not have horizontal movement amongst polygons. For mobile functional groups, GoMAM is set-up to simulate "prescribed movement". This means density dependent movement is not allowed and instead mobile functional groups move based on distributions that define the horizontal shift a functional groups throughout the year. GoMAM prescribes quarterly shifts, and quarterly shifts differ between adults and juveniles. Atlantis calculates the abundance (A, in biomass for biomass pool groups and numbers for age structured groups) of a functional group in a polygon (p) at any given time-step as

$$A_p = A_{total} \left(\varepsilon \left(F_{(Q+1),p} - F_{Q,p} \right) + F_{Q,p} \right), \tag{4.1}$$

where ε is the proportion of the quarter of the year that has passed (12 hour time steps), and $F_{Q,p}$ is the proportion of biomass in polygon p during quarter Q provided by the prescribed parameters. If Q is the last quarter of the year then $Q+1$ is the first quarter of the next year. Atlantis can also simulate density dependent movement, which means that the spatial distribution will be determined by the food availability, but GoMAM has density dependent movement deactivated for all functional groups. Thus, any changes in catch outside fishery closures are because of changes in total biomass and not changes to local biomass due to groups responding to changes in food availability.

Simulated functional groups are allowed to migrate out of and into the Gulf of Mexico modeling domain. Abundance of functional groups migrating out of the Gulf of Mexico system are stored in a boundary polygon until the time is reached which the abundance starts to migrate back into the model domain. The abundance of functional groups while outside of the modeling domain is allowed to change (i.e., this biomass is subjected to mortality, growth, etc.). In GoMAM, migration inputs have been parameterized for functional groups that correspond to mammals, birds, sea turtles, large sharks, mackerels, billfish, yellowfin tuna, and bluefin tuna (Ainsworth et al., 2015). This is particularly important for bluefin tuna as they are a species of concern for pelagic longline fishery closures.

In GoMAM, migration inputs for adult bluefin tuna (age-classes 2 - 10) differ from those for juvenile bluefin tuna (age-class 1). Bluefin tuna are outside the modeling domain throughout most of the year. Migration of mobile functional groups occurs gradually rather than all at once. For bluefin tuna, the migration of juveniles spans a couple of months, while the migration of adults spans a couple of days. Some mortality is applied to juveniles while outside the system in that 4% of the abundance does not return. Mortality outside of the system is currently not applied to adults. The abundance of juveniles and adults increases while groups are outside of the modeling domain, which adds nitrogen to the system. Preliminary work was done to adjust some of the migration inputs of bluefin tuna to reflect observations in the literature, but these alterations were not used for this study because they caused bluefin tuna to quickly collapse (Appendix C).

4.3.2 Gulf of Mexico Pelagic Longline Closures

The Gulf of Mexico has two fishery closures pertaining to pelagic longline operations: the *DeSoto Canyon Pelagic Longline Closure*, and the *Spring Gear Restricted Areas* (Figure 4.1).

4.3.2.1 DeSoto Canyon Pelagic Longline Closure

DeSoto Canyon is a valley that cuts through the broad continental shelf in the northeast Gulf of Mexico. The area's bathymetry and physical forces driven by the Loop Current interact to form cyclonic eddys that upwell cool, nutrient-rich water. This causes relatively high primary productivity (Vukovich and Maul, 1985; Hamilton et al., 2000a,b; Yuan, 2002). During a comment period for a proposed highly migratory species bycatch rule, NMFS received many comments indicating that the DeSoto Canyon area should be closed to pelagic longlining due to the high occurrence of undersized swordfish (Highly Migratory Species Division, 2000). Based on an assessment of logbook data, two areas were identified and approved as a year-round pelagic longline fishery closure that went into effect November 1, 2000. A formal assessment of the effectiveness of *DeSoto Canyon Pelagic Longline Closure*, from here on referred to as *DeSoto Canyon*, has yet to be conducted. Landings data presented in Chapter 2 (Appendix A) suggests some evidence of decreased landings of some indicator species after *DeSoto Canyon* was enacted.

4.3.2.2 Spring Gear Restricted Areas

To protect the Atlantic bluefin tuna stock while spawning in the Gulf of Mexico, NMFS established a seasonal pelagic longline fishery closure (Highly Migratory Species Division, 2014). Several configurations were considered, but the final amendment establishing the *Spring Gulf of Mexico Gear Restricted Areas* consisted of two areas: one large area spanning the northwestern Gulf, and another smaller area bordering the *DeSoto Canyon* closure. Starting in 2015, from April 1 to May 31, pelagic longline operations are prohibited within *Spring Gulf of Mexico Gear Restricted Areas*, from here on referred to as *Spring Closure*.

4.3.3 Simulated Scenarios

Simulations start at the conditions from the end of the model fitted to historical data (2010) and spanned 30 years, under constant fishing mortality rates, because this was long enough to capture significant changes in the simulated ecosystem, and short enough to save on computation time. Results consist of comparing 30 year projections under the status quo scenario to the projections under other modeled scenarios. The study considers two types of scenarios: (1) fishing mortality sensitivity scenarios (the increasing and decreasing of fishing mortality rates), and (2) pelagic longline fishery closure scenarios (evaluation of pelagic longline fishing closures *DeSoto Canyon* and

Spring Closure). All scenarios have the same parameterized biology, ecology, and oceanography. The only variations were changes to fisheries.

4.3.3.1 Status Quo

This scenario allows the evaluation of system dynamics under a baseline representation of current fisheries. This includes *DeSoto Canyon* and *Spring Closure*. Fishery closures are modeled by reducing fishing mortality rate(s) within the polygon(s) corresponding to the closure's location. Often, polygons in the simulation map do not match a closure's geometry. The *Intersect* tool in *ArcGIS* was used to determine the polygon(s) covering the spatial range of a closure, and the percentage of the polygon corresponding to the closure. This information was used to develop the polygon-specific input files for simulating fishing closures, which, once a designated time step is reached in the simulation, reduce a fleet's fishing mortality within the polygon based on the regulation and the percentage of closure within the polygon. For instance, if a MPA occupies half of a polygon and the regulation closes pelagic longline fishing, then the pelagic longline fleet's fishing mortality is reduced by half within that polygon. This method does not effect fishing mortality rates in polygons that do not correspond to a closure, thus the underlining assumption here is that closed areas remove the effort that would have been in the closure. Input files were updated to include *Spring Closure* as it was not represented in the original calibration of GoMAM because the closure wasn't activated before 2010.

4.3.3.2 Fishing Mortality Sensitivity

Longline fishing mortality sensitivity scenarios are to i) evaluate the overall impact of longline fishing on the Gulf ecosystem in order to put the impact of closures into context, and ii) make sure the GoMAM behaves reasonably under large perturbations (Kaplan et al., 2012). Sensitivity scenarios consisted of two types: all longline, and pelagic longline. The former focused on all longline fleets in GoMAM, including shelf longline (reef fish), shelf longline (shark), and pelagic longline. The latter only focused on the pelagic longline fleet. These two types of sensitivity scenarios quantify the pressure pelagic longline fleets exert on pelagic predators compared to all longline fleets. Both of these two types of simulations consisted of 3 scenarios in which the fishing mortality of the indicated fleet(s) was multiplied by 0, 0.5, and 2. Thus, in total, there are 6 fishing mortality sensitivity scenarios.

Some aspects of GoMAM's fisheries were not adjusted for this study. GoMAM contains 22 fleets (16 U.S. fleets, 5 Mexican fleets, and 1 Cuban fleet), and assumes the selectivity curve is logistic for all functional groups. Fishing mortality rates were altered for this study. Removal of biomass due to fishing is simulated with a series of constant, daily fishing mortality rates reflecting the pressure each fleet exerts on each functional group. Fishing mortality rates were originally computed using 2010 landings data (Perryman et al., 2015), but these did not include data on bycatch. To represent pelagic longline bycatch, GoMAM fishing mortality rates were updated using data describing the 2010 bycatch (National Marine Fisheries Service, 2013). In addition, these updated rates were iteratively adjusted to match 2010 simulated catch to 2010 catch data. For full details see Appendix C.

4.3.3.3 Pelagic Longline Closures

Because pelagic longline spatial closures *DeSoto Canyon* and *Spring Closure* are represented in the status quo scenario, to investigate their impacts to the system scenarios were simulated in which the two closures were removed from the status quo version of GoMAM. This includes a scenario in which *DeSoto Canyon* was removed, a scenario in which *Spring Closure* was removed, and a scenario in which both *DeSoto Canyon* and *Spring Closure* were removed. This allowed the assessment of individual impacts, as well as the possibility of compounding impacts. In addition, another scenario was investigated in which *Spring Closure* was altered to span the entire U.S. Gulf - simulating a seasonal, Gulf-wide closure of the U.S. pelagic longline fleet. This was an alternative measure considered instead of *Spring Closure*, but ultimately *Spring Closure* was preferred due to the estimated ecological gains with low fisheries impact (Highly Migratory Species Division, 2014). Thus, in total, there are 4 pelagic longline closure scenarios.

4.3.4 Management Objectives and Performance Measures

The primary management objectives for *DeSoto Canyon* are to i) reduce bycatch and incidental catch, ii) minimize the reduction in target catch, and iii) optimize survival of bycatch and incidental catch species (Highly Migratory Species Division, 2000). Performance measures for these objectives were tracked for the appropriate GoMAM functional groups. U.S. pelagic longliners target swordfish, yellowfin tuna, bigeye tuna, skipjack tuna, albacore, dolphin fish, wahoo, and some coastal sharks (Highly Migratory Species Division, 2000). The corresponding GoMAM functional groups are: *swordfish*, *yellowfin tuna*, *other tuna*, *large pelagic fish*, and *large sharks*.

U.S. pelagic longline incidental catch (organisms that are not targeted but may be retained if caught) primarily consists of bluefin tuna (Highly Migratory Species Division, 2000), which has its own GoMAM functional group. Catches of marine mammals and sea birds, which are always either released alive or discarded dead, were not evaluated here since more work is necessary for GoMAM to appropriately represent their spatial heterogeneity and bycatch. U.S. pelagic longline discarded bycatch (organisms caught but not retained) includes: Atlantic billfish, undersized swordfish, bigeye tuna, pelagic sharks (e.g., blue sharks), prohibited sharks, and sea turtles (Highly Migratory Species Division, 2000; National Marine Fisheries Service, 2013). The corresponding GoMAM functional groups are: *white marlin*, *blue marlin*, *billfish*, *swordfish*, *other tuna*, *large sharks*, *loggerhead*, *Kemp's ridley*, and *other sea turtles*.

Reducing the catch of undersized swordfish caught by U.S. pelagic longlines was a specific concern (Highly Migratory Species Division, 2000). Undersized swordfish caught by U.S. pelagic longlines are individuals weighing less than 25kg whole weight (Cramer, 1996). In GoMAM, vertebrate functional groups, including *swordfish*, are represented with age structured models. The 10 age-groups were adjusted to cover the whole lifespan of the fish. In GoMAM, swordfish are first selected by pelagic longline gears by age-group 3. The median weight of swordfish of age-group 3 is 23.2 kg, so the parameterization of GoMAM is consistent with the fishery data, and catch of swordfish of age-group 3 was tracked to represent catch of undersized swordfish. The parameterization of some model inputs can be different between adult age-groups and juveniles age-groups (e.g., seasonal spatial distribution, migration, diet, etc.). GoMAM assumes swordfish become sexual maturity at age-group 3, thus all of the age-groups selected by the fishery are considered adults and have the same parameterization.

Performance measures tracked for the reduction of bycatch and incidental catch included: catch of bluefin tuna, total catch of all bycatch groups, catch of individual bycatch groups, and proportion of *swordfish* catch being age-group 3 (i.e., age-at-first-capture). Performance measures tracked to minimize the reduction in target catch included: the total catch of all target groups, and catch of individual target groups. Performance measures tracked for optimizing the survival of bycatch and incidental catch species included: the total biomass of all bycatch groups, biomass of individual bycatch groups, and biomass of bluefin tuna. For consistency, total biomass of target groups, and biomass of individual target groups were also monitored. See Table 4.1 for details.

The FMP amendment proposing *Spring Closure* reports a variety of socioeconomic, fisheries quota, and biological objectives (Highly Migratory Species Division, 2014), the primary objective being to prevent overfishing and rebuild bluefin tuna. The primary objective for the gear restricted areas was to reduce bluefin tuna interactions with pelagic longliners, thereby decreasing dead discards (bycatch). Thus, this work tracked the reduction of incidental catch of bluefin tuna using bluefin tuna catch as a performance measure, and the rebuilding of bluefin tuna using bluefin tuna biomass as a performance measure.

U.S. fleets targeting highly migratory pelagics, in addition to the pelagic longline fleet, include U.S. recreational groups, and U.S. hook-and-line fleets not using pelagic longling gear (e.g., fleets using vertical lines, or bottom longlines). It is possible that changes to the U.S. pelagic longline fishing may change catches from these fleets.

To evaluate this, total catches of tuna billfish, and large shark functional groups from simulated U.S. recreational fleets and non-pelagic, U.S. hook-and-line fleets (i.e., handline, shelf longline (reef fish), and shelf longline (shark)) were compared across the investigated scenarios.

Ecological objectives were also monitored to identify if closures could have broad scale ecosystem impacts, some of which have been observed for coastal spatial closures. See Table 4.1 for a summary of indicators and equations. In many fished ecosystems, the size of individuals, particularly top predators, has decreased over time due to heavy exploitation and fishing practices such as minimum size regulations focusing fishing pressure on larger organisms (Bianchi et al., 2000; Swain et al., 2007; Darimont et al., 2009). This could impact food webs and trophic structure (Woodward et al., 2005; Brose et al., 2006; Shackell et al., 2010). The reduced number of larger individuals also means a reduced number of sexually mature individuals, which can have a negative impact on spawning (Hutchings, 2000). As discussed in the introduction, spatial closures can mitigate and potentially reverse these impacts. The metric proportion of mature fish (biomass) was used to track shifts in the amount of sexually mature stock. The metric average individual size was used to track the size structure of functional groups. Changes to the average weight of multi-species functional groups should be interpreted with caution as they are composed of different species with different growth trajectories. The proportion of mature fish and size related metrics, such as average individual size, are important indicators of overfishing (Froese, 2004; Shin et al., 2005). These two stock-specific metrics were computed for individual pelagic predator functional groups, and functional group assemblages (e.g., billfishes, tunas, sharks, etc.). Results discussed in the main text will focus on billfishes and tunas, and the corresponding functional groups. Additional results of other functional groups are shown in Appendix C.

Objectives relating to the ecosystem community were also monitored. The pelagic:demersal ratio was tracked for the catch and for the ecosystem. The pelagic:demersal ratio is primarily linked to the eutrophication (Caddy, 1993; Caddy and Bakun, 1994; Caddy et al., 1998a; Caddy and Garibaldi, 2000; Caddy, 2000; de Leiva Moreno et al., 2000), and the Gulf of Mexico experiences periodic, large-scale eutrophication which has meaningful ecosystem impacts (Malakoff, 1998; Rabalais et al., 2002b,a). In addition, the pelagic:demersal ratio can show large shifts in fishery targeting, and Fulton et al. (2005) found it to be strongly correlated with a marine ecosystems population and community attributes. Functional groups were categorized as pelagic or demersal/benthic based on life history of adults. Information from FishBase (Froese and Pauly, 2016) and SealifeBase (Palomares and Pauly, 2016) was used to classify individual species and Atlantis functional groups. The ratio was calculated as the total biomass of pelagic groups divided by the total biomass of demersal groups.

Marine ecosystem biodiversity was also monitored. Marine protected areas are used as a means to restore and/or preserve biodiversity since anthropogenic impacts (i.e., overfishing) can diminish biodiversity (Coleman and Williams, 2002; Jones et al., 2007) which can reduce ecosystem resources, resilience, and water quality (Duffy, 2002, 2003; Worm et al., 2006; Stachowicz et al., 2007; Cardinale et al., 2012). Much of the research on using MPAs to protect biodiversity is from coastal systems, but there is growing discussion regarding the use of pelagic MPAs to protect biodiversity (Worm et al., 2003; Game et al., 2009; Morato et al., 2010; Grantham et al., 2011). The Q90 biodiversity statistic was used to monitor marine ecosystem biodiversity.

Q90 is the Kempton and Taylor (1976) species diversity statistic adapted for use with ecosystem models (Ainsworth and Pitcher, 2006), which aggregate individual species into functional groups. Q90 is the interdecile slope of the cumulative log-abundance curve:

$$Q90 = \frac{0.8S}{log(R_2/R1)} \tag{4.2}$$

where S is the total number of functional groups in the model, and R_1 and R_2 are the biomass values of the 10th and 90th percentiles in the cumulative abundance distribution across all functional groups.

Performance measures were calculated as the average of the values spanning the last four time steps, which are the four seasons of the last year of the simulation. All performance metrics were computed at multiple spatial scales: Gulf-wide (the entire spatial map), U.S. Gulf (all polygons within the U.S. EEZ), U.S. pelagic (all polygons within the U.S. EEZ, and a max depth greater than 200m), *DeSoto Canyon* waters (all polygons intersecting *DeSoto Canyon*), and *Spring Closure* waters (all polygons intersecting *Spring Closure*). This is allows the assessment of the spatial extent of the impacts of management measures.

4.4 Results

Performance measures for management objectives are summarized in Table 4.2. *DeSoto Canyon* caused meaningful reductions on catches within the Desoto Canyon region. Within the *DeSoto Canyon* polygons, removing the *DeSoto Canyon* closure increased catch of bycatch tunas by 53.6%, bycatch billfishes by 37.2%, and incidental bluefin tuna by 63.0%, compared to doubling pelagic longline fishing mortality which increased catch of bycatch tunas by 89.5%, bycatch billfishes by 88.2%, and incidental bluefin tuna by 52.0% within the *DeSoto Canyon* polygons. Within the polygons around *Spring Closure*, removing *Spring Closure* increased catch of bycatch tunas by 6.4%, bycatch billfishes by 7.9%, and incidental bluefin tuna by 1.5%, compared to doubling pelagic longline fishing mortality which increased catch of bycatch tunas by 89.5%, bycatch billfishes by 89.7%, and incidental bluefin tuna by 19.7%.

At the scale of the whole U.S. Gulf, removing *DeSoto Canyon* increased catch of bycatch tunas by 18.8%, bycatch billfishes by 3.1%, and incidental bluefin tuna by 10.2%. Removing *Spring Closure* increased catch of bycatch tunas by 3.4%, bycatch billfishes by 0.7%, and incidental bluefin tuna by 0.6%. When compared to doubling pelagic longline fishing mortality, which increased catch of bycatch tunas by 89.9%, bycatch billfishes by 15.7%, and incidental bluefin tuna by 39.9%, it suggests that *DeSoto Canyon* is more effective than the *Spring Closure* at reducing U.S. Gulf catch of bycatch groups and incidental bluefin tuna. Removing *DeSoto Canyon* increased U.S. Gulf catch of target groups by 0.7%, while removing *Spring Closure* increased U.S. Gulf catch of target groups by 0.1%. When compared to doubling pelagic longline fishing mortality, which increased U.S. Gulf catch of target groups by 3.8%, it is apparent that *DeSoto Canyon* and *Spring Closure* did not have meaningful impacts on U.S. Gulf catch of target groups.

DeSoto Canyon and *Spring Closure* had smaller impacts on U.S. Gulf biomass. Doubling pelagic longline fishing mortality decreased U.S. Gulf biomass of bycatch tunas by 4.2%, bycatch billfishes by 0.7%, incidental bluefin tuna by 1.7%, and target groups by 0.8%. Removing *DeSoto Canyon* decreased U.S. Gulf biomass of bycatch tunas by 0.9%, bycatch billfishes by less than 0.01%, incidental bluefin tuna by 0.4%, and target groups by less than 0.01%. Removing *Spring Closure* decreased U.S. Gulf biomass of bycatch tunas by less than 0.01%. The biomass of incidental bluefin tuna was more affected by simulated scenarios within *Spring Closure* polygons than *DeSoto Canyon* polygons or U.S. Gulf polygons. For instance, eliminating pelagic longline fishing increased the U.S. Gulf biomass of bluefin tuna 4.4%, the *DeSoto Canyon* biomass of bluefin tuna 4.0%, and the *Spring Closure* biomass of bluefin tuna 13.3%. This is likely related to the fact that *Spring Closure* waters include a hot spot for bluefin tuna (see spatial distribution maps in Appendix B).

The impact *DeSoto Canyon* had on management objective performance measures varied amongst species (Figure 4.3). Within *DeSoto Canyon* waters, the presence of the *DeSoto Canyon* closure increased the biomass of miscellaneous tunas, green turtles, yellowfin tuna, and swordfish (Figure 4.3a, 4.3b). Increases in biomass were visible across spatial scales of the Gulf, especially for green turtles, miscellaneous tunas, and swordfish. Also within *DeSoto Canyon* waters the closure was associated with reductions in catches of billfish groups, miscellaneous tunas, bluefin tuna, green turtles, yellowfin tuna, and swordfish (Figure 4.3c, 4.3d). Gulf-wide catch of yellowfin tuna increased with the presence of *DeSoto Canyon* (Figure 4.3d).

Within *Spring Closure* waters, *Spring Closure* increased the biomass of yellowfin tuna but had very little effect on the biomass of other functional groups (Figure 4.4a, 4.4b). The biomass of bluefin tuna did not change within *Spring Closure* waters, but there was a slight increase across the Gulf ecosystem (Figure 4.4a). Within *Spring Closure* waters, catches of billfish groups, miscellaneous tunas, green turtles, swordfish, and yellowfin tuna were reduced (Figure 4.4c, 4.4d). Gulf-wide catches of miscellaneous tunas, green turtles, and swordfish decreased, but catches of yellowfin tuna increased within Gulf-wide polygons as well as *Spring Closure* polygons.

U.S. pelagic longline effort and U.S. pelagic longline spatial closures impact catches of U.S. hook-and-line fleets other than pelagic longliners (Figure 4.5). *Spring Closure* had little impact on the catches from non-pelagic U.S. commercial hook-and-line fleets, but *DeSoto Canyon* increased the catches of billfishes from non-pelagic U.S. commercial hook-and-line fleets by 2.8%, compared to an increase of 4.6% when U.S. pelagic longline fishing is reduced by half, or 9.6% when U.S. pelagic longline fishing is eliminated. In addition, *DeSoto Canyon* increased recreational catches of billfishes by 1.4% and tunas by 1.6%. Eliminating U.S. pelagic longline fishing caused a 5.3% increase in recreational billfish catch, and a 14.1% increase in recreational tuna catch. None of the closures reduced the catch of non-pelagic U.S. hook-and-line fleets, but increasing U.S. pelagic longline fishing mortality did. In particular, there was a 8.2% reduction in billfish catch from non-pelagic U.S. commercial hook-and-line fleets, and a 7.7% reduction in tuna catch from recreational fleets when U.S. pelagic longline fishing mortality was doubled.

Results for ecosystem performance measures are shown in Table 4.3. *Spring Closure* had less influence on ecosystem metrics than *DeSoto Canyon*. Removing *DeSoto Canyon* decreased billfish U.S. Gulf average individual weight by less than 0.01%, compared to a 0.3% reduction when U.S. pelagic longline fishing mortality is doubled. In addition, removing *Desoto Canyon* decreased tuna U.S. Gulf average individual weight by 0.2%, compared to a 0.8% reduction when U.S. pelagic longline fishing mortality is doubled. Impacts to average individual weight and proportion mature are species specific (Figure 4.6). A reduction in pelagic longline fishing mortality had some influence increasing U.S. Gulf average individual weight for swordfish, but no influence on other billfish groups. Reducing pelagic longline fishing mortality had the most influence on the U.S. Gulf average individual weight of tunas: increasing it for miscellaneous tunas and yellowfin tuna, and decreasing it for bluefin tuna. Reducing U.S. pelagic longline fishing mortality increased U.S. Gulf proportion mature for all billfish and tuna groups, with bluefin tuna experiencing the largest increase (53.4%). Removing *DeSoto Canyon* increased U.S. Gulf catch pelagic:demersal ratio by 0.6%, compared to a 2.8% reduction when U.S. pelagic longline fishing mortality was doubled. In addition, removing *DeSoto Canyon* decreased U.S. Gulf ecosystem pelagic:demersal ratio by 0.2%, compared to a 1.1% reduction when U.S. pelagic longline fishing mortality is doubled. None of the scenarios changed the ecosystem's Q90 biodiversity metric.

4.5 Discussion

4.5.1 Model Findings

Model simulations show that the Gulf of Mexico pelagic longline spatial closure *DeSoto Canyon*, which has been in affect since 2000, could be achieving some management objectives. Considering U.S. Gulf metrics, first, *DeSoto Canyon* reduced catch of the incidental group, bluefin tuna. Total catch of bycatch groups did not change, but there were meaningful changes on a species-specific level. Specifically, catch of functional groups representing bycatch tunas, and green sea turtles were reduced. In addition, *DeSoto Canyon* reduced the proportion of swordfish catch being of age-class 3 (age-at-first-capture). Second, total catch of target groups was reduced only slightly. Thus, *DeSoto Canyon* did not negatively impact the catch of target species. In fact, *DeSoto Canyon* increased the Gulf-wide catch of yellowfin tuna, suggesting that spill over is occurring, and increased the biomass of yellowfin tuna. It would be expected to have increased catch or increased biomass, but having both is peculiar. This could be explained by the possibility of the stock being overfished in the model, which would be consistent with the latest stock assessment (ICCAT, 2016b). *DeSoto Canyon* also increased the biomass swordfish and miscellaneous tunas. Lastly, biomass of the incidental group bluefin tuna increased slightly, and, although total biomass of bycatch groups did not change, the biomass of groups representing bycatch tunas and green sea turtles increased slightly.

DeSoto Canyon had some influence on ecosystem objective performance metrics. Considering U.S. Gulf metrics, *DeSoto Canyon* increased the average weight of tunas and billfishes, particularly yellowfin tuna, miscellaneous tunas, and swordfish. Both density and biomass of these groups increased but biomass increased more, suggesting that individuals could be getting larger. The exception is bluefin tuna, which decreased in average individual weight because density increased more than biomass. *DeSoto Canyon* slightly increased the proportion of billfishes and tunas sexually mature. Fishing mortality sensitivity scenarios showed that bluefin tuna are especially sensitive - their proportion mature increased more than any other group. *DeSoto Canyon* reduced catch pelagic:demersal ratio because pelagic catches were reduced with little influence on demersal catches. In response, the ecosystem pelagic:demersal ratio increased.

None of the scenarios had a meaningful influence on ecosystem biodiversity. It is possible that these scenarios may not have enough impact on simulated biota to cause an impact to biodiversity since pelagic longline fleets interact with a small portion of the total functional groups. While scenarios have an impact on some functional groups in the pelagic waters, benthic and microbial functional groups in the same areas are not impacted. These functional groups are abundant, and could be buffering the Q90 calculation. Also, the Q90 metric is being computed over large spatial ranges, which may be masking a signal if one is there. The Q90 calculation can be made more sensitive by passing a filter over the calculation to omit the biomass of functional groups if their biomass falls below a reference value (Ainsworth and Pitcher, 2006). This would require defining reference values for each functional group, as well as a threshold. More research is needed to fill the gap of our understanding of how pelagic MPAs may preserve biodiversity (Game et al., 2009; Grantham et al., 2011)

Spring Closure had very little influence on performance measures corresponding to its management objectives. Considering U.S. Gulf metrics, as well as those from *Spring Closure* waters, *Spring Closure* only slightly reduced catch of bluefin tuna, and did not change bluefin tuna biomass. These results suggest that *Spring Closure*, which has only been in affect since 2015, may not meet biological management objectives over the next couple of decades. In addition, *Spring Closure* had little to no influence on ecological objective performance measures. These results could be a realistic reflection of the Gulf of Mexico due to the state and dynamics of the bluefin tuna stock as a whole, or this could reflect possible model limitations. It is worth noting that *Spring Closure* influenced performance metrics relating to *DeSoto Canyon* management objectives. Specifically, *Spring Closure* reduced the U.S. catch of bycatch and incidental groups, and increased the biomass and catch of yellowfin tuna. This shows that *DeSoto Canyon* and *Spring Closure* had compounding impacts on performance measures. Thus, objectives were more attainable when both closures were active. Networks of marine protected areas have shown to be successful management strategies (Balmford et al., 2004; Russ et al., 2008; Gaines et al., 2010).

Fishing mortality sensitivity scenarios reveal some important dynamics. First, pelagic fishery closures are not providing enough reduction in fishing mortality to cause meaningful increases in biomass. For instance, removing *Spring Closure* decreased bluefin tuna biomass around *Spring Closure* by 0.1%, compared to a 5.3% reduction when pelagic longlining is doubled. Removing *DeSoto Canyon* decreased biomass miscellaneous tunas around *DeSoto Canyon* by 0.9%, compared to a 4.4% reduction when pelagic longlining is doubled. Thus, increasing the biomass of indicator species may be dependent on complimentary management efforts further reducing fishing mortality (Allison et al., 1998; Myers and Worm, 2005). Second, alterations in longline fishing mortality influence bycatch and incidental groups more than target groups. For instance, decreasing longline fishing mortality increased the biomass of bycatch billfishes (0.7%) and tunas (4.5%), and incidental bluefin tuna (4.4%), compared to a 1.4% increase to biomass of target groups. Thus, increasing longline effort had more negative impacts on bycatch and incidental groups than a gain from target catch. In addition, decreasing longline effort had more positive impacts on bycatch and incidental groups than loss of target catch. Target catch amongst sensitivity scenarios remained relatively stable due to catches from U.S. recreational fleets and U.S. non-longline, hook-and-line fleets since these fleets also target these groups (e.g., landings of recreational and non-longline, hook-and-line fleets increased with reductions in pelagic longline effort).

4.5.2 Limitations

Diagnostics of GoMAM show potential issues with the current calibration of bluefin tuna biology. First, during the simulation there is a sudden loss of bluefin tuna beyond the 3rd age-class. Although the western Atlantic bluefin tuna stock is severely depleted and it is possible very few older organisms are in the stock, the loss of these organisms in the simulated system was very sudden. Body weight diagnostics suggested it could be due to unbalanced consumption dynamics for bluefin tuna. However, adjusting parameters relating to bluefin tuna consumption caused additional problems to model dynamics (Appendix C). Second, GoMAM's modeling of the bluefin tuna seasonal migration could be improved. For instance, adults are in the simulated ecosystem longer than what is currently suggested in the literature (e.g. Block et al., 2005; Teo et al., 2007). Also, adult bluefin tuna are not subjected to additional mortality outside the system, although the Atlantic Ocean is where bluefin tuna experience significant mortality (ICCAT, 2014b, 2016a). Adjusting bluefin tuna migration, like making the seasonality stronger, improved some diagnostics but made other diagnostics worse (Appendix C). If future projects using the GoMAM model intend to focus specifically on bluefin tuna, it is recommended to adjust the treatment of the functional group in order to improve model diagnostics while still representing their known ecology. This will not be a trivial task since model tuning can directly and indirectly impact various components.

GoMAM's fisheries module could be advanced. For instance, this study reduced pelagic longline fishing mortality proportional to the area of the closure when, in reality, spatial closures may displace fishing effort (Kellner et al., 2007). The decision to not redistribute fishing effort is an important limitation. This means indicator values for bycatch and incidental groups could be more optimistic, and indicator values for target groups could more pessimistic, than in reality since effort outside closures were not increased. Parameterizing GoMAM to model spatial closures with displaced fishing effort would require some work, but would benefit future fishery management investigations with GoMAM. It would also be beneficial to parameterize dynamic fisheries. Dynamic fisheries would be ideal especially for investigating *Spring Closure*, because spatial effort would respond to higher seasonal concentrations of stocks (e.g., bluefin tuna).

The fisheries module in GoMAM should also be advanced in order to improve the representation of bycatch. First, future fishery management studies with GoMAM would benefit if the model distinguished retained catches from discarded catches. Management objectives for pelagic fishery closures are not simply to reduce bycatch because this could be accomplished with lower quotas. In reality, these closures aim to reduce discards while preserving target catch, that is, increase the ratio between target catches and discarded catches. Currently, this can not be tracked in GoMAM since retained catches and discarded catches are not distinguished. Second, simulating the bycatch of sea turtles, birds, and mammals can be improved. Fairly homogenous spatial distributions were assumed for these groups, which could be improved with statistical models. Also, simple assumptions were made to parameterize fleet-specific bycatch of these groups, which could be improved by analyzing additional bycatch data.

4.5.3 Management Recommendations and Conclusions

Atlantic bluefin tuna is a indicator species for both *DeSoto Canyon* and *Seasonal Closure*. Both closures aim to reduce the bycatch of bluefin tuna, especially *Spring Closure* which aims to protect the mature stock whilst spawning in the Gulf. Gulf spawners are known to be within the Gulf of Mexico for a relatively short period of time before migrating back to their foraging grounds in the north Atlantic (Block et al., 2005). The Northern Atlantic is where the western stock spends most of their time, and it is also where most of the fishing mortality is exerted on the stock (ICCAT, 2014b). Although this study found Gulf pelagic longline closures, especially *Desoto Canyon*, had some influence on reducing bluefin catch these closures alone may not be providing enough protection to the spawning stock of bluefin tuna. Further reduction to the fishing mortality within the Atlantic Ocean may be necessary despite the fact the stock is already highly regulated due to its economic importance in international fisheries and the concern regarding the stock's ecological sustainability.

Replenishing the bluefin tuna stock depends on the survival and recruitment of larvae, which depends on a variety of environmental factors, including sea surface temperature (Teo et al., 2007; Muhling et al., 2010). Climate change could diminish spawning habitat within the next 50 years within the Gulf of Mexico (Muhling et al., 2011, 2014), which could have a negative impact on recruitment. This could be bad for the western bluefin stock as ICCAT (2014b) has shown that the stock is unlikely to rebuild under poor recruitment. However, there is potential for a shift in aggregation locations as ocean conditions continue to change (Martell et al., 2005). GoMAM should be considered to investigate impacts to bluefin given changes to physical and environmental conditions due to inter-annual variability and/or climate change. This could be done by building upon the current hydrology sub-model, which would also allow advanced investigations pertaining to pelagic spatial closures within the Gulf of Mexico. The success of pelagic spatial closures will likely depend on inter-annual variability and changing ocean conditions, which can shift aggregation locations (Martell et al., 2005). Dynamic fishery spatial closures, those not fixed in space or time, could be designated to protect hydrographic features where pelagics aggregate. Fronts, being predictable, could be the basis for setting the closure's boundaries (Hyrenbach et al., 2000).

For many pelagic predators (i.e., tunas and billfishes) pelagic longlining is the dominant form of commercial longline fishing mortality, as pelagic longline fishing mortality sensitivity scenarios often produced similar results as all longline fishing mortality sensitivity scenarios, however this is was not the case for shark groups. GoMAM combines many of the large shark indicator species into one functional group, so there is no distinction between coastal species and pelagic species. The functional group's dynamics are driven more by coastal species than by pelagic species since most of the species in the group are coastal. Coastal species are more susceptible to benthic gears, e.g., bottom longlining (Ingram et al., 2005; Henwood et al., 2006; Hale and Carlson, 2007) than pelagic gears, so it is not surprising that this study saw that pelagic longline fishing and spatial closures had little influence on the large sharks functional group. Efforts to reduce the bycatch and improve the biomass of large shark species need to also incorporate coastal fleets (see Appendix C). This could include adjusting current coastal longline restriction zones, like the *Reef fish longline and buoy gear restricted area* (Gulf of Mexico Fishery Management Council, 1989;

Coleman et al., 2004a; Gulf of Mexico Fishery Management Council, 2016) and/or the *Seasonal prohibition applicable to bottom longline fishing for Reef fish* (Gulf of Mexico Fishery Management Council, 2016), to include restrictions/bans directed at shark species.

Pelagic fishery spatial closures can be a useful tool to achieve management objectives pertaining to the protection and rebuilding of highly migratory pelagic predators, but it is imperative that science-driven analysis via mathematical modeling is done to address their utility and feasibility. Although there are uncertainties regarding results from the Gulf of Mexico Atlantis model, the tool remains useful for investigating broader impacts from fisheries regulations within the Gulf. Gulf of Mexico pelagic longline spatial closures are likely reducing the bycatch of some pelagic predators, *DeSoto Canyon* possibly being more successful than *Spring Closure*. However, the impacts of the closures are likely limited since closures tend to shift fishing pressure, and the closures constitute a small part of the range of many pelagics. Rebuilding overfished populations such as bluefin tuna and the billfishes will be contingent on a suite of management strategies aiming to reduce fishing mortality inside and outside of the Gulf of Mexico, both through ICCAT and in national fisheries management plans. Future studies should consider the use of an updated hydrology sub-model in order to investigate more advanced spatial closures (e.g., rotating MPAs) and impacts due to changing ocean conditions.

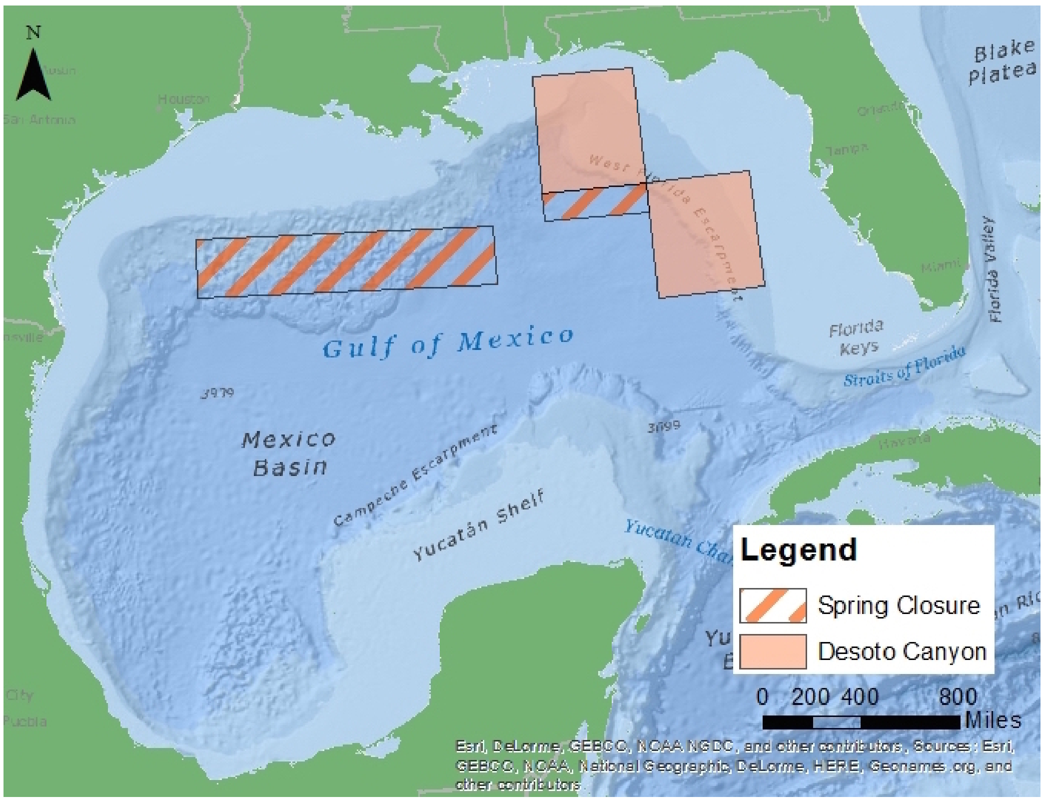


Figure 4.1: United States Gulf of Mexico Pelagic Longline Fishing Closures. The shapefile for *DeSoto Canyon* was provided by Frick (2011), and the coordinates for *Spring Closure* were provided by National Oceanic and Atmospheric Administration (2016c). Figure generated in *ArcGIS*.

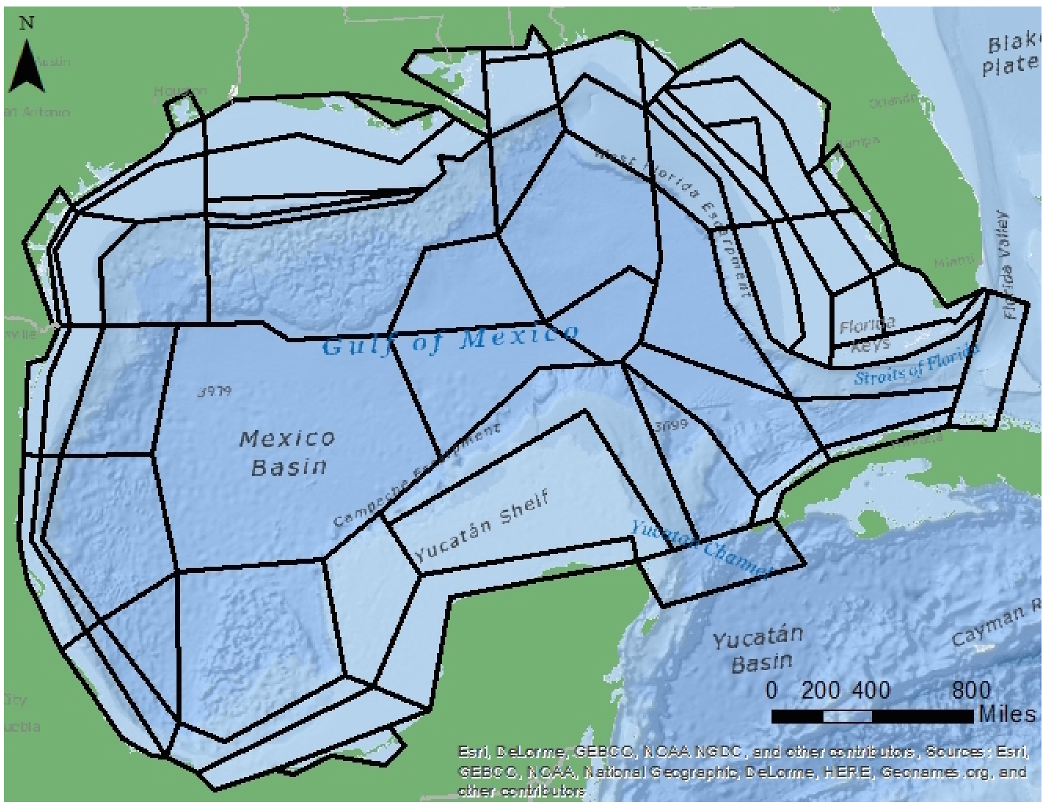


Figure 4.2: Gulf of Mexico Atlantis Model Spatial Map. Figure generated in *ArcGIS*.

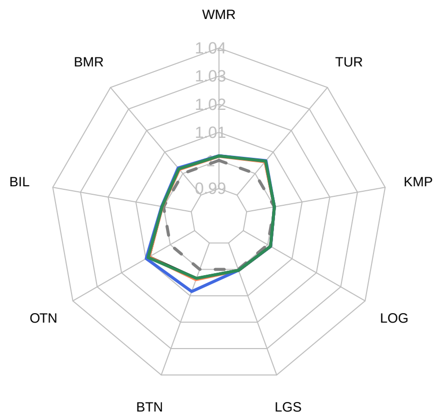
Table 4.1: Management and Ecosystem Goals and Performance Metrics. This table summarizes U.S. pelagic longline spatial closure management objectives, investigated ecological objectives, performance metrics corresponding to objectives, and computations of performance metrics. Computation variables include the time step (t), functional group (fid), number of functional groups in assemblage (X), catch (C), swordfish (SWD), age-at-first-capture (afc), biomass (B), bluefin tuna (BTN), density (D), mature age-classes ($mature$), pelagic functional groups ($pelagic$), and demersal functional groups ($demersal$).

Objective	**Performance Measures**	**Computation**
DeSoto Canyon Management		
Reduce catch of bycatch groups	Catch of bycatch groups	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(\sum_{fid=1}^{X} C_{fid}^{t}\right)$
Reduce catch of undersized swordfish	Proportion of swordfish catch being age-at-first-capture	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(C_{SWD_{afc}}^{t}/C_{SWD}^{t}\right)$
Reduce catch of incidental groups	Catch of bluefin tuna	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(C_{BTN}^{t}\right)$
Minimize reduction of target catch	Catch of target groups	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(\sum_{fid=1}^{X} C_{fid}^{t}\right)$
Optimize survival of bycatch and incidental	Biomass of bycatch and incidental groups	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(\sum_{fid=1}^{X} B_{fid}^{t}\right)$
Spring Closure Management		
Promote rebuilding of bluefin tuna	Biomass of bluefin tuna	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(B_{BTN}^{t}\right)$
Reduce catch of incidental bluefin tuna	Catch of bluefin tuna	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(C_{BTN}^{t}\right)$
Ecosystem		
Change in weight of individuals	Average weight of individuals in functional groups	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(\sum_{fid=1}^{X} B_{fid}^{t}/D_{fid}^{t}\right)$
Change in stock age structure	Proportion mature of functional groups	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(\sum_{fid=1}^{X} B_{fid_{mature}}^{t}/B_{fid}^{t}\right)$
Change in pelagic predator biomass	pelagic:demersal ratio of ecosystem	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(B_{pelagic}^{t}/B_{demersal}^{t}\right)$
Change in ecosystem biodiversity	Q90 biodiversity metric of ecosystem biomass	see Eqn. (4.2) in main text
Shift in fishing pressure	pelagic:demersal ratio of catch;	$\frac{1}{4}\sum_{t=tmax-4}^{tmax}\left(C_{pelagic}^{t}/C_{demersal}^{t}\right)$

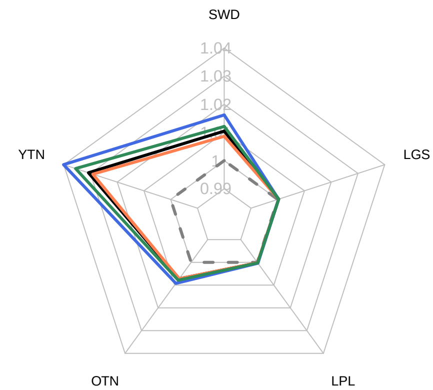
Table 4.2: Summary of Results for Management Objectives Performance Metrics. Management objective performance metrics relative to the status quo. Biomass and catch metrics for bycatch groups are the sum of all bycatch groups (total), the sum of only billfish bycatch groups (billfishes), and the sum of only tuna bycatch groups (tunas). Incidental biomass and catch metrics refer to bluefin tuna. Biomass and catch metrics for target groups are the sum of all target groups. The age structure of swordfish (SWD) catch represents the proportion of swordfish catch being age-at-first-capture.

Table 4.2: Continued.

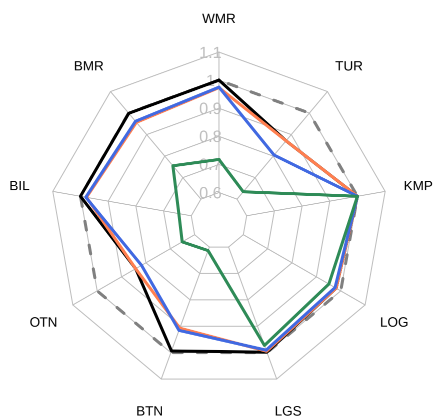
Scenarios	Biomass of Bycatch			Biomass of	Biomass of	Catch of Bycatch			Catch of	Catch of	Age structure
	Total	billfishes	tunas	Incidental	Target	Total	billfishes	tunas	Incidental	Target	SWD catch
Values computed within US Gulf											
Status Quo	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.000	1.007	1.045	1.044	1.014	0.972	0.839	0.000	0.004	0.942	0.957
All longlining F * 0.5	1.000	1.003	1.022	1.018	1.007	0.986	0.920	0.514	0.641	0.972	0.979
All longlining F * 2	1.000	0.993	0.957	0.983	0.987	1.026	1.157	1.894	1.399	1.050	1.042
Pelagic longlining F * 0	1.000	1.007	1.044	1.044	1.009	0.978	0.839	0.000	0.004	0.954	0.957
Pelagic longlining F * 0.5	1.000	1.004	1.022	1.018	1.004	0.989	0.920	0.514	0.641	0.978	0.979
Pelagic longlining F * 2	1.000	0.993	0.958	0.983	0.992	1.020	1.157	1.895	1.399	1.038	1.042
No DeSoto Canyon	1.000	0.999	0.991	0.996	0.999	1.004	1.031	1.188	1.102	1.007	1.013
No Spring Closure	1.000	1.000	0.999	1.000	1.000	1.001	1.007	1.034	1.006	1.001	1.001
No PLL Spatial Closures	1.000	0.998	0.990	0.996	0.998	1.004	1.038	1.221	1.106	1.009	1.014
Seasonal PLL Closure	1.000	1.001	1.006	1.001	1.001	0.997	0.967	0.822	0.984	0.994	0.995
Values computed within DeSoto Canyon											
Status Quo	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.000	1.008	1.047	1.040	1.016	0.978	0.095	0.000	0.000	0.944	0.957
All longlining F * 0.5	1.000	1.004	1.023	1.016	1.008	0.989	0.551	0.514	0.615	0.973	0.979
All longlining F * 2	1.000	0.992	0.956	0.985	0.985	1.020	1.882	1.894	1.520	1.048	1.042
Pelagic longlining F * 0	1.000	1.008	1.046	1.040	1.012	0.982	0.095	0.000	0.000	0.954	0.957
Pelagic longlining F * 0.5	1.000	1.004	1.023	1.016	1.006	0.991	0.551	0.514	0.615	0.978	0.979
Pelagic longlining F * 2	1.000	0.992	0.956	0.985	0.989	1.017	1.882	1.895	1.520	1.038	1.042
No DeSoto Canyon	1.000	0.998	0.991	0.997	0.998	1.010	1.372	1.536	1.630	1.034	1.013
No Spring Closure	1.000	1.000	0.999	1.000	1.000	1.000	1.020	1.018	0.995	1.000	1.001
No PLL Spatial Closures	1.000	0.998	0.990	0.996	0.998	1.010	1.392	1.553	1.624	1.034	1.014
Seasonal PLL Closure	1.000	1.001	1.006	1.001	1.001	0.997	0.804	0.809	0.983	0.992	0.995
Values computed within Spring Closure											
Status Quo	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.000	1.010	1.052	1.133	1.028	0.976	0.079	0.000	0.000	0.921	0.957
All longlining F * 0.5	1.000	1.005	1.026	1.050	1.014	0.988	0.543	0.514	0.686	0.963	0.979
All longlining F * 2	1.000	0.990	0.950	0.947	0.975	1.022	1.897	1.895	1.197	1.063	1.042
Pelagic longlining F * 0	1.000	1.010	1.052	1.133	1.026	0.976	0.079	0.000	0.000	0.925	0.957
Pelagic longlining F * 0.5	1.000	1.005	1.026	1.050	1.012	0.989	0.543	0.514	0.686	0.965	0.979
Pelagic longlining F * 2	1.000	0.990	0.951	0.947	0.977	1.021	1.897	1.895	1.197	1.059	1.042
No DeSoto Canyon	1.000	0.998	0.990	0.987	0.995	1.004	1.102	1.156	0.982	1.011	1.013
No Spring Closure	1.000	1.000	0.999	0.999	0.999	1.002	1.079	1.064	1.015	1.006	1.001
No PLL Spatial Closures	1.000	0.998	0.989	0.986	0.995	1.005	1.181	1.219	0.994	1.016	1.014
Seasonal PLL Closure	1.000	1.002	1.007	1.002	1.003	0.996	0.816	0.846	0.974	0.990	0.995



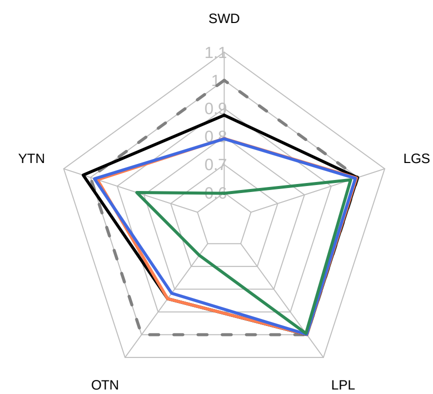
(a) Bycatch & Incidental Biomass



(b) Target Biomass

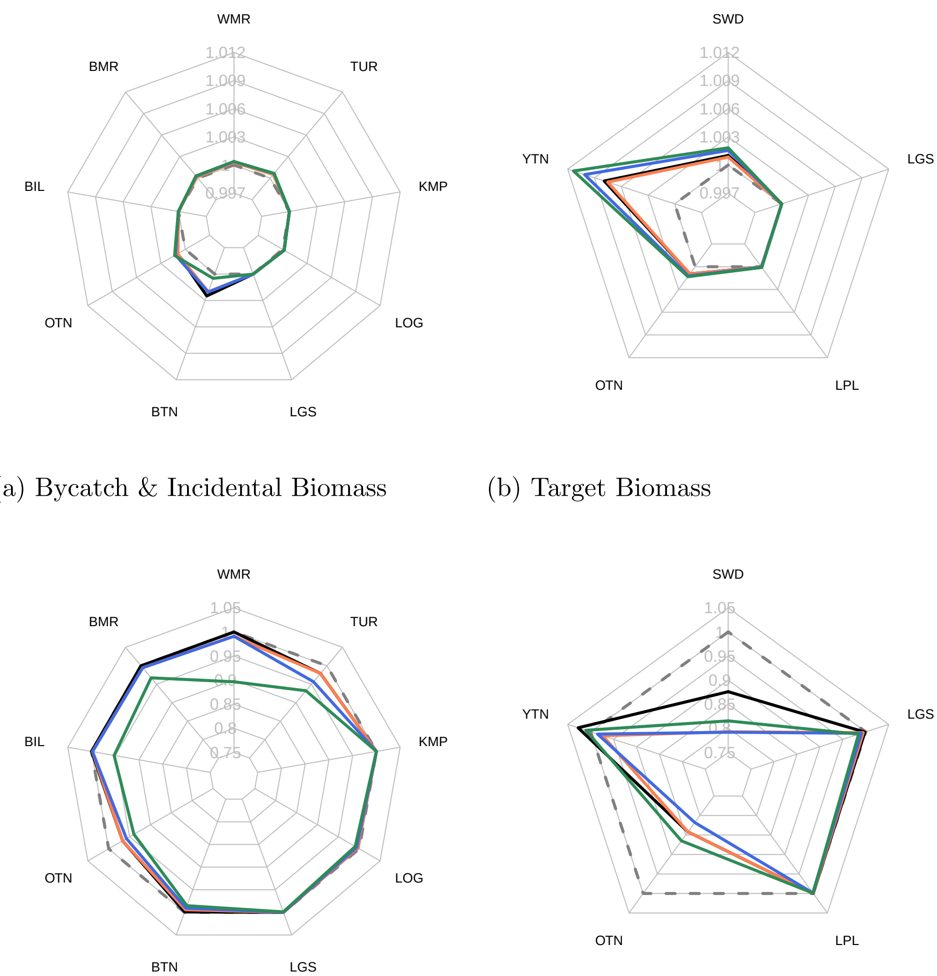


(c) Bycatch & Incidental Catch



(d) Target Catch

Figure 4.3: Evaluation of Functional Group Specific Management Objective Performance Measures Upon the Establishment of *DeSoto Canyon*. Functional group-specific impacts for white marlin (WMR), blue marlin (BMR), other billfish (BIL), miscellaneous tunas (OTN), bluefin tuna (BTN), large sharks (LGS), loggerhead sea turtles (LOG), kemp's ridley sea turtles (KMP), other sea turtles (OTN), swordfish (SWD), yellowfin tuna (YTN), and large pelagic fish (LPL). Performance metrics are compared across the whole Gulf (black), U.S. Gulf (red), U.S. Gulf open ocean (blue), and *DeSoto Canyon* (green). Axis values are from the status quo relative to no *DeSoto Canyon*.



(a) Bycatch & Incidental Biomass (b) Target Biomass

(c) Bycatch & Incidental Catch (d) Target Catch

Figure 4.4: Evaluation of Functional Group Specific Management Objective Performance Measures Upon the Establishment of *Spring Closure*. Functional group-specific impacts for white marlin (WMR), blue marlin (BMR), other billfish (BIL), miscellaneous tunas (OTN), bluefin tuna (BTN), large sharks (LGS), loggerhead sea turtles (LOG), kemp's ridley sea turtles (KMP), other sea turtles (OTN), swordfish (SWD), yellowfin tuna (YTN), and large pelagic fish (LPL). Performance metrics are compared across the whole Gulf (black), U.S. Gulf (red), U.S. Gulf open ocean (blue), and *Spring Closure* (green). Axis values are from the status quo relative to no *Spring Closure*.

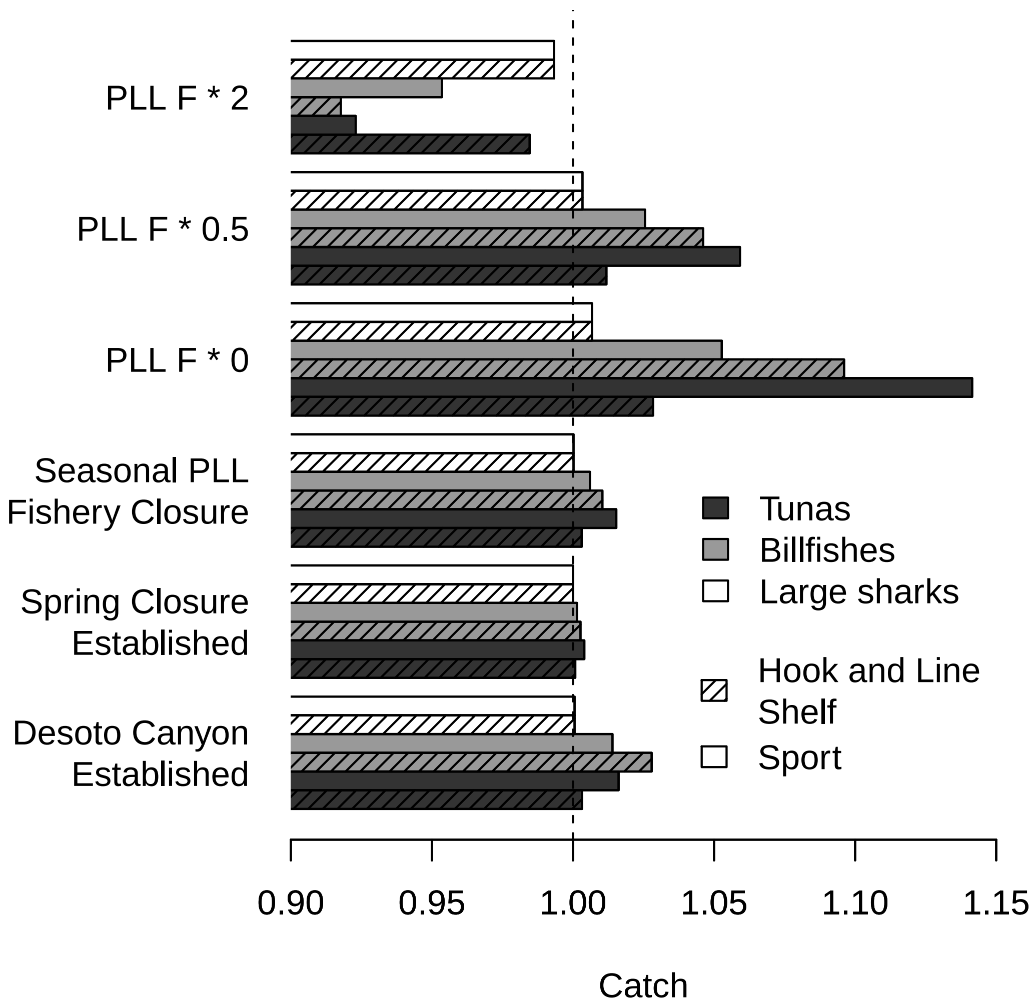
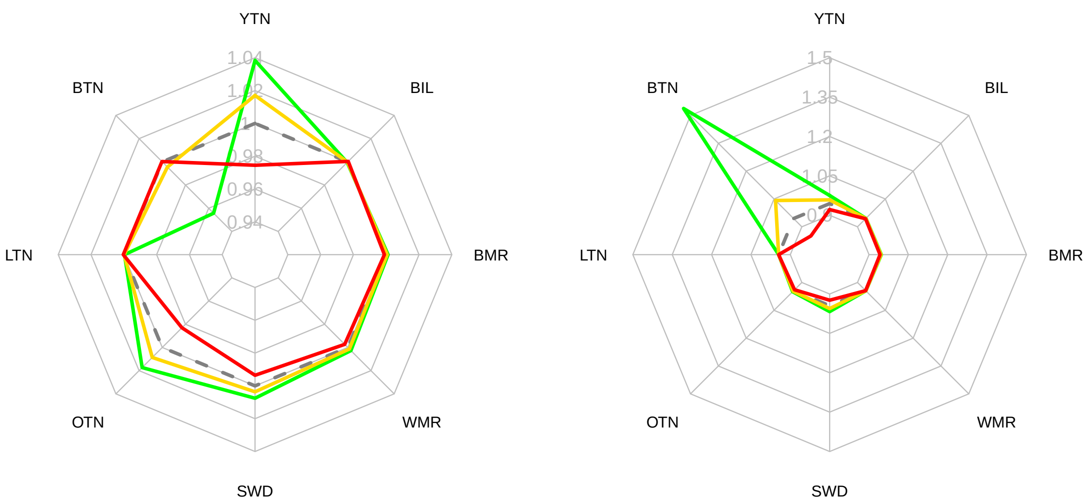


Figure 4.5: Changes in Catch from Non-pelagic, U.S. Hook-and-Line Fleets Resulting from Pelagic Longline Fishing Mortality Sensitivity and Spatial Closure Scenarios. Changes in catch of tunas (dark grey), billfishes (grey), and large sharks (light grey) from hook-and-line shelf fleets (dashed) and sport fleets (solid) amongst indicated scenarios. Values corresponding to pelagic longline fishing mortality sensitivity scenarios (PLLF) are relative to the status quo. All other values are from the status quo relative to pelagic longline spatial closure scenarios.

Table 4.3: Summary of Results for Ecological Objectives Performance Metrics. Ecological objective performance metrics are relative to the status quo. Average individual weight, and proportion mature is shown for all billfish groups (billfishes), and all tuna groups (tunas). The pelagic:demersal ratio (P:D) was computed based on biomass in the marine environment (ecosystem), and biomass caught by the fisheries (catch). The ecosystem Q90 biodiversity metric is based on biomass in the marine environment.

Scenarios	Average Ind. Weight		Proportion Mature		P:D ratio		Q90
	billfishes	tunas	billfishes	tunas	ecosystem	catch	ecosystem
Values computed within US Gulf waters							
Status Quo	1	1	1	1	1	1	1
All Longlining F * 0	1.003	1.011	1.007	1.004	1.014	0.974	1.000
All Longlining F * 0.5	1.001	1.005	1.004	1.002	1.007	0.988	1.000
All Longlining F * 2	0.997	0.992	0.993	0.996	0.988	1.019	1.000
Pelagic longlining F * 0	1.003	1.011	1.007	1.004	1.013	0.966	1.000
Pelagic longlining F * 1	1.001	1.005	1.004	1.002	1.006	0.984	1.000
Pelagic longlining F * 2	0.997	0.992	0.993	0.996	0.989	1.028	1.000
No DeSoto Canyon	0.999	0.998	0.998	0.999	0.998	1.006	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.001	1.000
No DC or SC	0.999	0.998	0.998	0.999	0.997	1.007	1.000
Seasonal PLL Closure	1.000	1.001	1.001	1.001	1.002	0.995	1.000
Values computed within DeSoto Canyon							
Status Quo	1	1	1	1	1	1	1
All Longlining F * 0	1.003	1.009	1.007	1.004	1.017	0.972	1.000
All Longlining F * 0.5	1.001	1.004	1.003	1.002	1.008	0.988	1.000
All Longlining F * 2	0.998	0.994	0.994	0.996	0.985	1.020	1.005
Pelagic longlining F * 0	1.003	1.009	1.007	1.004	1.015	0.960	1.000
Pelagic longlining F * 1	1.001	1.004	1.003	1.002	1.007	0.981	1.000
Pelagic longlining F * 2	0.998	0.993	0.994	0.996	0.986	1.032	1.005
No DeSoto Canyon	0.999	0.999	0.998	0.999	0.997	1.028	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No DC or SC	0.999	0.998	0.998	0.999	0.997	1.028	1.000
Seasonal PLL Closure	1.000	1.001	1.001	1.000	1.002	0.994	1.000
Values computed within Spring Closure							
Status Quo	1	1	1	1	1	1	1
All Longlining F * 0	1.001	1.006	1.005	1.002	1.022	0.938	1.000
All Longlining F * 0.5	1.000	1.003	1.002	1.001	1.011	0.972	1.000
All Longlining F * 2	0.999	0.997	0.995	0.998	0.980	1.047	1.004
Pelagic longlining F * 0	1.001	1.006	1.005	1.002	1.021	0.932	1.000
Pelagic longlining F * 1	1.001	1.003	1.002	1.001	1.010	0.968	1.000
Pelagic longlining F * 2	0.999	0.997	0.995	0.998	0.981	1.055	1.004
No DeSoto Canyon	1.000	0.999	0.999	1.000	0.996	1.009	1.000
No Spring Closure	1.000	1.000	1.000	1.000	0.999	1.004	1.000
No DC or SC	1.000	0.999	0.998	1.000	0.995	1.013	1.000
Seasonal PLL Closure	1.000	1.001	1.001	1.000	1.003	0.994	1.000



(a) Average Individual Weight

(b) Proportion Mature

Figure 4.6: Evaluation of Ecosystem Objective Performance Metrics for Billfish and Tuna Functional Groups. Ecosystem objective performance metrics average individual weight (a), and proportion mature (b) for billfish and tuna functional groups: yellowfin tuna (YTN), bluefin tuna (BTN), little tunny (LTN), miscellaneous tunas (OTN), swordfish (SWD), white marlin (WMR), blue marlin (BMR), other billfish (BIL). U.S. Gulf metrics are compared amongst longline fishing mortality sensitivity scenarios in which fishing mortality for all longline fleets were multiplied by 0 (green), 0.5 (yellow), and 2 (red). Axis values are relative to the status quo.

CHAPTER 5

Conclusion

5.1 Summary of Dissertation

The Gulf of Mexico is an important ecosystem for Atlantic predatory pelagics (e.g., sharks, tunas, billfish) due to the environmental and physical dynamics which drive areas of productivity. The sustainability of fisheries for Atlantic pelagic predators is a concern, and the reduction of top-predators could have negative socioeconomic and biological impacts. Management efforts have included the establishment of two pelagic longline spatial closures within the pelagic waters of the Gulf of Mexico. Considering the lack of empirical data regarding the direct and indirect impacts of pelagic fisheries closures, the parameterization of a mathematical ecosystem model was necessary to assess the utility of these closures. This dissertation aided the parameterization of the Gulf of Mexico Atlantis model (i.e., chapter 2 and chapter 3), and used the model to assess if Gulf of Mexico pelagic longline closures could meet management objectives, and identify potential ecosystem impacts (chapter 4).

The work presented in Chapter 2, *Landings Data for Ecosystem Fisheries Science: Lessons Learned from the Gulf of Mexico*, considered Gulf of Mexico landings data to evaluate potential uncertainties in ecosystem based fisheries management metrics, focusing on inputs to the Gulf of Mexico Atlantis model, and landings-based indicators. Meaningful portions of landings from commercial fisheries are ambiguous (not identified to species), especially in Mexico and Cuba which have large portions of unidentified landings (29.2% and 48.9%, respectively). U. S. recreational data have minimal ambiguous landings (0.4%), but landings are highly variable in part due to sampling error. U. S. ambiguous landings do not appear to be biasing the indicators. In addition, the aggregation of landings into Gulf of Mexico Atlantis functional groups do not appear to be biasing trends of landings-based indicators. While season-specific and State-specific U. S. landings do not introduce significant bias, much of the fleet-specific landings early in the time series could not be allocated to an Atlantis fleet due to the lack of detail in the landings dataset. This will not impact historical calibration because landings are not partitioned across fleets, but this should be considered when computing fleet-specific landings proportions for forecasting. Current landings time series appear to be sufficient for the development of ecosystem models, but ecosystem based fisheries management of the Gulf of Mexico would benefit from more precise landings data.

The work presented in Chapter 3, *Predicting the Biomass Distributions of Pelagic Species Across the Gulf of Mexico Using Generalized Additive Models*, Delta GAMs were fitted for describing the Gulf-wide spatial distributions of pelagic predatory functional groups using Gulf of Mexico U. S. bottom longline survey catch data (coastal models), and U. S. pelagic longline commercial catch data (pelagic models). This work advanced our knowledge on the environmental cues and spatial distribution of pelagic groups within the Gulf of Mexico, which can aid fisheries management by identifying areas of increased vulnerability. Fitted models for large, predatory sharks had some of the better fits, diagnostics, and performance. The large, predatory sharks model was influenced by minimum distance from a front, in addition to environmental drivers. There is little research linking the spatial patterns of predatory shark species to fronts, so this suggests further studies investigating possible connections between physical features and the presence of predatory shark species. The fitted model presented in this dissertation successfully identified areas of the Gulf known to have higher catch rates of sharks, which could aid spatial management and conservation of predatory sharks.

Although many of the fitted GAMs presented in this dissertation had poor diagnostics and performances, these models improved the representation of the spatial distribution of pelagics in spatially-explicit ecosystem models. In the case of the Gulf of Mexico Atlantis model, spatial distributions were previously assumed to be fairly homogenous, lacking variability across space and season. Thus, the heterogeneous profiles produced from the statistical models improved the characterization of food web dynamics, fisheries, and spatial regulations. Also, estimates are being aggregated into large polygons, so inaccuracies at the predicted level are probably averaged out. However, distribution profiles are only used in the initial setup of Atlantis and a new stable spatial distribution is formed based on a number of simulated factors (e.g., habitat affinity, predator/prey dynamics, fisheries, etc.). Thus, it is uncertain how the spatial distributions mesh with the rest of the model. For example, if the distribution of prey groups do not correspond to the distributions estimated by the GAMs to some extent, then Atlantis will not allow the spatial distribution of predator groups to persist because they can not find food. The spatial distributions estimated by GAMs should be compared to spatial distributions GoMAM stabilize to, and if there are significant differences than there are likely issues with the distributions of large pelagic functional groups, or their prey groups.

The work presented in Chapter 4, *Can Gulf of Mexico Pelagic Longline Fishery Closures Meet Management Objectives?*, conducted a policy exploration investigating if current pelagic longline spatial closures could meet management objectives, and possible ecosystem impacts. Current closures include a permanent closure over DeSoto Canyon (*DeSoto Canyon*), and seasonal closure off the Louisiana shelf (*Spring Closure*). Closures are intended to reduce bycatch and promote the rebuilding of biomass for pelagic predators. The Gulf of Mexico Atlantis model was used to simulate management scenarios altering spatial closures and pelagic longline fishing mortality, and tracked changes to performance measures. Closures reduced Gulf-wide catches of bycatch and incidental groups with little reduction to catches of target groups, but the reduction in fishing mortality was not enough to cause meaningful increases in biomass of bycatch and incidental groups. *DeSoto Canyon* was more successful at achieving management objectives, and had more influence to ecosystem metrics, than *Spring Closure*. Pelagic spatial closures can be useful tools to achieve management objectives pertaining to the protection of pelagic predators within areas where they are known to aggregate and be particularly vulnerable, but rebuilding the biomass of particular stocks may require additional reductions in fishing mortality across the Atlantic Ocean. In addition, the pelagic spatial closures may not reduce fishing mortality enough to cause meaningful impacts to ecosystem performance measures, but the pelagic:demersal ratio indicated that pelagic spatial closures can adjust the catch composition which may impact community structure.

5.2 Limitations

Data are a recurring limitation to this work. Gulf of Mexico landings time series from Mexico and Cuba used to calibrate the Atlantis historical model are likely an underrepresentation as data did not include recreational fisheries and historical reporting of artisanal landings are often incomplete, particularly for Mexico. In addition, there is uncertainty pertaining to U. S. recreational landings as data are estimates based on surveys of fishers that are expanded to the whole fishery.

Catch data used to fit GAMs were the primary limitation to describing the spatial distribution of pelagic predators. First, pelagic models were fitted with fisheries-dependent data. Using fisheries-independent data is preferable as it adheres to the statistical assumption of data independence (i.e. random sampling has a better representation of where species are and are not common). In addition, fisheries-independent data often contains more environmental data allowing for the consideration of a variety of model descriptors. While incorporating estimates of some model descriptors into fisheries-dependent data allowed the improvement of some model fits, this also introduces uncertainty. Second, coastal models only considered bottom longline data and lacked mid-depth hook-and-line data. Thus, organisms feeding within the water column and not at bottom (e.g., tunas, billfish) were not considered. Incorporating mid-depth hook-and-line data into this study would expand the species coverage and improve fits for coastal models. Lastly, catch data only spanned the northern Gulf, and extrapolating across the southern Gulf produced highly uncertain predictions.

GAMs were an appropriate method for modeling the spatial abundance of pelagic predatory groups. Smoothing splines allowed adequate flexibility when fitting the environmental data, and the relaxed statistical assumptions of GAMs allowed the use of fisheries-dependent data. There are ongoing efforts for developing a GAM framework, using carefully chosen environmental predictors and a blending of available fisheries-independent and fisheries-dependent survey data, for enhancing Gulf of Mexico ecosystem models (Grüss et al., 2016a). Residual analysis of the GAMs presented in this dissertation showed that many of the gamma GAMs did not represent the data very well. This could possibly be addressed in future research by transforming the response variable using transformations like the Basic or Box-Cox (as recommended by Mateu (1997) when normalizing environmental data).

This dissertation found some parameterizations of the Gulf of Mexico Atlantis model worth adjusting to benefit future studies investigating the fisheries management of pelagic predatory groups. First, the harvesting module can be altered to distinguish bycatch from landings. This will allow more nuanced investigations of management strategies aiming to reduce bycatch while maintaining landings. In addition, the representation of fleets can be advanced to allow the redistribution of fishing mortality around MPAs, rather than reducing mortality. Also, diagnostics for some of the pelagic predatory functional groups, specifically bluefin tuna, could be improved. Model diagnostics show a sudden loss of adults seemingly due to unbalanced consumption, and bluefin diagnostics got worse when bluefin migration patterns are adjusted to better represent migration described in current literature. These may be related, as bluefin tuna spawning in the Gulf do most of their foraging in the north Atlantic. Conservation of bluefin tuna while the stock is breeding in the Gulf of Mexico is a pressing issue. To conduct this investigation strictly focusing on bluefin tuna impacts, not only would the above need to be addressed, but methods should include different scenarios modeling possible fisher behavior regarding the pelagic longline spatial closures (especially *Spring Closure* as it was specifically established for spawning bluefin tuna). In addition, metrics describing the overlap between migrating bluefin tuna and the spatial closures should be analyzed, as well as catch rates in areas outside of the closures.

This dissertation project has identified several areas where the Gulf of Mexico Atlantis model could be refined to advance its functionality, and improve its modeling of the system (e.g., partitioning the *large coastal sharks* functional group into two functional groups: coastal sharks, and pelagic sharks), but the Gulf of Mexico Atlantis model was a very useful tool for study. The Atlantis framework allowed for the detailed, spatially-explicit representation of biota, fleets and spatial closures, and provided a means to explore broad-scale, ecosystem impacts. To take this study one step further, it would be interesting to simulate the investigated scenarios with another spatially-explicit ecosystem model to compare and contrast results. However, currently the other spatially-explicit ecosystem models of the Gulf of Mexico do not span the whole ecosystem.

5.3 Future Research

Qualitative assessment indicators shown in Chapter 2 reveal that a majority of U. S. commercial landings are of species that are not overfished, but the majority of U. S. recreational landings are of species of unknown overfished status. Because U. S. recreational fleets are important sources of fishing mortality in Gulf of Mexico waters, expanding assessment coverage to incorporate these species would be informative for fisheries management. Data-limited methods may be desirable as these species are not commercially important and data are probably not adequate for the usual assessment methodologies. In addition, methods for reducing the uncertainty in U. S. recreational data would help landings-based investigations of the Gulf of Mexico.

Because fisheries-independent datasets are preferable to fisheries dependent datasets for statistical investigations, developing an annual pelagic longline fisheries-independent survey within the Gulf of Mexico would be beneficial for tracking and monitoring the status of pelagic predatory stocks within the Gulf of Mexico. Getting funding for such a project may be difficult since the open ocean is expansive and oligotrophic. Considering the importance of physical metrics (e.g., fronts) when fitting GAMs, these efforts should collect metrics relating to physical oceanography (e.g., altimetry, currents) in addition to at-depth data from CTDs. Such surveys have been previously done in the Gulf but they have been discontinued(Fitzhugh et al., 2012; Campbell et al., 2012). Such a survey may become more necessary in the future as changing ocean conditions might impact recruitment and shift productive areas were pelagics aggregate.

Because foraging pelagic predators are actively seeking out food, incorporating model descriptors relating to predator-prey dynamics into GAMs could improve model fits and performance, and could be informative for the spatial ecology of some species. Schick and Lutcavage (2009) found that the fit of a generalized model predicting the distribution of bluefin tuna improved with the inclusion of prey dynamics. However, Benoit-Bird et al. (2013) found that many studies have found weak or ephemeral spatial associations between predators and prey within pelagic environments, and reported that their statistical models were unable to find a spatial relationship between predators and their prey. Instead, authors found that habitat use by predator groups considered in their study were most strongly predicted by prey patch characteristics (i.e., depth and local density within spatial aggregations).

Mitigating the bycatch of sea turtles, birds, and mammals are also objectives for the management of pelagic longline gears. Mapping the Gulf-wide spatial distribution of these groups would benefit the parameterization of spatially explicit ecosystem models, and be informative for spatial management of the Gulf of Mexico. Considering the Gulf of Mexico Atlantis model, data should be located or collected in order to appropriately parameterize the bycatch modeling of these groups.

APPENDIX A

Additional Methodology and Results for Chapter 2

A.1 Additional Methods for Section 2.3.1

Table A.1: NOAA Commercial Gear-types Assigned to Atlantis Fleets.

GillnetEst	**LLPelgc**	**PotCrbEst**	**OtherUS**
Entangling Nets (Gill) Unspc	Lines Troll, Other	Brush Trap	By Hand, Other
Gill Nets, Drift, Runaround	Lines Long Set With Hooks	Pots And Traps, Crab, Blue	By Hand, Oyster
Trammel Nets	Lines Long Drift With Hooks	Pots And Traps, Crab, Other	Cast Nets
Gill Nets, Stake		Pots And Traps, Eel	Diving Outfits, Other
Gill Nets, Sink/Anchor, Other	**OytEst**		Dip Nets, Drop
PotLbtShf	Rakes, Other	**LLReefShf**	Dip Nets, Common
Pots And Traps, Spiny Lobster	Dredge Other	Lines Long, Reef Fish	Fyke And Hoop Nets
	Tongs and Grabs, Oyster	Lines Trot With Baits	Haul Seines, Beach
LLShkShf	Tongs and Grabs, Other		Haul Seines, Long
Lines Long, Shark		**PotCrbShf**	Hooks, Sponge
	HLReefShf	Pots And Traps, Fish	Lampara & Ring Nets
TwlShpEst	Reel, Electric or Hydraulic	Pots And Traps, Other	Spears
Beam Trawls, Butterfly Nets	Rod and Reel	Pots And Traps, Shrimp	
Skimmer Net	Lines Hand, Other		**Not Assigned**
	Lines Long, Vertical	**SeineMenShf**	Not Coded
TwlShpShf	RoyalRed	Encircling Nets (Purse)	Combined Gears
Otter Trawl Bottom, Shrimp	Otter Trawl Bottom, Shrimp	Purse Seines, Other	Unspecified Gear
Otter Trawl Bottom, Fish	Skimmer Net	Purse Seines, Menhaden	Troll & Hand Lines Cmb
Otter Trawl Bottom, Scallop			Slat Traps (Virginia)
Trawls, Unspecified			

A.1.1 Landings Data Discrepancies

To determine if there are any discrepancies between the annual and itemized datasets from either NOAA and MRIP, plots were made to describe time series of i) the ratio between total landings in the itemized dataset against total landings in the annual dataset, and ii) the ratio between the total number of groups identified in the itemized dataset against the total number of groups identified in the annual datasets.

A.2 Additional Methods for Section 2.3.1.1

A.2.1 Spatial Distribution

Seasonal landings time series were distributed across space (i.e., Atlantis polygons) using the seasonal biomass distributions of the functional groups. The construction of the seasonal biomass distributions are described above under Biomass distributions. First, the polygons that make up the region where each of the territorial fleets (i.e., U.S. commercial, U.S. recreational, Mexican commercial, and Cuban commercial) operate within were determined. Commercial landings are harvested from polygons that lie within the appropriate EEZ boundaries (note, all commercial fleets can harvest in international waters at the center of the Gulf, in the area called the donut hole). Polygons within the U.S. EEZ that do not exceed 200 m in depth were designated to contain U.S. recreational harvesting. However, U.S. recreational landings for the functional group *crabs and lobsters* were restricted to polygons 27 and 28 (SEDAR, 2005). Since boundary polygons 0 and 65 are reserved for flux characteristics, they were not included in the spatial distribution of landings.

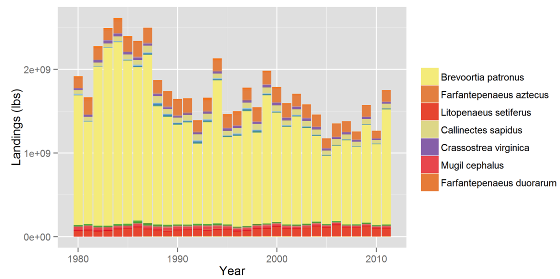
Landings were only partitioned for the polygons described above; since the seasonal biomass distributions of the functional groups consider the entire polygon grid, they were partitioned in the same manner. Then, for each season and each territorial fleet, seasonal biomass distributions of the functional groups for the polygon subsets were adjusted so the distributions summed to 1. We utilized these adjusted seasonal distributions to allocate the corresponding seasonal landings across the appropriate polygons for U.S. commercial, U.S. recreational, Mexican commercial, and Cuban commercial landings.

A.3 Additional Methods for Section 2.3.2

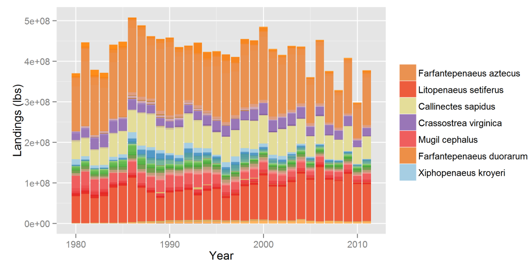
Table A.2: Functional Group Metrics for Ecological Indicator Computations.

FID	Functional group	Trophic Level	Trophic Level Standard Error	Pelagic/Demersal
GAG	Gag grouper	3.6	0	D
RGR	Red grouper	3.6	0	D
SCM	Scamp	4.4	0	D
SSR	Shallow serranidae	3.9	0.5	D
DSR	Deep serranidae	4.1	0.3	D
RSN	Red snapper	4	0	D
VSN	Vermilion snapper	4.3	0	D
LUT	Lutjanidae	4	0.3	D
BIO	Bioeroding fish	2.5	0	D
LRF	Large reef fish	3.4	0.6	D
SRF	Small reef fish	3.3	0.7	D
BDR	Black drum	3.9	0	D
RDR	Red drum	4.1	0	D
SEA	Seatrout	4.1	0.3	D
SCI	Sciaenidae	3.4	0.3	D
LDY	Ladyfish	3.9	0	D
MUL	Mullets	2.4	0.1	D
POM	Pompano	3.7	0.6	D
SHP	Sheepshead	3.5	0	D
SNK	Snook	4.2	0	D
FLT	Flatfish	3.4	0.3	D
ODF	Other demersal fish	3.7	0.6	D
SDF	Small demersal fish	3.7	0.5	D
YTN	Yellowfin tuna	4.3	0	P
BTN	Bluefin tuna	4.5	0	P
LTN	Little tunny	4.4	0	P
OTN	Other tuna	4.2	0	P
SWD	Swordfish	4.5	0	P
WMR	White marlin	4.5	0	P
BMR	Blue marlin	4.5	0	P
BIL	Other billfish	4.4	0.1	P
AMB	Greater amberjack	4.5	0	P
JCK	Jacks	4.1	0.4	P
KMK	King mackerel	4.5	0	P
SMK	Spanish mackerel	4.2	0.3	P
SAR	Spanish sardine	3.1	0	P
LPL	Large pelagic fish	4	0.5	P
DWF	Deep water fish	3.6	0	P
MEN	Menhaden	2.3	0.1	P
PIN	Pinfish	3.6	0	P
MPL	Medium pelagic fish	3.5	0.7	P
SPL	Small pelagic fish	3.3	0.4	P
TIP	Blacktip shark	4.4	0	P
BEN	Benthic feeding sharks	4.3	0	P
LGS	Large sharks	4.3	0.2	P
FIL	Filter feeding sharks	3.4	0	P
SMS	Small sharks	4.3	0	P
RAY	Skates and rays	3.7	0.5	P
BSH	Brown shrimp	2.5	0	D
WSH	White shrimp	2.5	0	D
PSH	Pink shrimp	2.5	0	D
OSH	Other shrimp	2.5	0	D
DBR	Diving birds	3.6	0	D
SBR	Surface feeding birds	3.6	0	D
MAN	Manatee	4.5	0	D
MYS	Mysticeti	3.2	0	D
DOL	Dolphins and porpoises	4.7	0	D
DDO	Deep diving odontocetae	4.7	0	D
LOG	Loggerhead	3.4	0	P
KMP	Kemps ridley	3.3	0	P
TUR	Other turtles	3.3	0	P
BCR	Blue crab	2.7	0	D
SCR	Stone crab	2.7	0	D
LOB	Crabs and lobsters	2.7	0	D
COR	Stony corals	2.3	0	D
CCA	Crustose coralline algae	2.3	0	D
OCT	Octocorals	2.3	0	D
SPG	Sponges	2.3	0	D
CMB	Carnivorous macrobenthos	2.2	0	D
INF	Infaunal meiobenthos	2	0	D
ECH	Herbivorous echinoderms	2	0	D
OYS	Oysters	2	0	D
BIV	Bivalves	2	0	D
SES	Sessile filter feeders	2	0	D
EPI	Epiphytes	1	0	D
GRS	Sea grass	1	0	D
ALG	Macroalgae	1	0	D
MPB	Microphytobenthos	2.1	0	D
LPP	Large phytoplankton	1	0	D
SPP	Small phytoplankton	1	0	D
DIN	Toxic dinoflagellates	1	0	D
PRO	Protists	1	0	D
JEL	Jellyfish	3.1	0	D
SQU	Squid	3.2	0	D
LZP	Large zooplankton	2.1	0	D
SZP	Small zooplankton	2.1	0	D
PB	Bacteria	1	0	D
BB	Sediment bacteria	1	0	D
DC	Carrion detritus	1	0	D
DL	Labile detritus	1	0	D
DR	Refractory detritus	1	0	D

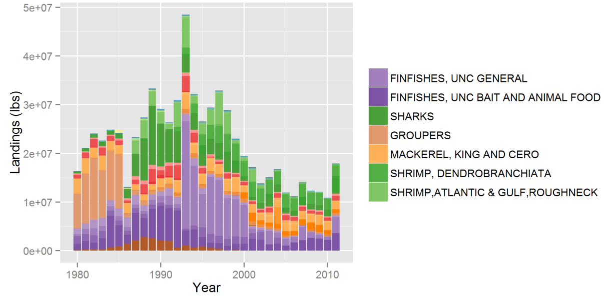
A.4 Additional Results for Section 2.3.1



(a)

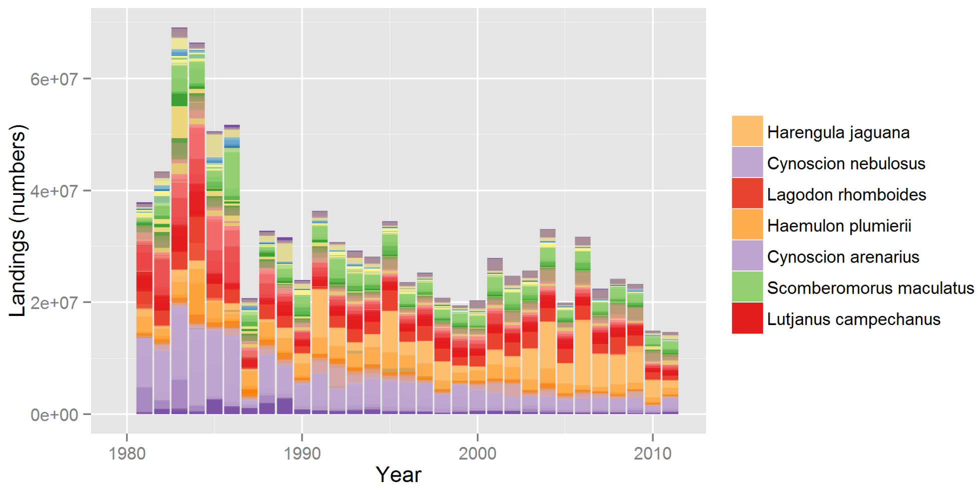


(b)

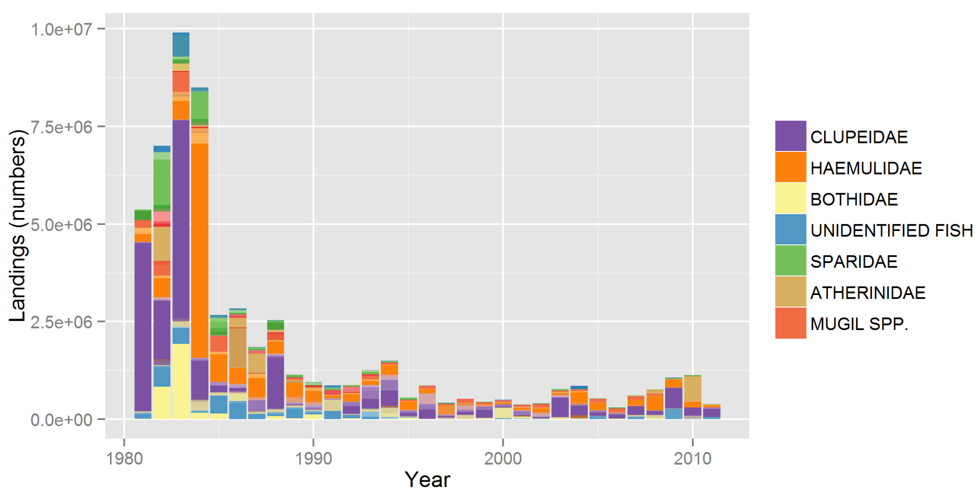


(c)

Figure A.1: Species Composition Time Series of United States Commercial Data. Panel (a) shows the species composition for total landings. Panel (b) shows the species composition for total landings, excluding menhaden. Panel (c) shows the species composition of ambiguous landings. Legend shows only the seven most common species.

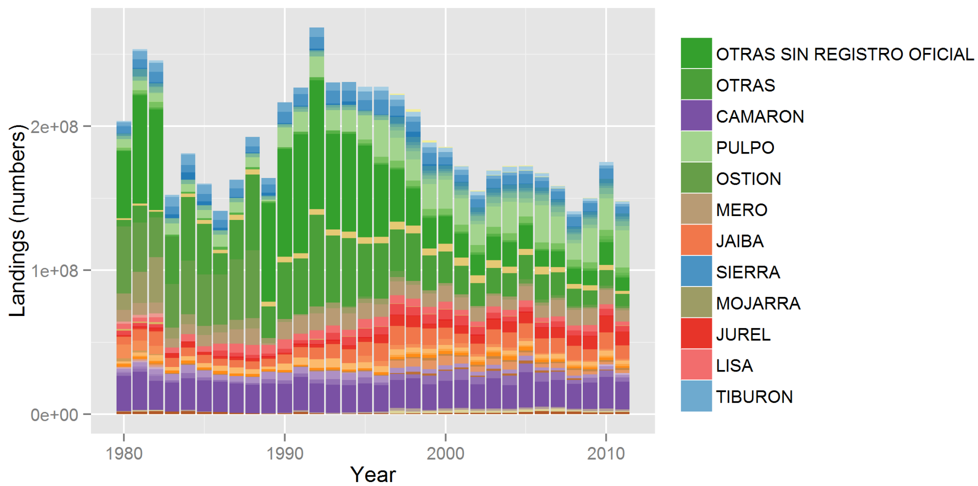


(a)

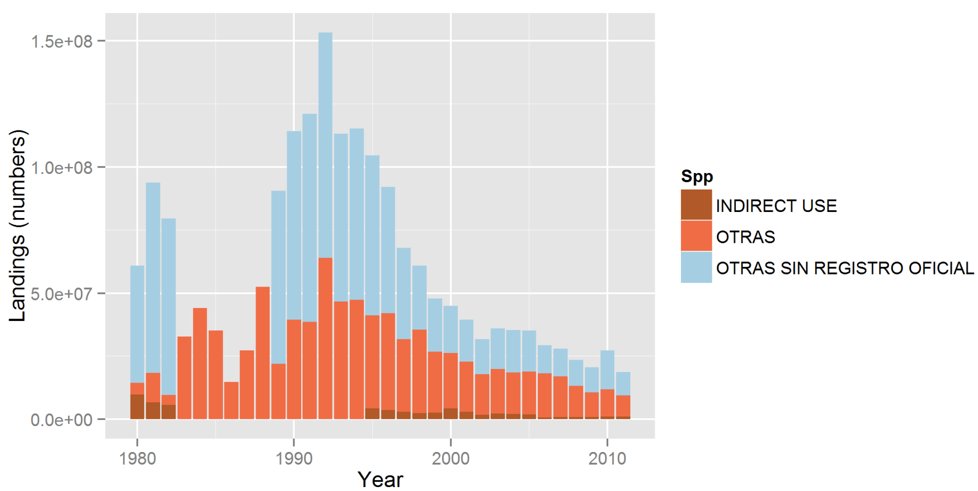


(b)

Figure A.2: Species Composition Time Series of United States Recreational Data. Panel (a) shows the species composition for total landings. Panel (b) shows the species composition for ambiguous landings. Legend shows only the seven most common species.

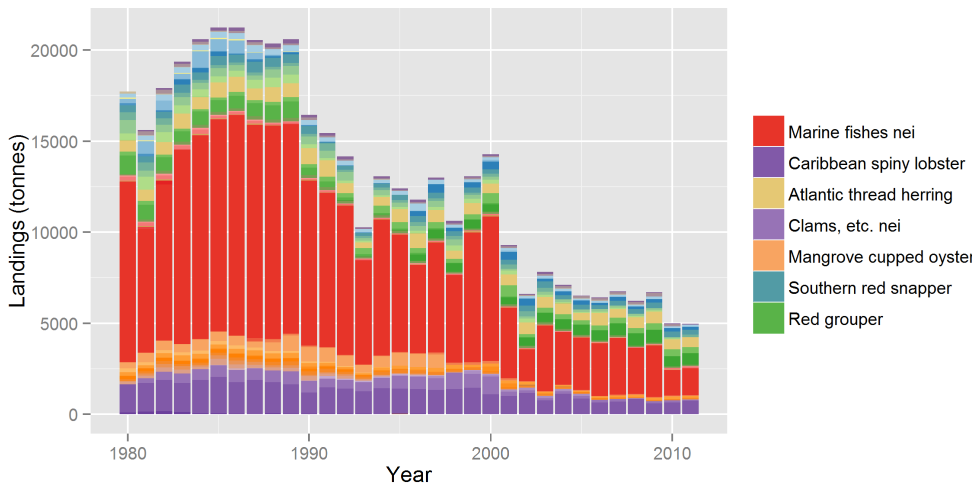


(a)

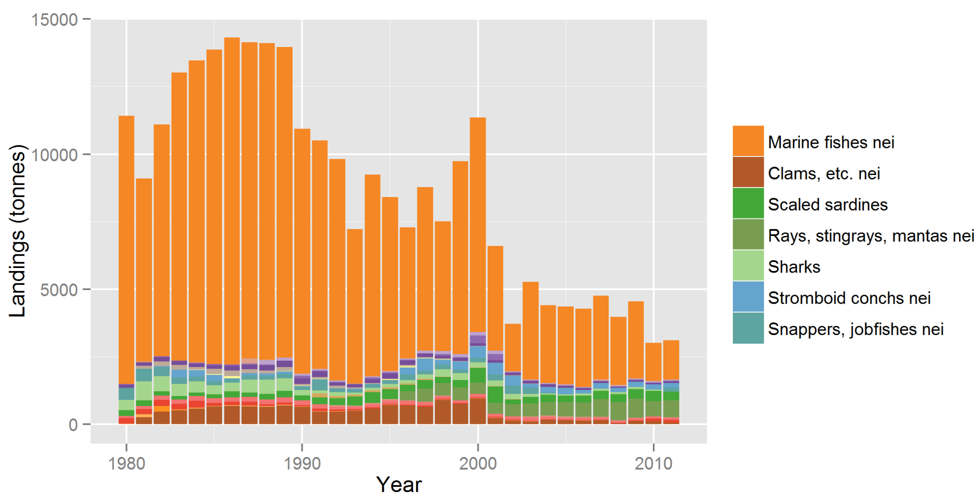


(b)

Figure A.3: Species Composition Time Series of Mexican Commercial Data. Panel (a) shows the species composition for total landings. Panel (b) shows the species composition for ambiguous landings. Legend shows only the seven most common species.

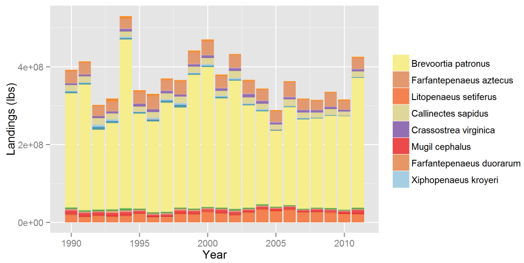


(a)

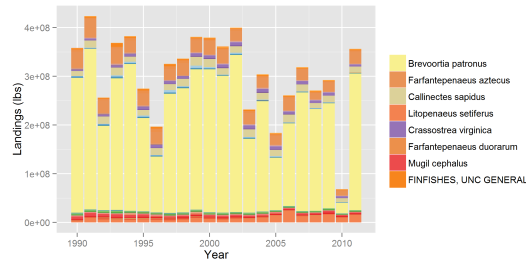


(b)

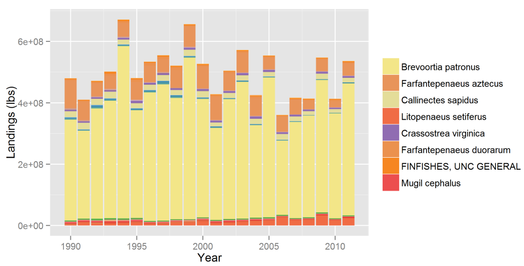
Figure A.4: Species Composition Time Series of Cuban Commercial Data. Panel (a) shows the species composition for total landings. Panel (b) shows the species composition for ambiguous landings. Legend shows only the seven most common species.



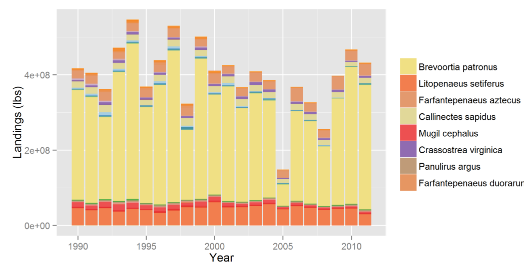
(a)



(b)

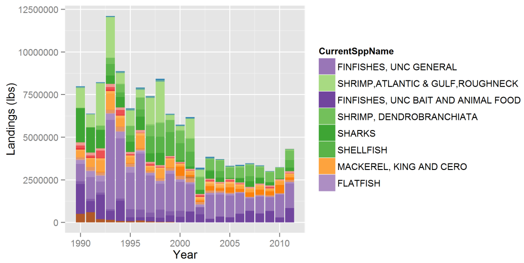


(c)

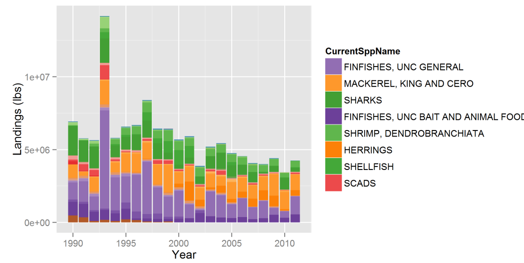


(d)

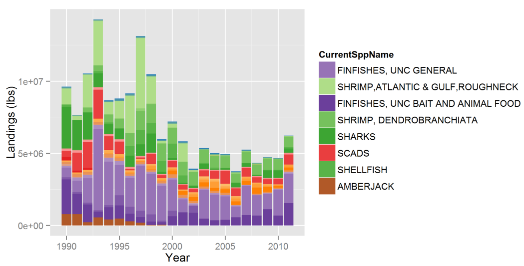
Figure A.5: Species Composition Time Series of Seasonal U.S. Commercial Data. Species compositions are shown for winter, Jan. - Mar. (a), spring, Apr. - Jun. (b), summer, Jul. - Sep. (c), and fall, Oct. - Dec. (d). Legend shows only the seven most common species.



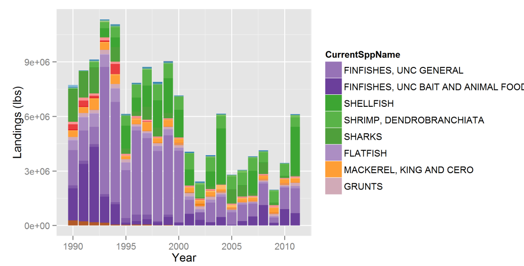
(a)



(b)



(c)



(d)

Figure A.6: Species Composition Time Series of Seasonal U.S. Commercial Ambiguous Landings. Species compositions are shown for winter, Jan. - Mar. (a), spring, Apr. - Jun. (b), summer, Jul. - Sep. (c), and fall, Oct. - Dec. (d). Legend shows only the seven most common species.

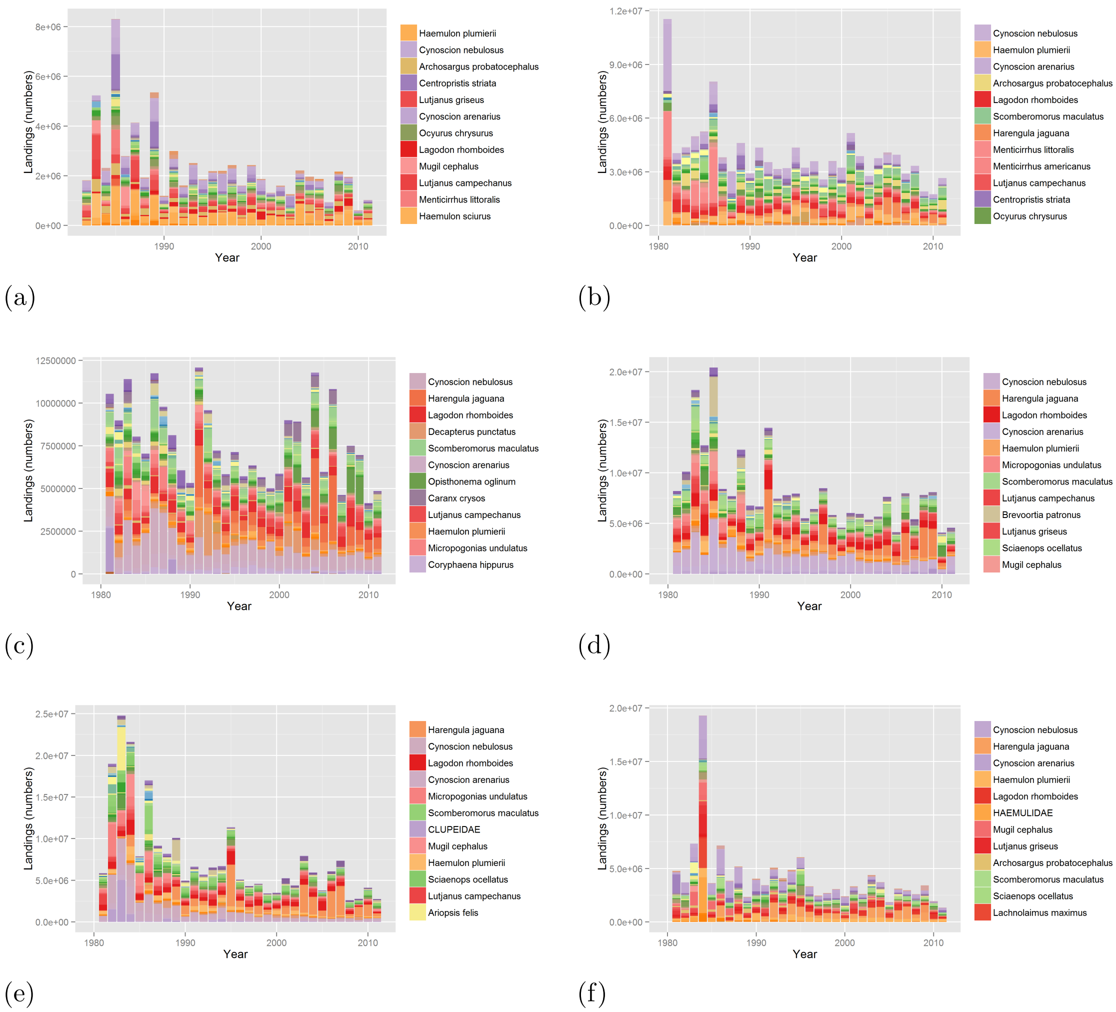
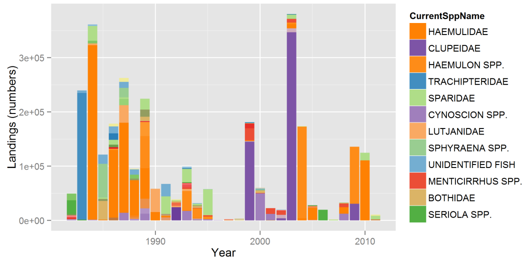
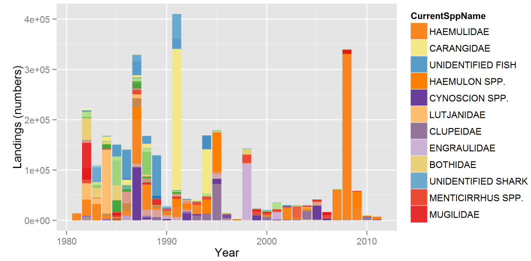


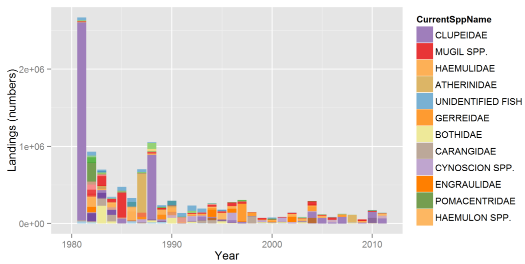
Figure A.7: Species Composition Time Series of Seasonal U.S. Recreational Landings. Species compositions are shown for wave 1, Jan. - Feb. (a), wave 2, Mar. - Apr. (b), wave 3, May. - Jun. (c), wave 4, Jul. - Aug. (d), wave 5, Sep. - Oct. (e), and wave 6, Nov. - Dec. (f). Legend shows only the seven most common species.



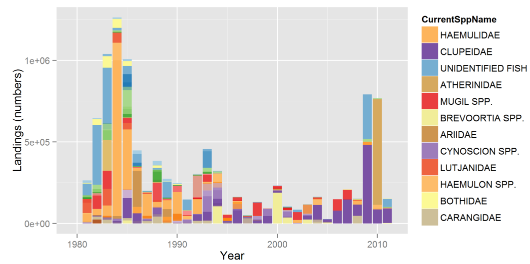
(a)



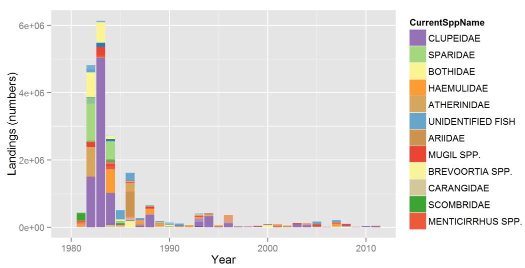
(b)



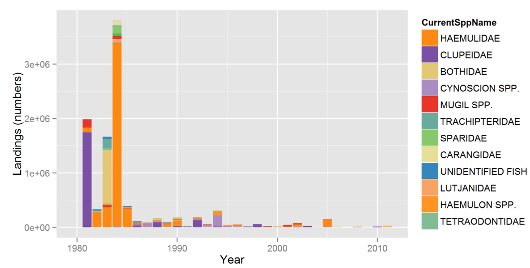
(c)



(d)

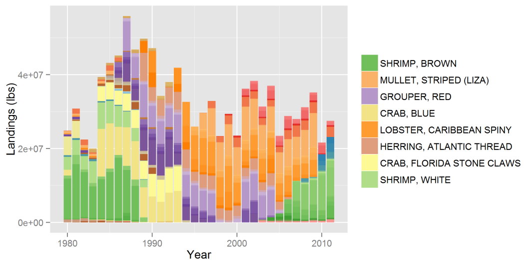


(e)

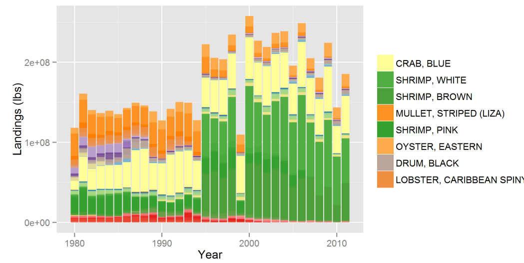


(f)

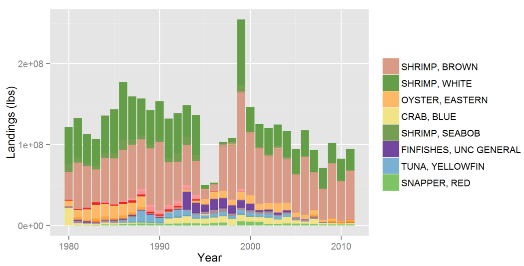
Figure A.8: Species Composition Time Series of Seasonal U.S. Recreational Ambiguous Landings. Species compositions are shown for wave 1, Jan. - Feb. (a), wave 2, Mar. - Apr. (b), wave 3, May. - Jun. (c), wave 4, Jul. - Aug. (d), wave 5, Sep. - Oct. (e), and wave 6, Nov. - Dec. (f). Legend shows only the seven most common species.



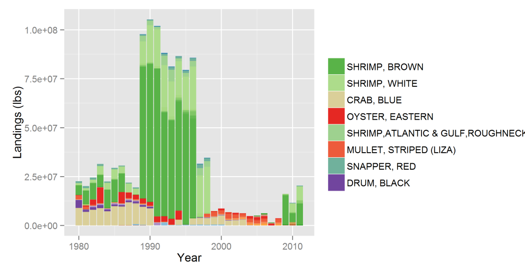
(a) Alabama



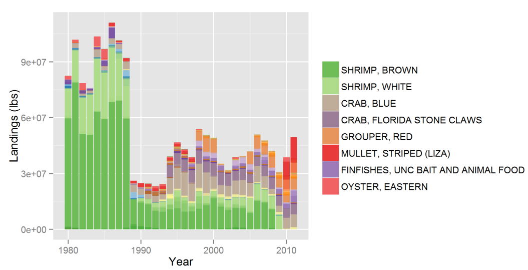
(b) Florida



(c) Louisiana

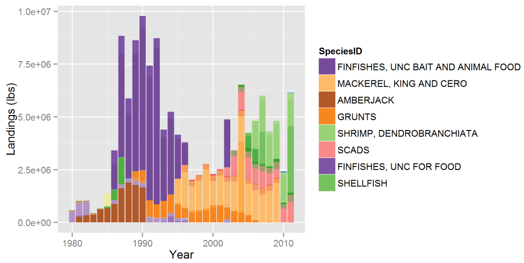


(d) Mississippi

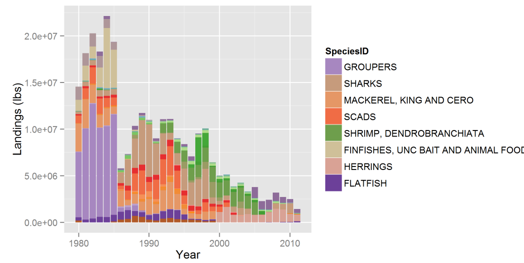


(e) Texas

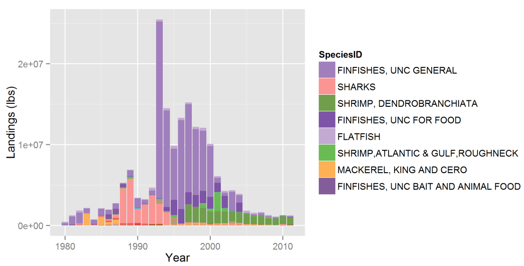
Figure A.9: Species Composition Time Series of United States Commercial Data by State. Menhaden landings were excluded from the figures. Legend shows only the seven most common species.



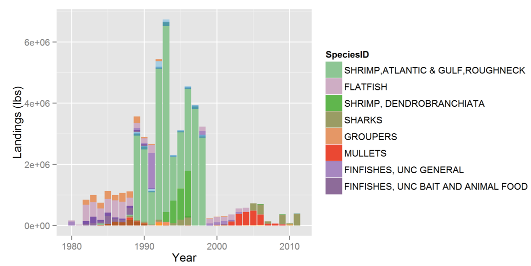
(a) Alabama



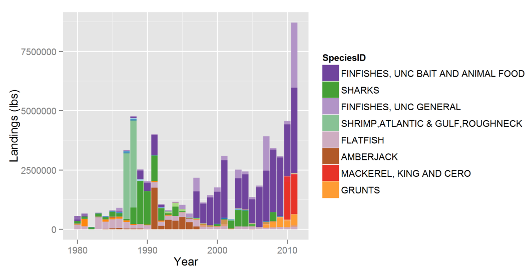
(b) Florida



(c) Louisiana

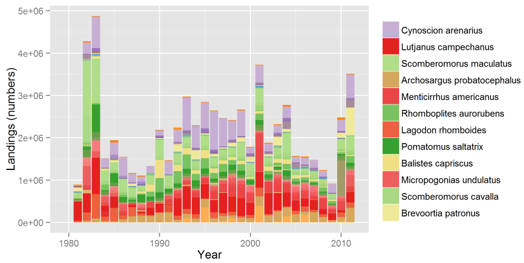


(d) Mississippi

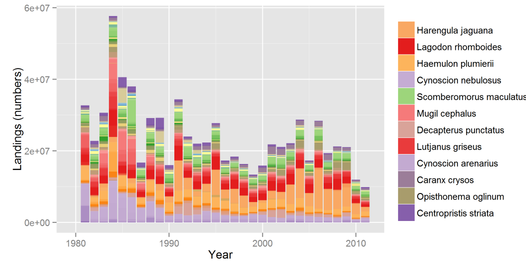


(e) Texas

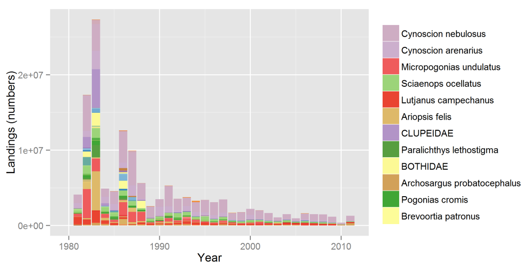
Figure A.10: Species Composition Time Series of United States Ambiguous Commercial Data by State. Legend shows only the seven most common species.



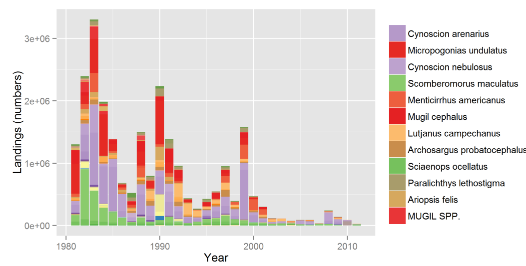
(a)



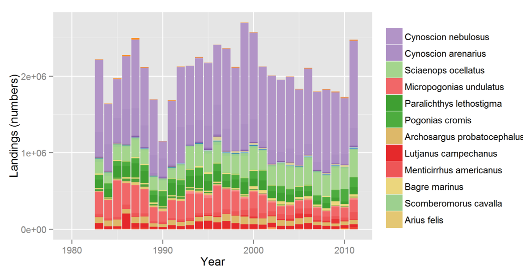
(b)



(c)

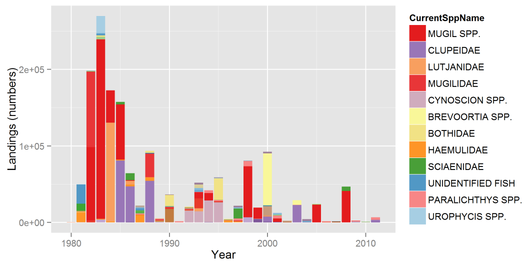


(d)

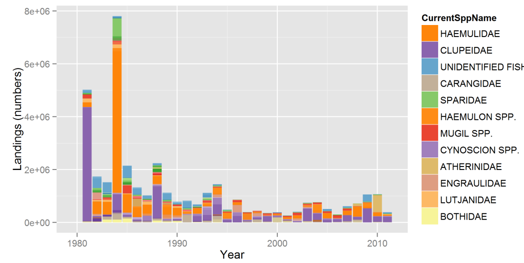


(e)

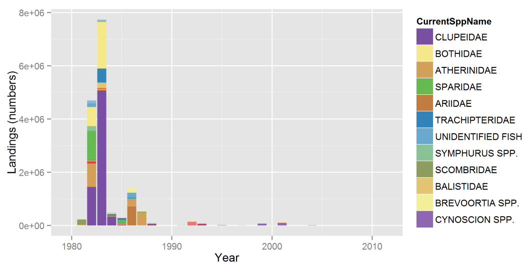
Figure A.11: Species Composition Time Series of United States Total Recreational Data by State. Legend shows only the seven most common species.



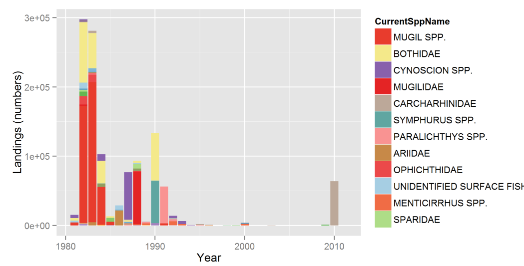
(a)



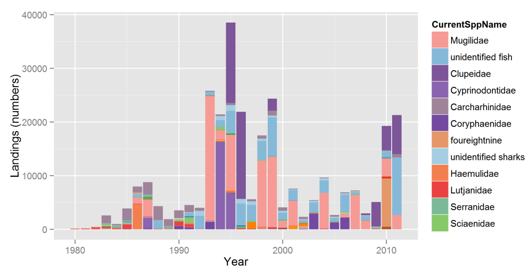
(b)



(c)

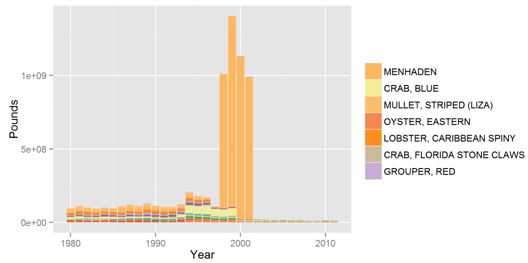


(d)

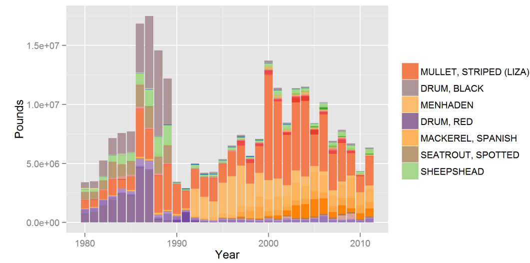


(e)

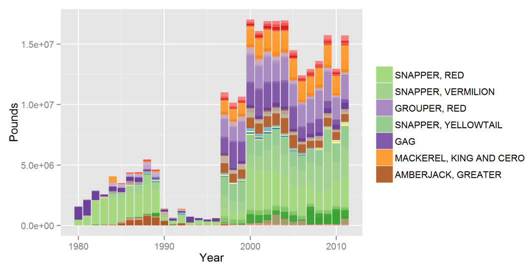
Figure A.12: Species Composition Time Series of United States Ambiguous Recreational Data by State. Legend shows only the seven most common species.



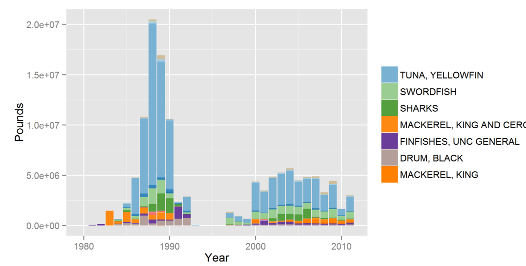
(a) Combined Gears



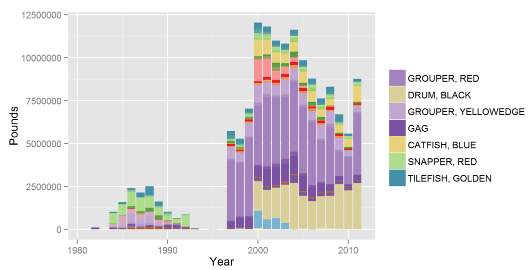
(b) GillnetEst



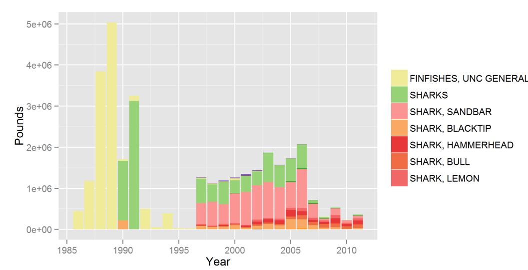
(c) HLReefShf



(d) LLPelagc

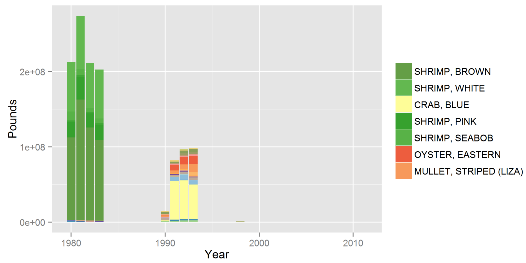


(e) LLReefShf

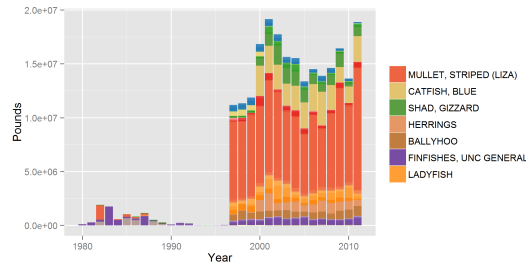


(f) LLShkShf

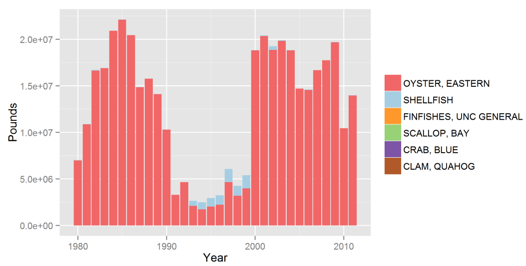
Figure A.13: Species Composition Time Series of United States Total Commercial Data by Gear. Plot legends are restricted to only show seven identifications with with the most landings data associated to the plot.



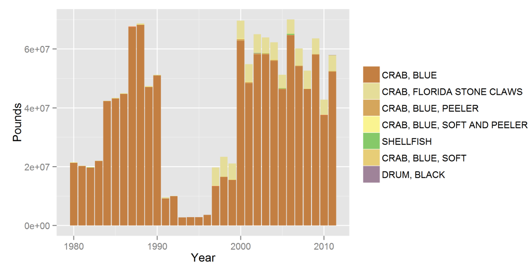
(a) Not Coded



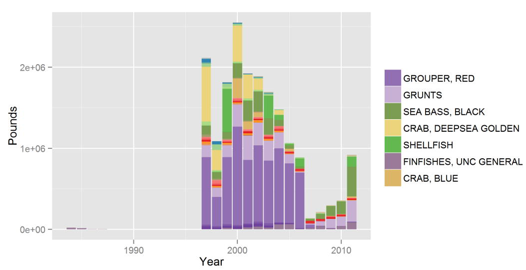
(b) OtherUS



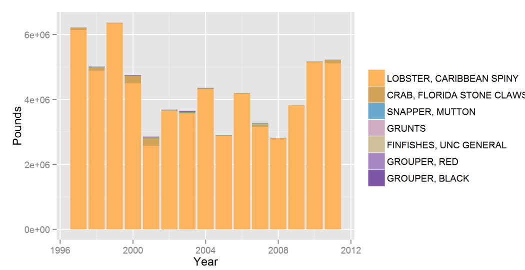
(c) OytEst



(d) PotCrbEst

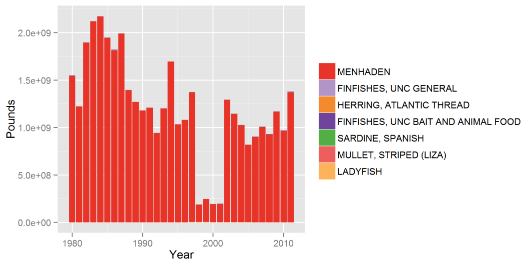


(e) PotCrbShf

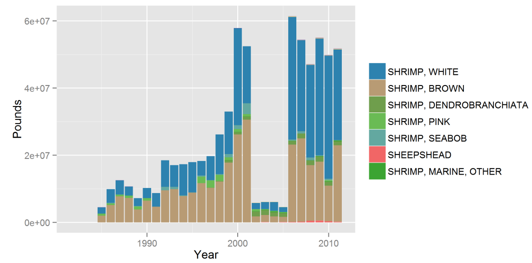


(f) PotLbtShf

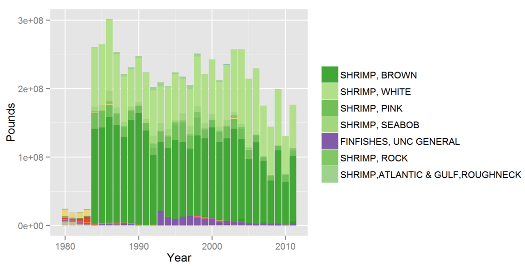
Figure A.13: Continued.



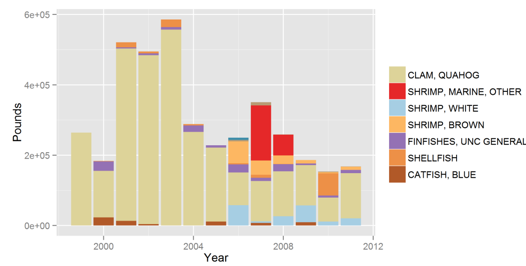
(a) SeineMenShf



(b) TwlShpEst

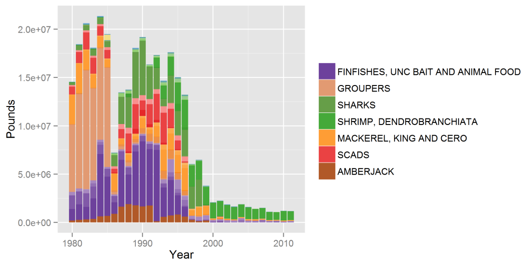


(c) TwlShpShf

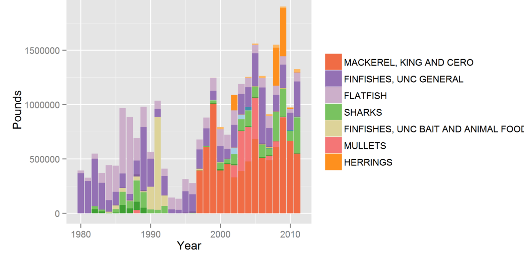


(d) Unspecified Gear

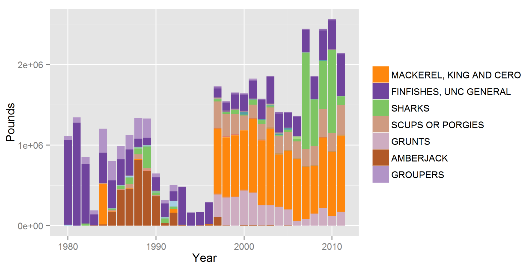
Figure A.13: Continued.



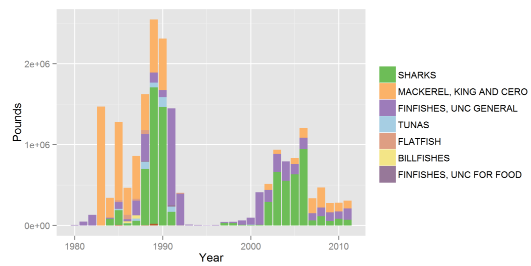
(a) Combined Gears



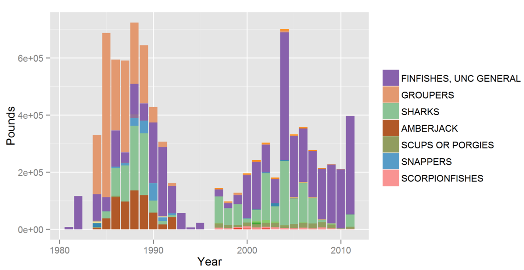
(b) GillnetEst



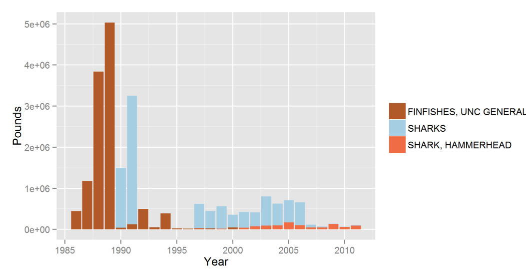
(c) HLReefShf



(d) LLPelagc

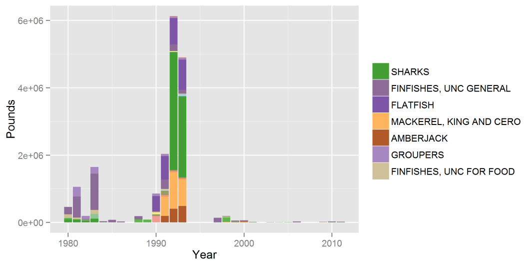


(e) LLReefShf

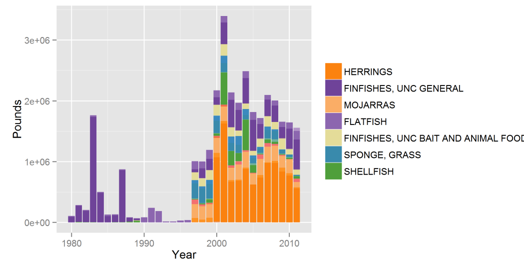


(f) LLShkShf

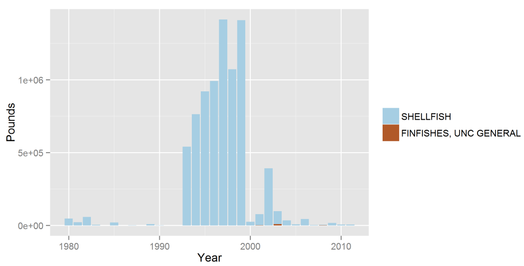
Figure A.14: Species Composition Time Series of United States Ambiguous Commercial Data by Gear. Plot legends are restricted to only show seven identifications with with the most landings data associated to the plot.



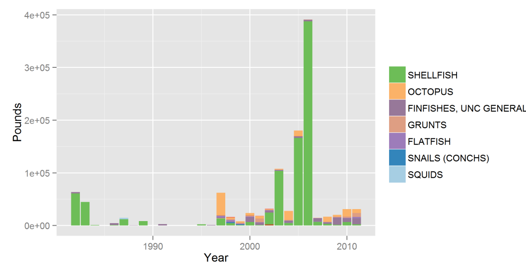
(a) Not Coded



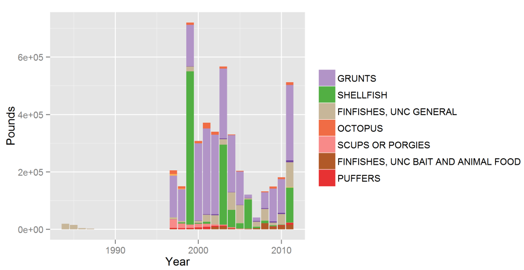
(b) OtherUS



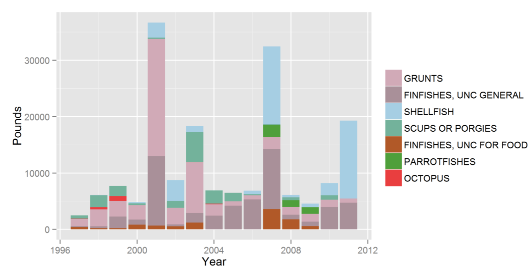
(c) OytEst



(d) PotCrbEst

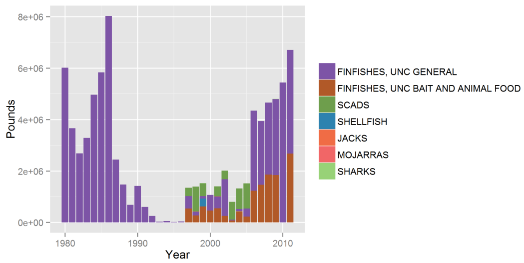


(e) PotCrbShf

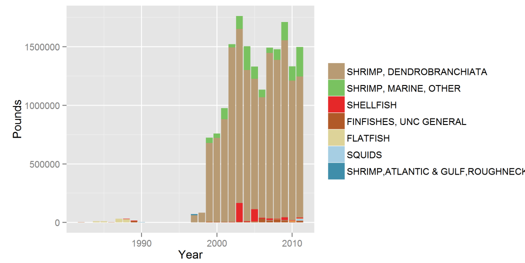


(f) PotLbtShf

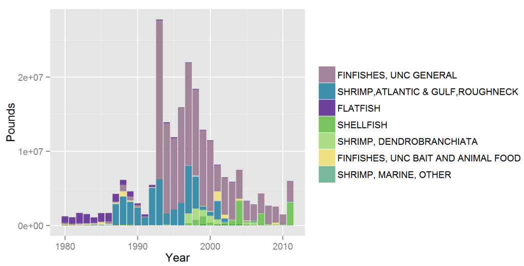
Figure A.14: Continued.



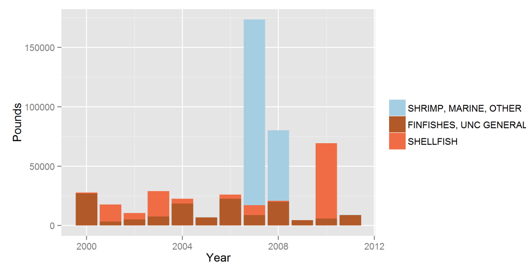
(a) SeineMenShf



(b) TwlShpEst



(c) TwlShpShf



(d) Unspecified Gear

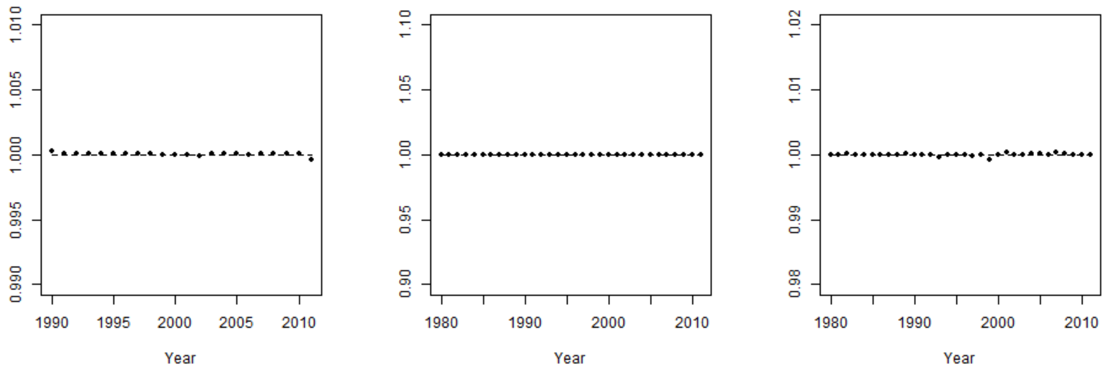
Figure A.14: Continued.

A.4.0.1 Landings Data Discrepancies

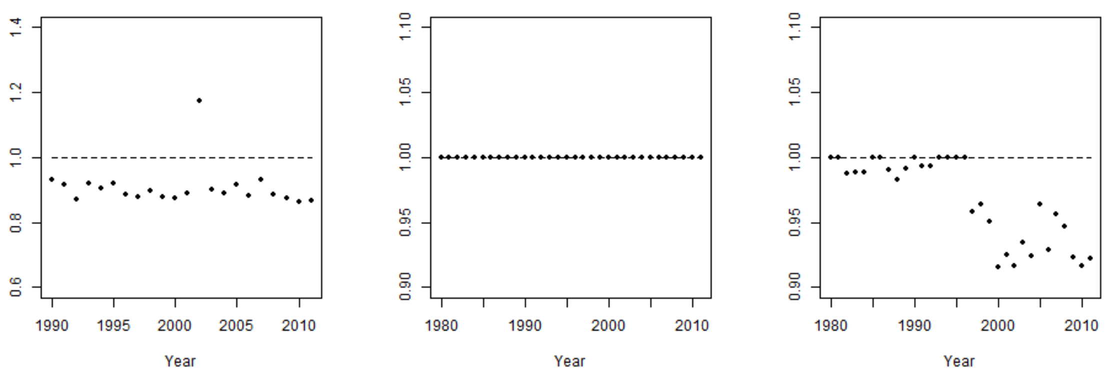
To evaluate discrepancies between annual landings datasets and itemized landings datasets, plots were constructed showing the changes in the ratios comparing i) total landings from itemized datasets and total landings from annual datasets, and ii) total number of landed groups from itemized datasets and total number of landed groups from annual datasets.

U.S. commercial data series have some discrepancies between itemized data series and the annual data series (Figure A.15). The landings dataset itemized by season tends to have more landings represented than the annual landings dataset (Figure A.15a), but less identified taxonomic groups (Figure A.15d). The landings dataset itemized by state and the annual landings dataset tend to have the same amount of landings (Figure A.15b), as well as the same number of identified groups (Figure A.15e). The landings dataset itemized by gear appears to have less landings represented than the annual dataset (Figure A.15c), as well as fewer identified groups (Figure A.15f).

U.S. recreational data series have more discrepancies between itemized data series and the annual data series (Figure A.16). The landings dataset itemized by season tends to have more landings represented than the annual landings dataset (Figure A.16a). In the earlier years, the seasonal dataset tends to have more identified groups, but since 1990 the annual dataset tends to have more identified groups (Figure A.16c). The landings dataset itemized by state tends to have more landings represented than the annual landings dataset (Figure A.16b). In the earlier years, the dataset itemized



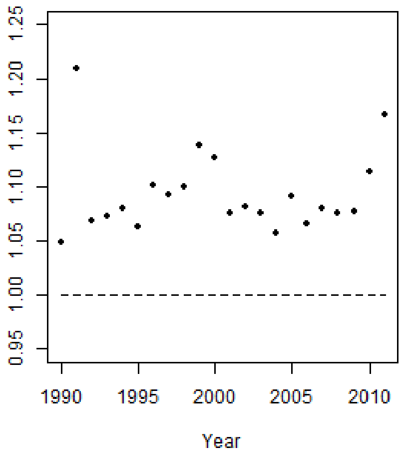
(a) Seasonal Data Series (b) State Data Series (c) Gear Data Series



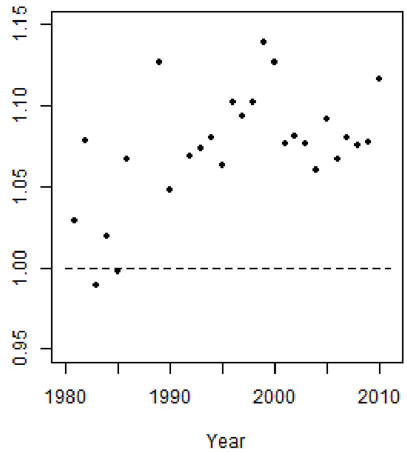
(d) Seasonal Data Series (e) State Data Series (f) Gear Data Series

Figure A.15: Data discrepancies between NOAA's landings data itemized by season (a,d), state (b,e), and gear (c, f) and annual landings data. Panels (a - c) show the ratio between landings from itemized data series and landings from annual data series. Panels (d - f) show the ratio between the number of groups identified in itemized data series and the number of groups identified in annual data series.

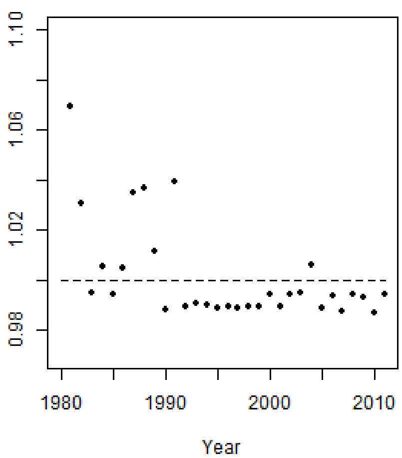
by state tends to have more identified groups, but since 1990 the annual dataset tends to have more identified groups (Figure A.16d).



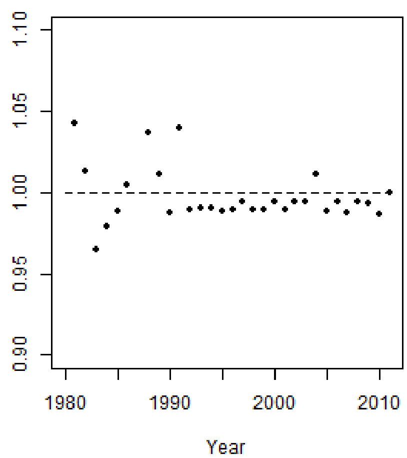
(a) Seasonal Data Series



(b) State Data Series



(c) Seasonal Data Series



(d) State Data Series

Figure A.16: Data discrepancies between MRIP's landings data itemized by season (a,c), and state (b,d), and annual landings data. Panels (a - b) show the ratio between landings from itemized data series and landings from annual data series. Panels (c - d) show the ratio between the number of groups identified in itemized data series and the number of groups identified in annual data series.

A.5 Additional Results for Section 2.3.1.1

A.5.1 Historical Landings Time Series for Atlantis

Information was developed for the calibration and implementation of the Gulf of Mexico Atlantis model. Historical time series of U.S. commercial, U.S. recreational, Mexican commercial, and Cuban commercial landings for model calibration are shown in Tables A.3, A.4, A.5, and A.6 (respectively). Average seasonal distributions for functional groups identified in the U.S. commercial, U.S. recreational, and Mexican historical time series are shown in Table A.7, A.8, and A.11 (respectively). The proportions for distributing landings across fleets are presented in Table A.10.

Table A.3: United States Historical Commercial Landings by Atlantis Functional Group (tonnes)

Group	1980	1981	1982	1983	1984	1985	1986	1987	1988
GAG	643.7	898.8	1069.9	788.4	703	819.7	771.8	697.7	551.8
RGR	1316.8	1542.5	1792.9	2715	2466.6	2598.3	2863.5	3047.2	2151.2
SCM	0	0	0	0	0	14.4	174	164.4	125.3
SSR	218.9	256.4	259	269.3	340	279.1	993.6	900.7	715.7
DSR	223.2	372.8	406.5	280.7	294.9	403.5	703	711.9	1002.2
RSN	2273.4	2706.1	2907.1	3302.6	2604.5	2013	1798.5	1522.7	1841.6
VSN	139.9	164.1	180.4	258.8	652.4	670.7	793.5	728.2	705.1
LUT	715.8	767.7	1194.2	1002.6	939.3	797.4	960.6	1226.2	1085.6
BIO	0	0	0	0	0	0	0	0	0
LRF	72.6	84.8	76.7	85	142.5	110.8	87.2	152.9	119.5
SRF	267	509.9	490.2	475.7	727.3	593	475.1	818.3	878.1
BDR	2691.9	2954.4	1932.2	2389.5	2691.5	3180.2	3455.5	4828.2	4748.5
RDR	1240.2	1249.7	1103.3	1422.1	1972.6	2881.8	6410.6	2223.9	136.5
SEA	2234.7	2112.4	1847	1921.3	1684.3	1491.8	1862	1878	1599
SCI	3474.5	3612.1	2147.5	1282	1121.7	939.6	844.1	1120.5	827.2
LDY	612.5	1814.4	1494.3	1888	1560.3	1342.9	2032.6	2322.7	1881.5
MUL	13896.6	15270.3	12211.1	11718.3	10292.9	9006.8	11899.1	10758.6	11602.5
POM	300.8	247.4	320.7	274.4	247	213.1	240.2	250.1	263.1
SHP	539.9	474.8	558.5	760.6	683.8	749.5	791.7	1518.3	1439.1
SNK	0	0	0	0	0	0	0	0	0
FLT	697.6	713.2	990.2	931.3	937.2	987	1034.5	1207.7	724.4
ODF	569.9	694.1	728.4	792.3	1292.8	1046.6	740.5	1377.7	1155.4
SDF	42.1	55.7	55.9	62.4	112.1	81.5	45.7	96.4	70
YTN	33	18.2	63.6	100.2	376.7	1505.9	3393.6	4179.4	7815.8
BTN	5.1	12.1	16.4	38.8	70	69.1	108.5	175	138.6
LTN	0.7	0.5	2.9	2.3	1.9	2.3	0.1	1.5	108.7
OTN	0	0	0	0	0	0	0	0	0
SWD	837.8	532.3	587.9	327.7	307.2	511.7	320.9	666.3	970.1
WMR	0	0	0	0	4.1	9.4	39.1	24.6	0.2
BMR	0	0	0	0	0.9	5	16.2	16.4	3.2
BIL	0	0	4.3	1.2	5	10.2	11.2	18.1	0
AMB	81.6	107.5	102.3	127.5	240.9	346.2	506.4	705.7	932.4
JCK	2424.6	2125.5	2335.1	2261.8	1679.1	1499.2	1414.9	2034	2868
KMK	1543.2	2399.6	662.4	1437.7	978.8	826.5	917	1109.1	865
SMK	887.9	1670.2	1524.1	1031.5	1596.8	1375.8	1244.5	1300.6	1054.4
SAR	1348.2	1264.6	1268.3	1217.6	1601.9	2069.4	2774.4	2925.9	1594.2
LPL	1226.1	860	869.7	705.8	641.8	588.2	631.3	684.2	1115
DWF	0	0	0	0	0	0	0	0	0
MEN	702081	553684.4	861426.8	962982	985411.7	884189.2	830743.7	911642.5	639787.1
PIN	34.6	45.9	46	51.4	92.3	67.2	37.6	79.4	57.6
MPL	71.8	91.8	115	125.5	180.5	132	68.5	151.8	128.3
SPL	158.2	334.2	824.5	939.2	415.7	406.2	1417.6	825.8	1678.8
TIP	60.6	60.6	60.6	65.5	89.5	83.1	596.5	825.1	1460
BEN	0	0	0	0	0	0	0	0	0
LGS	155.6	258.3	304.5	352.9	306.7	417.6	855.9	2052.8	3781
FIL	0	0	0	0	0	0	0	0	0
SMS	0	0	0	0	0	0	0	0	0
RAY	0	0	0	0	0	0	40.2	0	77.7
BSH	49861.9	72678.6	56121.7	48553	62929.2	63706	72075.9	67305.6	59535.4
WSH	29835.2	32212.8	27443.7	29559.9	39196.7	41175.1	49417	37339.1	31600.1
PSH	9345.8	13625.5	8454.8	9196.7	10632.4	11526.7	8502.1	7557.5	6583.4
OSH	6276	4700.6	3073.6	3772.8	3546.5	3491.3	8644.1	5572.3	4855.6
TUR	0	0	0	0	0	0	0	0	0
BCR	19444.9	19248.4	16761.2	18362.6	25558	25335.4	24047.6	35592.7	35992.1
SCR	1710.6	1894	2583.3	2173.4	1798.3	1847.2	1834.9	2160.4	2367.2
LOB	2594	2292.7	2594	1708.4	2772.1	2787.6	2010.5	2513.2	2648.5
SPG	0	0	0	0	0	0	0	0	43.8
CMB	0	0	0.2	0.9	0	0	0.6	0.5	1.5
OYS	7039.7	8785.8	11408.8	13229	12520.5	12024.8	10220.3	8515.2	8103.4
BIV	7.9	21.3	5.9	17	44	55.6	8	8.9	33.5
SQU	26.9	43.9	35	32.1	55.4	67.2	80.1	75.3	104.7

Table A.3: Continued

Group	1989	1990	1991	1992	1993	1994	1995	1996	1997
GAG	767.9	814.4	710.1	754.8	847.6	734.4	751.1	712.6	727.4
RGR	3342	2181.5	2310.8	2024.5	2893.8	2223.9	2152.8	2020.4	2199.2
SCM	137.5	131.7	163	146.8	164	112	123	122.5	153.4
SSR	967.2	919.1	715.1	625.5	1049.3	747.5	545.1	646.6	572.8
DSR	548.1	817.3	741.2	813.7	679.9	939.7	698.7	513.4	610.4
RSN	1406.1	1207.5	1016.5	1380.3	1544.5	1475.1	1339.9	1973.6	2187.7
VSN	752.4	1113.1	814.1	1028.7	1233.6	1197.1	987.9	828.8	964.3
LUT	1348	1213.6	1396.2	1324.1	1700.4	1500.9	1267.2	1070.3	1202.3
BIO	0	0	3.6	1.5	0.3	0.5	0.5	0.3	0.4
LRF	170.2	198.6	198.3	202.7	465.3	361.7	250.5	273.5	266.2
SRF	812.9	829.3	812.2	831.5	1846.9	1396.3	1026	1128.4	1200.1
BDR	2490	1722.4	1215.7	1801.4	1890.9	2596.1	2737	2729.9	2569.6
RDR	81.6	9.5	17.3	35.2	58.7	32.6	19.3	25.9	21.7
SEA	1485	1010.3	1312.8	1131.5	1552.5	1446.2	882.3	806.6	686.5
SCI	1071.1	1171.8	1154.2	1258.8	2232.4	1683.1	1765.3	1294	1277.8
LDY	2073.1	2629.7	2058.3	2073	1819	1935.4	1245.1	844	858.1
MUL	12818.3	13307.5	11624.9	11675.4	13804.4	12392.1	9624.6	7023.6	7941.1
POM	245.9	327.6	278.5	253.6	253.1	266.4	179	120.6	261.9
SHP	1927.4	1796.3	1472.6	1880.7	2113	1964.9	1818.6	1558.8	1685.3
SNK	0	0	0	0	0	0	0	0	0
FLT	813.8	831	1062.9	1022.7	1712.5	1399.9	995.8	847.3	841
ODF	1550.8	1765.6	1859.3	1666	3971.5	2841.7	1932.8	2338.9	2254.6
SDF	105.3	121.7	123.7	119.2	338.8	221.4	144	192.2	186.7
YTN	5786.2	3665	2567.7	4229.4	2910.3	2105.4	1588	2125.2	2407.4
BTN	66.4	102.1	120.4	81.4	47	34.2	26.9	22.5	16.9
LTN	49.2	51.6	51	460.7	263.7	28.4	29.5	89.1	171.9
OTN	0	0	0	0	0	0	0	0	0
SWD	957.1	445.8	632.5	590.1	466.9	339	583.6	752.9	593.8
WMR	0	0	0	0	0	0	0	0	0
BMR	0	0	0	0	0	0	0	0	0
BIL	0	0	0	0	0	0	0	0	0
AMB	886.9	555.2	817.3	461.2	729.5	578.2	573.1	576.6	507.4
JCK	3101.6	2981.6	3031.7	3062.6	3497.9	2499.3	1403.1	661.1	766.1
KMK	788.7	912.4	881.4	1045.9	1352.3	1140	1007.7	1363	1367.4
SMK	1448.2	1212.7	1646.6	1816.2	1303.6	1310	769.1	412.6	367.3
SAR	1079.1	974.4	760.8	848.4	772.2	984.2	173	498.6	413.3
LPL	1177.4	1258.3	1881.7	1814.9	1728.6	1958.5	1387.8	1211.4	1287.6
DWF	0	0	0	0	0	0	0	0	0
MEN	583185.8	539421.6	552946.5	432763.4	551534.6	774825.8	472059.7	491689.1	622013.7
PIN	85.8	99.5	106.6	112.9	296.5	221.3	128	166.5	168.3
MPL	234.3	243.7	250.3	290.6	635.3	487.2	354.7	383.7	333.6
SPL	4339.6	2160.8	2475.8	2676	3216.9	3059.7	2082.6	2449.5	2425.9
TIP	1594.7	960.3	388.2	444.6	476.8	1002.3	708.7	489.9	377.6
BEN	0	0	0	0	0	0	0	0	0
LGS	5543.5	4005	3505.5	3237	1757.1	2000.1	1914.3	1827.7	1727
FIL	0	0	0	0	0	0	0	0	0
SMS	0	0	0	0	0	0	0	0	0
RAY	224.9	280.9	132.7	122.9	73.3	33.8	45.3	8.7	0.1
BSH	69213.4	76343.7	64545.4	50898.6	50212.5	49684.1	57209.3	55140.8	49559.2
WSH	25567.2	30912.2	32000.3	33681.8	27581.2	32467.8	34996.8	25561.6	27993.3
PSH	6274.6	5470.3	4921.5	4651.9	6937.8	7313.9	10356.9	13969.2	9227.5
OSH	4362.6	3183.9	3311.3	10745.2	8642.4	5862.2	4241	7716.2	9957
TUR	0	0	0	0	0	0	0	0	0
BCR	25240.2	26467.1	29866.1	31664.8	29781.1	24164.4	24800.9	28331.3	29095.9
SCR	2337.2	2853.7	2843.4	3013.5	3021.5	2976.1	2713	2924.7	2897.2
LOB	3265.1	2467.1	2762.1	1840.7	2066.8	2885.6	3537.6	3386.7	3276.1
SPG	277.5	360.5	381.2	338.9	338.7	387.8	357.4	324.3	236.4
CMB	0	0	0	0.7	1.1	1.3	0	1.7	1.4
OYS	7177.7	5600	5607.1	7414.2	8252.6	9219.5	10016.8	10571	10881.1
BIV	1322.2	28.7	0.4	2.7	2206.9	868.9	23.8	94.2	180.8
SQU	61.4	58.4	38.7	69.2	54.2	64.5	70.6	97.2	68.7

Table A.3: Continued

Group	1998	1999	2000	2001	2002	2003	2004	2005	2006
GAG	1151.8	952.3	1053.9	1470.5	1385.6	1239.8	1369.9	1233.8	661.3
RGR	1799.5	2705.3	2646.6	2697.4	2678.4	2239.5	2605.2	2454.4	2333.2
SCM	115.9	138	104.4	143.3	163.4	168.3	172.6	164.9	117.3
SSR	506.8	530.8	521.9	370.6	343.9	364.9	347.2	221	217.9
DSR	513.8	763.6	899	737.5	756	976.4	767.6	664.1	614.8
RSN	2129.2	2212.2	2197.2	2116.5	2187.7	2016.2	2121.4	1863.7	2103.5
VSN	785.9	899.2	662.2	778	911.1	1095.8	968.1	847.4	800.3
LUT	1056.5	1178.2	1108.9	977.7	996.5	936.3	1009.8	856.1	836.8
BIO	0.2	0.3	0.2	0.1	0.3	1.1	0.4	0.7	0.4
LRF	203	239	246.5	133.2	166.2	142.8	141.4	82.1	87.8
SRF	940.3	950.2	916	602.1	648.6	588.7	614.4	542	437.6
BDR	2066.2	2308.3	2630.1	2560.1	2510.1	2379.4	2526.1	2060.4	1909.5
RDR	24.4	26.2	24.6	13.8	11.4	13.3	11.2	15.5	12.2
SEA	393.2	403	342	239.2	219.3	177	145.3	113.8	107.7
SCI	992.9	972	856.8	477.1	423.3	402.8	378.9	246.4	280.8
LDY	970.4	1917.3	154.8	544.2	760.5	866.2	665.1	870.8	795.8
MUL	7153.1	9092.1	7625.7	7295.6	5742.8	5877.3	6237.1	4092.6	5772.9
POM	305.8	210.5	222.6	166.1	135.9	130.1	108.8	102.8	160.9
SHP	1299.6	1661.8	1433	1186.3	1036.3	1072.1	911.3	681.5	442.5
SNK	0	0	0	0	0	0	0	0	0
FLT	729.4	774.7	695.9	435.2	438.6	385	370.4	281.8	277.5
ODF	1794.4	1778.6	1706.3	1125.4	990.6	968.7	879.4	641.2	577.7
SDF	140.3	136.1	124.1	59.6	56	53	48.5	31.6	36.7
YTN	1721.3	2369.2	1957.1	1329.6	1927.4	1711.6	1584.6	1202.1	1096.2
BTN	13.7	36.1	34.5	16.9	29.5	38.5	66.3	43.5	16
LTN	105.3	232.1	54.1	193.3	207.6	506.2	81.1	110	144
OTN	0	0	0	0	0	0	0	0	0
SWD	510.5	447.8	467.8	347	413.2	375.7	402.4	345.8	267
WMR	0	0	0	0	0	0	0	0	0
BMR	0	0	0	0	0	0	0	0	0
BIL	0	0	0	0	0	0	0	0	0
AMB	317.6	354.2	415.7	332.9	357.2	451.1	442.7	337.4	286.9
JCK	1176.7	891.7	835	878.9	775.8	967.6	1013	956.1	736.8
KMK	1374.7	1363	1135.5	1281.9	1218.1	1098.2	1273.6	1113.9	1515.1
SMK	303.9	552.1	610.3	701.8	533.8	839.6	617.4	819.5	820.3
SAR	371.5	312.4	621.7	626.6	653.4	725.3	964	458	1023.2
LPL	1162.7	947.4	840.7	1018.6	1024.6	982.8	894.7	539.2	623.9
DWF	0	0	0	0	0	0	0	0	0
MEN	495684.2	694272.6	591487.6	528569.9	585341.5	518362.8	464162.4	369914.8	408881.9
PIN	128.9	124.3	116.2	64.4	61.1	62.2	60.4	46.3	52.5
MPL	274.7	280.5	274.5	192.9	175	190.4	199.7	131.1	180.6
SPL	2543.2	2559.8	2453.7	2675.8	2919.6	2311.9	2728.5	2012.7	1327.2
TIP	521.8	436.8	351.8	329	250.9	597.4	368.9	242.2	364.8
BEN	0	0	0	0	0	0	0	0	0
LGS	1924.3	691.7	658	775.9	1053.2	1230.2	1059.9	907.2	1238.4
FIL	0	0	0	0	0	0	0	0	0
SMS	0	0	0	0	0	0	0	0	0
RAY	10.2	0.4	23.4	0	22.1	1.3	6.6	0.6	8.6
BSH	59092.6	60651.8	71592.5	65725.2	55472.7	62187.3	54625.3	43559.1	64925.7
WSH	39036.9	39187.3	49640.8	37874.8	38050.8	43369.7	51317.1	46179.7	60594.6
PSH	12436.6	5912.8	5417.9	7000.7	7760.6	6844.1	7015.1	6508.3	4379
OSH	9517.6	4902.7	4391.8	6020.2	4776.8	4178.2	3086.1	1938.6	1189.7
TUR	0	0	0	0	0	0	0	0	0
BCR	30715.2	31432.3	31283.1	24722.9	29953.2	29088.6	27484.8	22718.3	30612.2
SCR	3171.8	2579.9	3109.9	3031.1	2918.7	2409.1	2708.8	2058.9	2180.5
LOB	2530	3270.3	2557.2	1479.4	1914	1774.6	2099.2	1394.3	1983.5
SPG	280.2	285.1	268.1	235.8	234.2	187.3	202.1	185.5	140.2
CMB	1.2	0.7	0	0	0	0	0	0	0
OYS	9349.9	10946.5	11699.9	11622	10939.2	12291.5	11365.6	9158.7	8925.2
BIV	1293.1	1267.7	250.6	230.9	218.3	257.6	121.1	97.5	43.6
SQU	108	58.5	57.6	85	55.5	55.1	49.1	34.4	45.8

Table A.3: Continued

Group	2007	2008	2009	2010	2011
GAG	621.3	678.6	384.6	264.9	161.4
RGR	1670.5	2141.6	1990.8	1582.6	2512
SCM	147.4	149.4	135.9	84.1	69.3
SSR	251	166.2	136.8	126.3	245.2
DSR	673.7	650.7	696.5	422.2	620.9
RSN	1360	1074.2	1135.3	1478.3	1605.7
VSN	1081.3	1273.8	1722.2	956.9	1391.3
LUT	654.7	831.1	1072.7	879.6	1043.4
BIO	1.2	0.7	0.8	0.6	0
LRF	113.3	99.3	99.1	71.5	143.6
SRF	561.9	538.5	482.2	344.5	641.4
BDR	1907.3	1838.2	2254.9	2079.4	2402.6
RDR	14.1	15.6	17.1	18.7	18.2
SEA	175.6	149	146.3	129.8	225.8
SCI	446.2	357.9	320.3	295	597
LDY	547.3	664.5	389.2	660.5	415.3
MUL	4052.1	4799	5126.8	4064	6455.8
POM	156.3	147.3	125.5	39.4	33.2
SHP	631	664.3	690.6	611.3	562.2
SNK	0	0	0	0	0
FLT	347.8	303.9	307	236.9	508.5
ODF	897.1	801.3	884.1	680.7	1416.8
SDF	64.7	49.7	43.3	37.2	91.4
YTN	1348.8	731.3	1114.4	302	658.1
BTN	32.9	25.2	17.4	20.5	3.1
LTN	127.7	34	119.6	266.2	26.7
OTN	0	0	0	0	0
SWD	337.9	301.2	398.4	174.1	320.4
WMR	0	0	0	0	0
BMR	0	0	0	0	0
BIL	0	0	0	0	0
AMB	280.6	228.7	287.1	452.4	386.4
JCK	834.9	647.4	599.3	633.2	681
KMK	694.6	1017.5	1306.6	1042.8	1208.2
SMK	500.6	610.9	890.5	615.7	660.9
SAR	3.8	986	628	909.3	5.4
LPL	731	768.3	1081.5	271.9	1007.6
DWF	0	0	0	0	0
MEN	456034.1	420734.8	528882.8	438650	623408.5
PIN	88.3	61.2	53.8	134.2	102.9
MPL	213.7	185.9	155.3	158.3	165.5
SPL	1395.2	1867.6	2009.5	1496.9	1565.7
TIP	382.2	117.3	121.4	175.4	228.7
BEN	0	0	0	0	0
LGS	477.9	585.6	650.9	652.9	471
FIL	0	0	0	0	0
SMS	0	0	0	0	0
RAY	5.5	15.4	2.8	1	3.2
BSH	52838.1	36466.2	56968.4	33909.1	54333.2
WSH	46157.7	44995	53315.2	42053.1	41705.1
PSH	2449.4	3286.9	3132.5	4539.3	3845.3
OSH	1171.1	894.8	581.4	1006.9	1746.2
TUR	0	0	0	0	0
BCR	26416.7	22346.4	27795.8	18694.7	25464
SCR	2686.7	2777.6	2420.4	2318.8	2512.9
LOB	1558.4	1355.4	1792.4	2398.3	2438.3
SPG	200.8	184.3	91.5	100.9	46.7
CMB	0	0	0	0	0
OYS	10262.4	9369.8	10358	7199	8439.7
BIV	59.4	66.5	68	70.7	76.3
SQU	23	33.2	30.4	39	60.4

Table A.4: United States Historical Recreational Landings by Atlantis Functional Group (tonnes)

Group	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
GAG	992.2	829.9	1459.2	2893.6	884.7	2980.5	1631.8	1110.3	1699.8	1049.8
RGR	446.1	446.1	739.6	1577.6	3218	1533	1088.8	664.4	1123.1	1252.5
SCM	34.1	34.1	40.6	54.9	5.2	6.9	52.4	10.1	19.4	21.5
SSR	1236.6	1236.6	1347.4	4753.9	1678.5	2507.4	4026.8	2311.6	2976.2	1846.4
DSR	21090.8	21090.8	22237.9	12566.1	12845.7	87930.8	22805.7	10596.5	9651.9	45938.7
RSN	3669.7	3669.7	3255.4	5683.7	2095.1	2069.7	1816.5	1455.6	1757.4	1537.4
VSN	52.2	52.2	6.1	34.3	44.9	128.4	482.3	500.2	665.1	416.1
LUT	138125.2	138125.2	1535.9	64608	123888.6	7214.3	29803.7	54095.4	46023.9	27297.3
BIO	19.4	19.4	5.6	139.7	16.8	8	14	15.5	4.7	61.5
LRF	941.7	941.7	561.3	1262.1	2526.9	233.8	249.4	2004.8	277.2	106.7
SRF	2175.8	2175.8	5854.4	1239.6	860.1	660.8	2089.8	2728.3	1002.6	695.3
BDR	685.7	685.7	1349.4	1589.8	800.5	912.8	1350.7	1799.6	1098.9	936.3
RDR	2248.2	2248.2	3428.2	3703.3	3577.6	3435.9	2853.5	2675.4	1820.1	3050.1
SEA	8504.4	8504.4	10298.5	12081.6	11544.1	10475.4	12391.3	1665.1	8085.3	6172.4
SCI	1327.5	1327.5	1303.7	1112.4	1010	1045.2	1442	120.4	583.6	249.1
LDY	528.9	528.9	216.2	128.5	206.8	234	172.2	130.1	152	65.3
MUL	979.3	979.3	1064.9	6272.4	10711.2	11478.4	6321.3	2674.9	3190	1072
POM	11.4	11.4	64.6	345.6	98.6	29.1	60.9	62.4	30.4	50.4
SHP	875.8	875.8	1104.8	2032.6	1499.7	1575.1	1164.5	985.8	2181.2	2346.3
SNK	31	31	23.6	35	0	16.8	7.2	18.8	19.8	8.8
FLT	312.9	312.9	3096.9	4475.3	774.4	913.4	897.4	448.8	557.8	318.7
ODF	40392.9	40392.9	232027.2	57408.7	60719.3	287598.9	245347.4	214242.1	313932.5	74275
SDF	0.9	0.9	9.5	2.5	2.2	0.6	0.9	0.5	6.5	5.5
YTN	0	0	71.3	0	109.6	0	115.4	13.7	48.6	20.2
BTN	0	0	0	4.1	9.5	0.4	2.8	6.2	0.7	0
LTN	293.7	293.7	419.7	292.4	190.4	167	743.4	610	568.7	308
OTN	6	6	5	0.6	0.5	0	1.7	2.7	0	0
SWD	0	0	0	0	0	0	0	0	0	0
WMR	87.6	81.3	30.5	12.2	16.1	6.1	5.7	16.9	3.7	0.7
BMR	43.1	66.4	3269.1	3754	453.2	11427.4	1203.9	799.3	4995.3	18.1
BIL	464.9	464.9	762.6	13	682.8	15	268.8	207.7	71.7	12.5
AMB	261	283.7	2094.5	1220.8	592.8	1055.3	2634	2106.8	1024	1588.8
JCK	1828.7	1828.7	8004.8	30669.1	13265.5	7785.2	9947.4	8595.2	7307.7	23103.9
KMK	1695.1	4536.1	5949	2360	2521.8	1309.9	1452.2	3493.6	2704.1	2237
SMK	65.7	65.7	65.7	3717.3	1504.7	1619.5	11585.1	143.4	24.3	1759.7
SAR	3.9	3.9	2	7.9	10.7	22.1	0	1.2	0	0.4
LPL	21673.1	21673.1	12376.3	15977.2	8819.5	12481.2	25097.2	15537.4	10401.7	13981.1
DWF	0	0	0	0	0	0	0	0	0	0
MEN	210	38	54	24	5	449	258	209	488	440
PIN	368.7	368.7	423.7	372.1	622.6	217.8	363.2	188.5	375.1	309.7
MPL	98	98	117.6	88.6	4.1	9.4	160.9	65.4	11.9	48
SPL	279.3	279.3	170.5	364.4	254.9	54.5	50.7	239.1	103.5	85.4
TIP	45.8	45.8	162.9	29.1	60.3	250	500	184.8	397.2	322.1
BEN	0	0	0	0	0	0	0	0	0	0
LGS	9068.6	9068.6	7832.1	10199.8	12170.8	11404.7	16225.9	7752.1	15590.6	8700.2
FIL	0	0	0	0	0	0	0	0	0	0
SMS	0	0	0	0	0	0	0	0	0	0
RAY	25.1	25.1	109.7	77	379.8	466.7	146.4	77.9	199.6	170.2
LOB	640.2	798.9	692.8	717.2	535.7	582.3	564.5	528.1	627.5	841.3

Table A.4: Continued

Group	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
GAG	571.5	1246.6	1018.7	1264.6	907.1	1224.8	1067.5	1167.1	1596.3	1688.2	2255.5
RGR	511.5	805.2	1205.1	948.5	820.2	844.8	405.4	255.1	291.7	522.9	956
SCM	2.3	8.6	14.8	17.5	31.5	2.2	5.5	30.6	36.9	46.7	12.3
SSR	353.6	236	233.9	225.6	243.6	214.5	210.1	269.5	177.2	108.9	105
DSR	15256	3815	1195.6	3289.8	3629.9	3518.9	732.6	570.3	1096	1018.4	373.3
RSN	964	1511.7	2217.9	3002.3	2263.6	1936.4	1674.6	2252.8	1769.8	1434.9	1428.4
VSN	570	627.4	657	581.2	477.9	594	283.2	300.6	152	204.5	161.8
LUT	31589.9	37691.2	39300.8	40448.9	19691	24318.1	15058.2	10916.5	9706.1	14222.9	3585.5
BIO	19.2	2.8	0	3.1	36.3	9	2	0	0	0	0
LRF	742.2	157.7	516.5	576.6	644.8	432	267.4	267.4	252.3	267.2	156
SRF	645.4	820.2	688.3	762.2	795	768.4	982.1	1156.8	497	535.1	411
BDR	463.1	619.9	773.2	775.4	664.3	713.5	651.7	915.7	1052.7	658.5	1610.9
RDR	2201.9	2724.9	4004.6	4736.5	4161.4	6144.5	6016.4	6132.4	4492.1	4984.2	7260.7
SEA	3781.7	6523.2	4760.3	4591.2	5466.8	5558.2	5332.6	5209.1	3636	5318.4	4501.9
SCI	262.6	475.9	318.5	194.8	282.7	264.5	310.5	253.1	322.9	358.3	329
LDY	58.3	39.2	105.2	30.7	84	47.5	62.6	40.1	93.4	46.3	124.3
MUL	388.8	1860.5	1067.3	1501.1	908.9	660.2	1023.2	699.9	642.6	741.1	1102.2
POM	4.1	564.4	82.3	18.5	48.6	65.3	54.7	36.2	383	72.5	47.4
SHP	1216.3	1538.3	2346.5	2201.8	1378	2405.3	1726.1	1959.6	1790.2	1815.2	1698.2
SNK	0.6	7	12.8	14.8	6.1	10.9	5.8	48.1	13.7	29.8	10
FLT	579.9	676.5	371	348.8	292.9	282	222.9	251.6	233.2	327.7	189.6
ODF	88709.9	82406.3	38978	51599.6	61849.9	76264.3	66112	60576.2	40935.4	31167.5	29843.4
SDF	0	0.6	0.7	2.1	0.6	1	0.8	2.7	1.7	0	4.3
YTN	0	39.2	76.6	312.5	30.9	0	2.9	34.8	57.1	115.1	112.8
BTN	0	1.9	0	0	15.1	0	0	0	0	0	0.6
LTN	655.1	1106.1	679.6	412.1	609.7	369.4	359.6	282.4	313.3	311.4	259.1
OTN	0.7	0	0	0	0	0	12.7	2.9	0	0	0.6
SWD	0	0	0	0	0	0	0	0	0	0	0
WMR	1.1	1	1.1	0.6	1	0.8	0.6	0.8	0.2	0.1	0
BMR	16.5	196.2	16.4	9.4	17.1	18.6	10.7	13.5	5.7	10.3	6.2
BIL	75.7	144.6	34.6	122.6	56.9	81.9	122.4	5.7	45	33.6	3.7
AMB	429.8	1345.7	1132.2	1370	732.5	394.2	583.8	538.4	295.1	384.7	470.6
JCK	6003.4	9699.6	4751	69465.3	17795.4	6885.5	3614.3	5165.3	8563.5	7714.4	19771.1
KMK	3162.3	4872.4	3236.6	4144.6	4428.8	4059.7	4750.9	4461.1	3782.1	2971.1	3498.6
SMK	2140.8	2587.2	3060.5	1931.6	1702.4	1677.1	1265.6	1218	1247.8	1854.7	1781.7
SAR	26	2.2	0.5	0.2	0	28.7	0.9	0.3	3.4	2.6	0.9
LPL	8613.7	12145.9	13422.1	17121.7	11245.4	18779.2	13452.6	20680	23391.2	17655.7	17692.6
DWF	0	0	0	0	0	0	0	0	0	0	0
MEN	135	51	138	170	189	56	82	20	47	51	207
PIN	257.5	364.8	402.4	446.7	475.3	547.3	397	604.4	788.1	487.7	852
MPL	57.7	3.5	14	27.1	28.8	15.9	26.5	229	44.8	12.3	19.2
SPL	59.2	366.7	136.6	158.9	168.7	387.3	147.1	175.6	146.7	112.1	90.4
TIP	300.1	302.1	274.9	128.6	88.6	154.6	170.1	236.9	173.9	132	287.4
BEN	0	0	0	0	0	0	0	0	0	0	0
LGS	6216.1	3521.7	1953.5	2903	2462.7	2890	5336.8	3130.8	2062.8	1366.1	1599.6
FIL	0	0	0	0	0	0	0	0	0	0	0
SMS	0	0	0	0	0	0	0	0	0	0	0
RAY	113.2	43.8	43.6	22.6	36.3	33.4	30.4	4.8	0.5	7.9	6.8
LOB	827.3	720.7	963.4	613.4	854.2	830.6	845.3	847.3	1022.5	568.4	1088.8

Table A.4: Continued

Group	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
GAG	1828.6	2011.9	1711.5	2228.7	1618.1	1087.3	1001.3	1369.5	579.8	604.3	262.8
RGR	602.3	730.8	578.7	1377.6	664.5	420	435.3	390.5	444.7	338.5	290.2
SCM	26.4	26.1	30.6	55.6	34.9	66.3	32.2	49.6	40.3	22.6	25.2
SSR	59.5	88.4	107.9	218.3	123.5	108.3	138.8	118.3	91.4	10.5	20.9
DSR	635.7	608.4	512.5	895.1	1098.3	621.9	390.5	451.9	568.3	348.6	817.3
RSN	1537.3	1982.2	1819.9	1866.2	1489.7	1735.3	1932.8	1249.2	1666.9	799.2	1626.6
VSN	303.7	248.3	288.9	396.4	123.2	161.5	176.8	161.2	167.6	114.3	302.8
LUT	3317.8	9390.9	16721.9	8973.8	3028.6	25879.3	34000.6	30384.9	12403.3	9761.6	5762.6
BIO	2.4	0	1.5	2.9	0	0	0.6	0	0	0	0
LRF	183.4	240.1	314.7	412.5	278.3	234.6	274.5	274.3	205.2	177.1	178.3
SRF	595.4	460.7	643.8	795.6	606.5	488.5	585.1	842.2	434.7	2709.7	592.7
BDR	1224.8	1238.9	1403	1341.9	1106.9	1146	1285.1	1613.7	1357.1	1310.5	1313.5
RDR	6771.9	5907.1	6706.5	7321.6	5640.4	6080.8	6801.2	7327.1	6141.1	6870.8	7945.6
SEA	3744.6	3379.4	2848.5	3254.7	2951.2	3508	3234	3250.7	2887.2	1764.6	3216.5
SCI	625.4	231.7	271.8	208.1	153.2	193.3	122.8	174.3	102.1	127.6	129.4
LDY	130.9	77.4	223.1	299.3	156.2	265.7	145.2	358.1	206.9	151.7	150.7
MUL	917.9	415.4	442.7	531.3	732	1172.4	500.2	750.1	192.8	521	787.9
POM	93	75.9	43.5	142	34.5	244.1	61.4	156.7	37.9	36.9	11.1
SHP	2168.9	1900.6	2440	3147.7	2531.8	1489	1700.7	2106.8	1847.7	1606.1	3289.8
SNK	16.9	10.4	8	35.4	4.9	3.8	3.9	1.7	3.1	0	0
FLT	262.7	197.7	189.8	198.6	133.7	104.3	146.6	118.2	133	122.4	184.6
ODF	38494.5	34102.4	40969	67956.9	44269.9	48908.3	79342.7	79270.3	48483.9	70510.6	139676.5
SDF	0.1	2.2	0	0	0.1	0.2	0.4	0.1	0	1.6	0
YTN	350.3	141.9	455.6	267	288.1	337	204.7	444.4	121.1	18.4	417.4
BTN	0	0	0	0	3.4	0	0	0	0	0	0
LTN	268.9	398.7	269.2	484.7	158.6	292.7	265.5	200.4	235.7	192.1	198.6
OTN	0	0	0	0	0	0	4.3	0	0	0	0
SWD	0	0	0	0	33.4	0	0	47.1	308.1	24.3	7.1
WMR	0.1	0	0	0	0	0	0	0	0	0.1	0
BMR	6.8	6.4	60.6	3211.9	6.5	8.9	4.5	3.5	3.4	2.2	4.3
BIL	0	0	2	0	0	8.5	3.4	0	0	0	0
AMB	571.1	928.8	1206.6	1080.2	655.3	640.5	489.2	589.8	723.2	675	430.2
JCK	13856	8727.9	7732	8953.6	4109.1	8870.1	20958.2	13329	15333.2	7257.1	2957.1
KMK	3442.4	3573.4	2996.3	2883.3	2537.1	4937.2	1884.8	881.6	1789.2	869.1	855.8
SMK	3233	2110.6	1909.6	3230.7	1678.3	2656.6	1818.6	2614.1	1651.6	1795.1	1944
SAR	4	16.8	13.6	8.5	3.5	28.5	3.6	3.8	0.7	0.3	0.4
LPL	11270.6	9787.2	9947.1	14615	9106.1	19110.4	16336.7	17906.4	18674.7	8642.5	17294
DWF	0	0	0	0	0	0	0	0	0	0	0
MEN	48	108	118	64	48	55	30	28	61	44	78.7
PIN	708.7	761.1	789.4	1253.2	587.2	395.9	632.7	921	364	920.6	680.1
MPL	11.4	8.2	16.9	61.8	0.1	21.5	29.8	36.6	18.6	0.5	0.5
SPL	456	266.2	364.8	568	260.5	1234.2	559.8	735.5	1805.4	476.6	166.1
TIP	163.2	134.1	89.7	125.6	134.2	73.1	102.9	29.8	42.6	57.3	75
BEN	0	0	0	0	0	0	0	0	0	0	0
LGS	2325.8	1092.4	950.7	1461.6	908.4	1105.8	825.9	442.7	694.4	3318.4	716
FIL	0	0	0	0	0	0	0	0	0	0	0
SMS	0	0	0	0	0	0	0	0	0	0	0
RAY	5.6	8.8	8.1	1.5	18.6	0.5	0.3	13.4	0.3	1.9	9.5
LOB	870.7	540.1	607.7	572.1	572.1	572.1	572.1	572.1	572.1	572.1	572.1

Table A.5: Mexican Historical Commercial Landings by Atlantis Functional Group (tonnes)

Group	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990
AMB	1242.8	1906.2	1590.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
BCR	6282.7	9142.2	10864	6841.4	6784.1	6304.8	4891.7	5569.2	12042.1	7053.6	8360.9
BFS	1240.2	1905.8	1624.4	701.5	940.1	753.8	332	587.1	1145.6	1861.2	2339.2
BIL	1219.2	1874.4	1590.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
BIV	3176	3756.8	3784	2477.4	3148.2	2292.7	1943.6	1635	2200	2225	2832.7
BMR	1219.2	1874.4	1590.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
BSH	22946.2	25402.5	19493.1	18763.3	20866	20304.3	19104.9	18732.5	37423.7	20640.3	20478.5
BTN	1219.2	1874.4	1591.7	662	893.8	710	301.1	547.7	1068.2	1812.9	2288.2
CMB	3006.4	4316.6	4927	2144.4	4367.5	2714.5	1452.8	1879.1	4550.5	4551.6	4573.3
DSR	1619.3	2283.2	1977.8	962.6	1225.3	1097.8	679.3	1042.2	2233	1860.4	2882.9
FLT	1263.7	1963.3	1634	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
JCK	2662.5	3829.4	4439	3598.7	4711.3	2610.2	1968.1	2375.3	4322.8	3190	3325.7
KMK	3186.4	4415.5	4957.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
LGS	4310.2	8466.3	8746.8	9013.9	10056.2	8787.6	7958.1	8008.5	17597.7	8322.6	10943.8
LOB	1436.7	2073.3	1904.7	889.8	1166.6	904.1	514	884.5	2311	2226.5	2481
LOG	2.5	3.8	14.8	147.6	101.3	89.7	0.2	0.4	0	0	0
LPL	4431.1	6160	7341.3	3315.8	3808.7	3358.6	3090.1	3475.7	5186	4823	6348.6
LRF	1339.9	2416.9	1884.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
LTN	1291.3	2057.7	1763.2	655.7	1220.5	799	294.3	547.3	1062.4	1909.5	2470.2
LUT	2590.4	7111.4	3963.6	693.3	916.9	738.6	360.2	589.6	1150.5	1846.7	2324.9
MPL	12575.3	23615.1	32905.5	8365.9	7870.1	7051.8	5727.5	7096.3	15792.3	5598.3	4303.3
MUL	7930.6	6968.3	7424.5	4695.4	6100.2	4472.6	8948.9	9675.4	19754.9	9703.2	11425.5
ODF	4878.8	7587.9	7733	695.7	3369.6	3246.1	2725.6	4192.4	8397.9	6081.8	7052.2
OSH	1702	2397.3	1988.3	1058.1	1327	1139.8	712.3	951.4	1870.4	2227.8	2689.5
OYS	47763.2	36080.7	29167	31051.9	38086.6	36430	35177.4	42572.7	95458.6	1809.3	2285.2
PIN	1472.8	2187.9	1906.6	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
POM	1465	2045	1764.6	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
PSH	2184.8	2920.1	2386.1	1460.5	1771.1	1575.3	1130.4	1355.6	2678.4	2646.2	3093.8
RAY	1355.5	1947.6	2077.1	701.5	940.1	753.8	332	587.1	1145.6	1861.2	2339.2
RDR	1903.7	2527.6	2225.9	1624.6	1850.9	1507.1	1386.6	1432.3	2873.1	2510.5	3078
RGR	8420.4	9233.2	8563.9	6178.3	7044.9	7788.7	7223.7	9455	22132.9	2729.5	13045.4
RSN	2361	3207	3441	3073.9	4082.9	3763.7	3977.1	4839	7881.3	3773.5	7067
SAR	1219.2	1986.9	1693.8	3282.1	6184.6	3575.4	1903.7	1348.4	2096.6	3684.4	2912
SCI	1860.6	2596.5	2372.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
SCR	1333.2	2038.1	1799.2	795	1015.9	830.3	397.8	660.4	1309.6	1927.4	2422
SDF	1219.2	1874.4	1590.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
SEA	2808.1	3775.9	3732.7	1624.6	1850.9	1507.1	1386.6	1432.3	2873.1	2510.5	3078
SHP	1472.8	2187.9	1906.6	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
SMK	3487.6	4655.9	5062.7	3302.5	3457.6	3254.7	3080.7	3475.3	5168.8	4703.7	6155.2
SMS	1261.3	1937.2	1658.4	747.3	997.1	803.4	369.8	626.8	1228.9	1913.2	2393.2
SNK	3767.5	5234.6	6331.4	4499.5	3876.7	4030.8	3244.5	3474.8	6983.6	3709.3	3782.6
SPL	2763.2	3567.2	4500.2	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
SQU	7104.1	8133.1	7449	8406.7	6115.6	6453.9	8752.9	7905.5	14791.7	2849.8	16124.3
SRF	1368	2209.2	2174.2	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
SSR	4150.3	4421.5	3955.5	962.6	1225.3	1097.8	679.3	1042.2	2233	1860.4	2882.9
SWD	1219.2	1874.4	1590.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
TIP	2482	3758.8	3629.4	3403.4	4307.2	3680.5	2557.6	2932.5	6058.1	4926.6	5527.6
TUR	22.9	34.3	133.1	1328.4	912	807.5	1.6	3.3	0	0	0
VSN	1395.2	2308.1	2083.9	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
WMR	1219.2	1874.4	1590.4	655.7	883	704.2	294.3	547.3	1062.4	1809.3	2285.2
WSH	2184.8	2920.1	2386.1	1460.5	1771.1	1575.3	1130.4	1355.6	2678.4	2646.2	3093.8
YTN	1219.2	1874.4	1701.8	1195.9	1819.2	1201	876	576.5	1562.8	2121.4	2547.7

Table A.5: Continued

Group	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
AMB	2422.2	10456.8	2262.9	2305	2092.5	1840.3	1356.5	1216.9	957.3	899.4	789.8
BCR	9591.7	36327.5	11940.7	11888.7	11531.8	14014.8	14126.5	12667.3	12079.7	8473.9	7252
BFS	2468.1	10688.9	2319.9	2353.9	2134.9	1886.6	1390.4	1252.6	986.3	927.2	818.6
BIL	2422.2	10456.8	2264.8	2309	2092.5	1840.3	1358.1	1217.9	958.8	902.6	789.8
BIV	4119.3	19048.5	2344.8	2821.1	2782.8	2444.7	1852.9	1870.1	1578.5	2008.9	1851.2
BMR	2422.2	10456.8	2264.8	2308.9	2092.5	1840.3	1363.3	1222.1	961.1	913.7	789.8
BSH	23350.7	101445.4	19778.6	19285	19879.2	18265.1	18457.3	19869.9	16827	17915.4	18178.9
BTN	2427.3	11716.9	2272.7	2317.4	2104.1	1848.6	1367.7	1228.7	977.1	914.4	802.5
CMB	4675.9	22640.4	6165.3	6000.5	6071.5	3860.4	5607	3990.3	7025.4	7828.5	8099
DSR	3060.6	12342.6	2871.4	2883.8	2682	2313.9	1830.2	1701.9	1432.1	1454.3	1228.1
FLT	2422.2	10456.8	2262.9	2305	2092.5	1840.3	1537.9	1411.1	1134.2	1001	948.6
JCK	4233	17082.8	4533.6	4719	4886.6	7352.3	10468.2	10470.2	5253.8	7688.8	7423.2
KMK	2422.2	10456.8	2262.9	2305	3493.6	3891.4	3714.7	3248.6	3191.2	2926.5	3085
LGS	8679.2	51992.8	10135.6	9925.1	9579	9920.7	6991.1	6387.5	6037	5652.5	5349.9
LOB	2896.8	13241.1	2801.7	2606.9	2511.3	2183.9	1823.1	1476.3	1208.2	1260.1	1184.7
LOG	0	0	0	0	0	0	0	0	0	0	0
LPL	7029.9	36502.5	7283.3	6504.1	7484.8	9491.1	7997.1	7602	7402.6	6334.1	6273.8
LRF	2422.2	10456.8	2262.9	2305	2092.5	1840.3	6399.5	6977.5	7056.3	7489.2	5403.8
LTN	2956.6	11539.5	2707	2691.4	2609.1	2431.8	2280.9	2210.3	1304.5	1678.2	1473.4
LUT	2482	10713.6	2332.1	2351.1	2137.3	1882.3	2067.4	3433.5	2902.1	2504	2865.7
MPL	3431	77238.4	6048.6	6414.4	5179.2	5632.6	4429.4	3737.6	3105	2715.1	2669.1
MUL	9233.6	37457.8	12004.8	12441.8	14258.6	13716.6	14189.7	12389.4	12137.6	13141.5	11231.4
ODF	7920.3	30116.2	8182.1	8689.9	8210.9	7911.2	8924.6	9212.9	7679.7	7683	7734.3
OSH	2887.3	12478.7	2652.2	2682.3	2487.7	2205.3	1736.5	1631.4	1310	1277.6	1176.2
OYS	2422.2	65833.1	2262.9	3097.8	3353.5	1840.3	5650.2	1216.9	979.1	899.4	789.8
PIN	2422.2	10456.8	2262.9	2305	2092.5	1840.3	1356.5	1216.9	957.3	899.4	789.8
POM	2422.2	10456.8	2262.9	2305	2092.5	1840.3	1934.3	1713.2	1432.7	1265	1078.3
PSH	3352.4	14500.7	3041.4	3059.6	2883	2570.3	2116.5	2045.9	1662.6	1655.7	1562.7
RAY	2468.1	10688.9	2319.9	2353.9	2134.9	1886.6	6444.3	6977	4697.6	3511.8	3189.1
RDR	2931.2	13695	3057.6	2885.1	2723.4	2756.5	2185.6	2215.7	1943	1973.1	1595.4
RGR	13913.2	44402.2	13215	12723.1	12213.4	9875.1	9884.4	9946.6	9503.6	10887.3	8679.3
RSN	7523.2	33762.9	8871.6	6778.9	6400.2	5998	5241	4355.9	4152.5	3435.3	3326.8
SAR	2913	241379.8	3165.6	4778	2400.9	2357.4	2270.9	4905.5	2201.1	1388.4	1128.2
SCI	2422.2	10456.8	2262.9	2305	2092.5	1840.3	2453.2	2857.1	2384.3	1449.2	1228.9
SCR	2583.7	11039.3	2480.9	2520.8	2305	2114.4	1644	1474.8	1207.8	1070	935.3
SDF	2422.2	10456.8	2262.9	2305	2092.5	1840.3	5792.6	4802.1	4247.7	3285.3	3460.6
SEA	2931.2	13695	3057.6	2885.1	6006.3	5595.1	5418.2	5473.4	5242.6	4903.1	3892.9
SHP	2422.2	10456.8	2262.9	2305	2092.5	1840.3	1356.5	1216.9	957.3	899.4	789.8
SMK	6489.1	25003.9	6817.9	6037.6	5552.5	6836.2	4696.7	4555.8	4750.2	3486.7	3196.6
SMS	2513.9	10921	2376.9	2402.8	2177.4	1932.9	1424.3	1288.3	1015.4	955	847.4
SNK	4323.3	15784.7	4087.7	4328.1	4193.5	4205.9	3676.8	3286.9	3286.1	3037.8	3578.5
SPL	2422.2	13911.8	2262.9	2319.5	2092.5	1840.3	2175.6	2815.4	2420.6	1953.6	1993.7
SQU	16202.4	55342.5	16441.3	17405.1	19015.1	27494.6	17379.2	16001.3	18262.8	21255.7	19388.9
SRF	2422.2	13911.8	2262.9	2319.5	2092.5	1840.3	1366.4	1265	1019.9	940.2	815.2
SSR	3060.6	12342.6	2871.4	2883.8	2654.7	2286.7	2122.3	1980.4	1728.7	1572.2	1413.2
SWD	2422.2	10456.8	2266.9	2310.1	2092.5	1840.3	1363	1222.8	964	911.5	789.8
TIP	5172.6	24383	5680.1	5239.3	4639.3	4617.9	3393.3	3358.8	2699.6	2567.7	2517.5
TUR	0	0	0	0	0	0	0	0	0	0	0
VSN	2422.2	10456.8	2262.9	2305	2092.5	1840.3	3282.4	2580.4	2457.8	2308.3	2743
WMR	2422.2	10456.8	2264.1	2307.1	2092.5	1840.3	1359.6	1217.7	958.9	907.8	789.8
WSH	3352.4	14500.7	3041.4	3059.6	2883	2570.3	2116.5	2045.9	1662.6	1655.7	1562.7
YTN	2860.7	119129.7	3100.1	3376.4	3091.4	2559.9	2325.4	2232.7	2668.8	2189.3	1880.7

Table A.5: Continued

Group	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
AMB	636.8	719.5	704.6	701.7	585.2	557.5	469.5	411.1	545.2	374.6
BCR	7783.3	10443.3	11117.1	10740.1	10710.6	10504.8	9972.3	8151.7	11912.3	9660.8
BFS	664.1	744.9	732.7	734.7	606.6	576.6	488.4	432.9	571.5	391.3
BIL	636.8	721.5	706	702.9	586.3	559.4	471.2	412.2	547	375.3
BIV	1617.5	1714.1	1702.7	2239.5	2767	2503.1	2231.7	1756.6	1781.3	1829.4
BMR	636.8	738.4	726.7	717.8	601.9	576.6	490.2	425.5	570.5	392.9
BSH	15626.8	19686	15392	22584.3	16008.2	17272.9	15870.8	16863.4	20449.7	17503.4
BTN	651.1	736.6	719.9	716	598.2	569.3	482.4	426.9	559.4	392
CMB	5927	5725.8	7182.4	6901.5	6689.5	6565.2	3332.1	3678.1	7348.4	5041
DSR	1122.1	1095.2	1072	1198.9	1006.8	1128.4	1018.2	978.1	1097.8	760.5
FLT	875.4	891.9	887	879.8	789.7	701.6	579.7	455	648.8	465.7
JCK	7452	9149.1	8832.1	9227.9	9081.2	8871.9	8654.3	10438.8	13143	11021.9
KMK	3213.6	3099.9	3196.2	2910.1	2803.8	2543.9	2880	2426.5	2755	2208.2
LGS	4342	4042.8	3958.8	4529.9	4007.7	3606.7	2880.7	2738.3	3657.1	2676.8
LOB	1184.5	1103.2	1048.2	1070.9	813.5	854.9	686.6	604.5	935.6	621.7
LOG	0	0	0	0	0	0	0	0	0	0
LPL	6739	7196.1	7230.6	6925.2	5974.6	5882.2	6878.1	6004.9	7236.1	5375.6
LRF	4149.9	5208.2	6002.6	3087.9	3012.3	3786	4540.2	2681.5	2448	2449.2
LTN	1272	1429.4	1405.4	1323.4	1305	1088.6	1000.9	1042.9	1360.3	1069.8
LUT	2399.4	2705.4	2356.9	2661.8	2151.1	2452.8	2736.4	2058.4	2400.4	2232.5
MPL	1838.7	2274.5	2585.6	2355.1	2686.5	2236.1	1860.6	1319.7	1721.9	1761.5
MUL	9263.6	8749.4	8387.3	8299.4	6888.3	7647.8	6976.5	7848.9	8096.1	7063.1
ODF	6991.5	7361	6670.3	6469.3	7486.4	5417.4	5151	5403.5	5893.2	3894.9
OSH	969.9	1141	1031	1188	927.9	929	811.8	776.7	987.6	755.3
OYS	636.8	893.7	788.1	3604.3	2632.5	2121.5	1683.9	2307.9	2411.2	1903.6
PIN	636.8	719.5	704.6	701.7	585.2	557.5	469.5	411.1	545.2	374.6
POM	1166.3	1262.9	1081.1	1223.3	884.3	938.9	841.6	887.6	1028.7	749.7
PSH	1303	1562.5	1357.4	1674.2	1270.6	1300.4	1154	1142.3	1429.9	1135.9
RAY	2841.1	3069.1	3262.8	3711.3	3632.7	3558.5	2914.2	2898.9	3382.9	3665.1
RDR	1680.4	2122.9	2039.6	1950.5	1499	1234.5	1076.9	1055.2	1359.4	1030.5
RGR	9371.2	7481.5	7317.2	9652.5	8175.5	10834.3	10345.5	10617	9369.6	7319.5
RSN	3055.6	3220.2	3419.5	3938.6	3228.1	3471.7	3094.6	3351.9	4198.2	3145.2
SAR	793.7	945.4	848.9	914.3	734.1	669	511	479.4	596.2	411.2
SCI	1208.2	1114.1	1266.2	1161.7	962.8	756.6	570	519.9	680.1	480.4
SCR	797.7	938.5	939.1	927.7	813.2	781.5	683.5	585.4	801.2	583.7
SDF	3764.3	3664.2	3446.1	3546.5	2790.2	2285.9	2217.4	2495.2	3401.2	2371.6
SEA	4450.8	5158.9	5620.4	4717.1	4086	2646.8	3036.1	2954.1	3646.8	3012.5
SHP	636.8	719.5	704.6	701.7	585.2	557.5	469.5	411.1	545.2	374.6
SMK	3411.4	3961.8	3876.6	3922.4	2866.1	3268.6	3903.1	3330.4	4185.9	2815.7
SMS	691.4	770.3	760.7	767.7	628	595.7	507.3	454.7	597.7	407.9
SNK	4156.2	5109.3	4309.4	4794.7	4570.2	4712.8	4408.3	4528.1	4946.3	3531
SPL	1597.9	2215.4	2155.2	2751.4	2132.5	1334.3	1487.7	601.3	1409.3	1151.4
SQU	15171	14914.2	22549.6	10556.9	26657.6	19226.2	11681.6	24259.2	22463.5	26057.5
SRF	643.7	757.6	729.1	712.8	597.2	571.7	472.6	414.4	1074.5	1061.9
SSR	1294.3	1273	1322.4	1440	1231.5	1239.1	1070.8	1020.2	1088	800
SWD	636.8	728	719.1	713.1	595.1	570.8	481.9	416.8	565.3	385.8
TIP	2275.2	2244.1	2387.6	2681.7	1869	1702.4	1604.3	1719.2	2120	1374.3
TUR	0	0	0	0	0	0	0	0	0	0
VSN	2166.9	2143.8	2049.1	2445.6	2233.5	2481.7	1441.3	1377.8	1521.2	971.6
WMR	636.8	724.2	712.5	707.3	589.6	560.3	473.8	415.7	556.2	387.2
WSH	1303	1562.5	1357.4	1674.2	1270.6	1300.4	1154	1142.3	1429.9	1135.9
YTN	1869.9	2197.6	2021.9	1940.8	1709.4	1578.3	1576.6	1772.8	1763.2	1873.4

Table A.6: Cuban Historical Commercial Landings by Atlantis Functional Group (tonnes)

Group	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991
BCR	0	80.5	104.4	132.1	147.5	153.6	174.8	132.1	216.2	227	0	139.9
BFT	0	0	0	0	0	0	0	0	0	0	1810.3	0
BIO	1983	1356.9	1715.6	2130.5	2234.8	2327	2419.4	2339.5	2342.7	2297.8	645	1691.9
BIV	0	263.1	682.3	525.8	583.4	653.9	683.4	660.1	649.4	698.5	33.5	475.3
BMR	102.1	155.3	159.4	105.3	44.3	54.9	34.8	4	43.6	18.4	30.6	38
CMB	0	0	28.4	281.9	263.5	250.9	93	78.2	80.8	100.4	96	30.3
JCK	30	13	28	23	38	44	42	56	24	24	3.3	45
KMK	5.7	3.3	0.1	0.3	1.3	0.7	0.5	0.1	0.3	0.3	197	1.3
LGS	369	702	561	445	422	335	319	470	524	471	1242.2	122
LOB	1551.3	1575.3	1704.6	1596.8	1848.7	1985.3	1728.8	2059	1899.2	1744.3	77	1496.8
LOG	200.3	155.9	162.8	170.9	173.4	201.6	193.4	149.6	115.8	88.9	606.3	52.6
LPL	723.4	556.3	628.6	624	499.8	498.7	433.9	392.1	558.3	593.3	1810.3	501.3
LRF	1983	1356.9	1715.6	2130.5	2234.8	2327	2419.4	2339.5	2342.7	2297.8	22.1	1832.6
LTN	0	0	11.6	2.1	5.3	5.6	8.4	19.3	18.6	29.1	574.7	22.1
LUT	825.5	883.8	900.1	844.2	735.6	693.4	701.7	790.1	715.1	753.5	8	777.3
MPL	0	0	0	0	5	8	10	15	17	22	46.9	8
MUL	214.9	184.8	216.7	204.1	249.6	111.3	132.7	136.9	68.6	78.1	44.1	90.7
OBL	41.7	46.9	63.4	9.8	59.2	45.5	17.5	59.9	27.3	19.3	373.9	29.1
ODF	189.3	233.5	318.9	290.6	308.3	317	339.6	328	372.9	396.5	794.1	361.6
OYS	332.8	514.8	526.6	446.5	629.2	516.2	529.5	330.3	479	854.6	0	757.2
RAY	0	0	0	0	0	0	0	0	0	0	407.4	1.1
RGR	1025.2	824.6	734.3	578.2	724.5	635.3	669.9	726.6	766.2	903	431.2	320.3
RSN	373.5	341.6	367.2	433.7	382.2	505.1	429.1	594.3	491.8	483	0.4	52.2
SCR	119.3	12.1	28.5	26.3	25.8	23.2	17.8	15.2	12.6	5.1	3.3	0.4
SMK	5.7	3.3	0.1	0.3	1.3	0.7	0.5	0.1	0.3	0.3	1061.6	1.3
SPL	829.9	813.8	833	963.6	799.4	979.7	1058.1	795.2	1001.7	994	1810.3	1151.2
SRF	1983	1356.9	1715.6	2130.5	2234.8	2327	2419.4	2339.5	2342.7	2297.8	3725.9	1691.9
SSR	4038.1	2886.2	3702.8	4504.1	4646.2	4911.2	5090.4	4897	4843.3	4786.3	20	3478.9
SWD	134.9	138.7	53.6	44.7	28.8	33.1	48.3	57.1	47.4	23.6	399.4	16.2
TUR	350.6	416.3	414.4	407.5	338.7	541.5	421.3	373.1	324.3	343.7	2.1	249.2
WMR	74.2	40.6	15.8	39.2	53.6	75.6	67.2	21.7	8.4	7.7	18.6	3.5
YTN	241.2	699	526.1	277.6	888.3	667.1	728.4	371.7	34.3	31.9	0	6.3

Table A.6: Continued

Group	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
BCR	166.2	74.9	122.6	108.6	131	102.8	155.5	82.6	85.3	77.1	59.9	113.9
BFT	0	0	0	0	0	0	0	0	0	0	25.9	3.9
BIO	1639.4	1139.7	1492.6	1286.9	969.2	1209.5	962.5	1426.4	1587.3	773.9	351.5	723.9
BIV	475.3	499.6	573.1	703	686.3	638	899.6	753.9	956.1	233.6	138.4	107
BMR	40.4	20.6	11.7	25.4	12.9	15.9	3.6	11.4	16.5	16.8	10.2	0.9
CMB	19.9	33.6	22.5	28.8	313.3	460.9	181.2	305.9	429.2	432.5	367.9	137.3
JCK	36	19	61	36.9	37.4	25.1	53.5	17.9	274.1	229	19.3	17.7
KMK	0.2	1.3	0.1	1.1	1.2	0.9	0.5	0.5	0.4	0.4	0.5	0.4
LGS	142	74	88	120	123.9	167.8	270.1	250.3	199.1	210.7	206.1	107.7
LOB	1412.4	1266	1460.6	1426.3	1423.2	1413.6	1488.2	1567	1225.1	1115.6	1201.9	792.2
LOG	40.1	30.1	14.4	6.9	6.3	4.4	3.1	3.1	5.6	4.4	5	5
LPL	514.2	167.3	360	289.4	351.3	462.7	397.7	482.5	369.9	310.4	320.5	364.6
LRF	1720.6	1205.2	1564	1356.2	1010.5	1243.4	975.5	1430.9	1593.3	779.8	355.4	725.3
LTN	11.6	4.6	5.3	9.5	8.1	6	3.2	1.1	0.7	0.4	1.1	1.8
LUT	494.9	384	475.4	506	767.7	590.4	543.8	413.9	464.9	518	570.3	458.9
MPL	8	8	8	9.2	7.1	5.6	5	4.2	4.5	4.6	3.6	3.3
MUL	50.4	55.3	46.9	37.8	32.6	55.7	42.7	37.8	41.7	39.9	43.8	27
OBL	24.5	14.7	16.1	11.6	13	14	9.8	68.6	72.8	23.8	11.2	6.3
ODF	295.4	232.7	318.8	358.5	306.6	264.5	214.4	209.3	219.1	199.9	196.5	265.5
OYS	564.2	440.6	607.7	695.6	696.7	742.1	0	0	0	0	0	0
RAY	0	4.2	0	1.8	334.3	475.3	466.9	473.2	417.6	391.7	447.3	465.5
RGR	150.2	119.4	104.3	73.9	94.2	68.3	24.2	38.5	59.9	31.9	30.1	36.1
RSN	211.4	166.6	218.1	283.2	350.7	318.2	282.5	267.1	241.2	270.6	309.8	345.1
SCR	1	0.4	0.3	0.7	4.1	1.3	5.1	7.6	7.9	11.1	7	7.3
SMK	0.2	1.3	0.1	1.1	1.2	0.9	0.5	0.5	0.4	0.4	0.5	0.4
SPL	792.4	640.2	873.6	1067.5	1073.8	996.5	677.3	882.7	1079.4	1206.1	806.8	860.7
SRF	1639.4	1139.7	1492.6	1286.9	969.2	1209.5	962.5	1426.4	1587.3	773.9	351.5	723.9
SSR	3399.4	2357.1	3027.2	2623.8	2015	2469.5	1970.4	2882.5	3211.1	1566.4	734.9	1476.1
SWD	7.5	2.4	3	4.5	2.1	3	3	1.5	3.3	0.9	3	0.9
TUR	289.8	154.6	102	49.5	35.7	23.2	22.5	12.5	17.5	10	14.4	10
WMR	3.5	0	0	0	0	0	0	0	0	0	0	0
YTN	3.9	0.4	0	0	0	0	0	11.9	99.4	54.6	22.8	24.9

Table A.6: Continued

Group	2004	2005	2006	2007	2008	2009	2010	2011
BCR	62.8	32.9	51	48.2	49.6	44.7	50.4	58.3
BFT	6.3	9.5	6.7	0	0	0	0	0
BIO	576.8	576.5	580.9	618	502.2	569.2	280.8	293.7
BIV	163.5	148.7	138	142.1	35.1	109.2	112.2	69
BMR	1.2	2.1	2.1	0.6	1.2	1.8	0.9	1.8
CMB	203.7	237.6	120.3	211.8	148	197.1	186.7	181.6
JCK	7.9	7.3	5.1	7.7	6.5	10.8	4.4	6.3
KMK	0.2	0.2	0.3	0.3	0.4	0.4	0.3	0.4
LGS	50.3	48.4	78.1	78.7	79.2	77.6	54.4	53.9
LOB	1137.3	891.5	669.7	761	902.1	647.2	712.5	769.1
LOG	3.8	4.4	1.9	1.9	0	0	0	0
LPL	373.5	369.5	287	244.5	241.9	305.1	209.8	265.2
LRF	577.9	577.9	581.2	618.4	502.2	569.2	280.8	293.7
LTN	2.8	2.8	1.1	1.4	2.5	1.4	4.9	8.1
LUT	251.7	159.4	192.3	212.2	233.1	227.7	223.5	335.2
MPL	3	3.2	2.9	3	3.6	4.5	5.5	5
MUL	16.5	14	20	18.2	21	37.8	87.2	85.4
OBL	17.5	25.2	16.5	19.6	6.7	6.7	9.1	20.7
ODF	247.6	196.1	189.6	183	137	150.6	155.8	184.9
OYS	0	0	0	0	0	0	0	0
RAY	497.4	536.6	534.5	648.9	674.1	709.5	559.7	614.6
RGR	19.6	0	0	0	0	0	0	0
RSN	219.5	248.2	223.7	269.5	265.7	322.4	296.8	263.2
SCR	19.3	16.6	11.2	13.9	13.1	0	0	0
SMK	0.2	0.2	0.3	0.3	0.4	0.4	0.3	0.4
SPL	871.9	655.2	944.7	781.6	876.8	984.9	912.5	881.3
SRF	576.8	576.5	580.9	618	502.2	569.2	280.8	293.7
SSR	1177.3	1163.2	1176.2	1245.3	1012.9	1149.4	567.7	595.2
SWD	0.9	0.9	0.6	0.3	0	0	0	0.3
TUR	5	8.1	6.9	1.3	0	0	0	0
WMR	0	0	0	0	0	0	0	0
YTN	6.7	6.7	6.7	12.6	0.7	0.7	2.8	0.7

Table A.7: Seasonal Distribution of Atlantis Functional Group Harvested by United States Commercial Fleets

Group	Winter (Jan.-Mar.)	Spring (Apr.-Jun.)	Summer (Jul.-Sep.)	Fall (Oct. - Dec.)
GAG	0.2837	0.2954	0.1858	0.2351
RGR	0.2042	0.2799	0.2833	0.2325
SCM	0.2396	0.29	0.2452	0.2252
SSR	0.2538	0.3272	0.1991	0.22
DSR	0.3054	0.3329	0.1742	0.1875
RSN	0.4027	0.2362	0.1471	0.214
VSN	0.1853	0.3173	0.2728	0.2246
LUT	0.1997	0.3384	0.2637	0.1982
BIO	0.5082	0.088	0.0887	0.315
LRF	0.192	0.3119	0.3232	0.173
SRF	0.2735	0.3429	0.1905	0.1931
BDR	0.3265	0.2044	0.2224	0.2468
RDR	0.3433	0.0972	0.0937	0.4658
SEA	0.3625	0.1934	0.1654	0.2787
SCI	0.1247	0.3797	0.3344	0.1611
LDY	0.2833	0.2301	0.1699	0.3167
MUL	0.1496	0.0993	0.1345	0.6166
POM	0.2145	0.1855	0.3386	0.2614
SHP	0.5021	0.1957	0.0761	0.2261
SNK	0.25	0.25	0.25	0.25
FLT	0.0793	0.2154	0.2564	0.4489
ODF	0.1954	0.3063	0.2756	0.2227
SDF	0.1309	0.4605	0.2993	0.1093
YTN	0.2107	0.2809	0.306	0.2024
BTN	0.3786	0.5336	0.0562	0.0317
LTN	0.0867	0.3047	0.4285	0.1801
OTN	0.25	0.25	0.25	0.25
SWD	0.3654	0.2216	0.1881	0.2249
WMR	0.0515	0.2434	0.5943	0.1108
BMR	0.0662	0.2946	0.5315	0.1077
BIL	0.2209	0.2683	0.3274	0.1834
AMB	0.3093	0.2938	0.2472	0.1497
JCK	0.1049	0.4795	0.2655	0.1501
KMK	0.4039	0.031	0.3902	0.1749
SMK	0.4086	0.2946	0.1166	0.1802
SAR	0.0042	0.5258	0.3699	0.1
LPL	0.1249	0.3599	0.4028	0.1124
DWF	0.25	0.25	0.25	0.25
MEN	0.0002	0.3833	0.5244	0.092
PIN	0.2709	0.2936	0.2526	0.1829
MPL	0.2789	0.4624	0.1125	0.1463
SPL	0.3551	0.301	0.1431	0.2008
TIP	0.3479	0.1551	0.3919	0.1051
BEN	0.25	0.25	0.25	0.25
LGS	0.3661	0.1752	0.3579	0.1008
FIL	0.25	0.25	0.25	0.25
SMS	0.25	0.25	0.25	0.25
RAY	0.3947	0.3293	0.2436	0.0324
BSH	0.0414	0.4218	0.3999	0.1369
WSH	0.0701	0.141	0.3328	0.4561
PSH	0.3107	0.3364	0.1165	0.2364
OSH	0.2156	0.1519	0.1686	0.4639
DBR	0.25	0.25	0.25	0.25
SBR	0.25	0.25	0.25	0.25
MAN	0.25	0.25	0.25	0.25
MYS	0.25	0.25	0.25	0.25
DOL	0.25	0.25	0.25	0.25
DDO	0.25	0.25	0.25	0.25
LOG	0.25	0.25	0.25	0.25
KMP	0.25	0.25	0.25	0.25
TUR	0.25	0.25	0.25	0.25
BCR	0.1369	0.2992	0.3252	0.2387
SCR	0.3436	0.1124	0.003	0.541
LOB	0.1283	0.009	0.4946	0.368
COR	0.25	0.25	0.25	0.25
CCA	0.25	0.25	0.25	0.25
OCT	0.25	0.25	0.25	0.25
SPG	0.2086	0.3385	0.2719	0.1811
CMB	0.25	0.25	0.25	0.25
INF	0.25	0.25	0.25	0.25
ECH	0.25	0.25	0.25	0.25
OYS	0.2872	0.2405	0.1926	0.2798
BIV	0.2593	0.2247	0.3167	0.1993
SES	0.25	0.25	0.25	0.25
EPI	0.25	0.25	0.25	0.25
GRS	0.25	0.25	0.25	0.25
ALG	0.25	0.25	0.25	0.25
MPB	0.25	0.25	0.25	0.25
LPP	0.25	0.25	0.25	0.25
SPP	0.25	0.25	0.25	0.25
DIN	0.25	0.25	0.25	0.25
PRO	0.25	0.25	0.25	0.25
JEL	0.25	0.25	0.25	0.25
SQU	0.1666	0.2854	0.3481	0.1998
LZP	0.25	0.25	0.25	0.25
SZP	0.25	0.25	0.25	0.25
PB	0.25	0.25	0.25	0.25
BB	0.25	0.25	0.25	0.25
DC	0.25	0.25	0.25	0.25
DL	0.25	0.25	0.25	0.25
DR	0.25	0.25	0.25	0.25

Table A.8: Seasonal Distribution of Atlantis Functional Group Harvested by United States Recreational Fleets

Group	Winter (Jan.-Mar.)	Spring (Apr.-Jun.)	Summer (Jul.-Sep.)	Fall (Oct. - Dec.)
GAG	0.1878	0.2831	0.2292	0.2999
RGR	0.129	0.2683	0.3897	0.2131
SCM	0.0815	0.3257	0.3474	0.2454
SSR	0.2875	0.3417	0.1894	0.1814
DSR	0.3065	0.2758	0.1726	0.2452
RSN	0.0891	0.3531	0.3759	0.1819
VSN	0.0978	0.3585	0.3726	0.1711
LUT	0.3385	0.2286	0.2152	0.2177
BIO	0.2721	0.2862	0.2537	0.1881
LRF	0.1094	0.2608	0.3634	0.2664
SRF	0.105	0.2384	0.3436	0.3131
BDR	0.2306	0.2302	0.2246	0.3147
RDR	0.1071	0.2139	0.3966	0.2824
SEA	0.1292	0.2537	0.3788	0.2383
SCI	0.0546	0.3032	0.4085	0.2337
LDY	0.0927	0.3571	0.3625	0.1876
MUL	0.1629	0.2763	0.2735	0.2873
POM	0.1447	0.2374	0.3026	0.3152
SHP	0.4475	0.2627	0.0827	0.2071
SNK	0.1127	0.298	0.2614	0.3279
FLT	0.0826	0.3033	0.394	0.2201
ODF	0.3448	0.3462	0.1342	0.1748
SDF	0.0872	0.303	0.3761	0.2337
YTN	0.1579	0.2273	0.4593	0.1555
BTN	0.1111	0.4444	0.2222	0.2222
LTN	0.1081	0.3017	0.4262	0.164
OTN	0.23	0.27	0.35	0.15
SWD	0.2	0	0.7	0.1
WMR	0	0.25	0.6664	0.0836
BMR	0	0.5264	0.35	0.1236
BIL	0.2457	0.2038	0.2114	0.3392
AMB	0.1577	0.3881	0.2762	0.1779
JCK	0.1938	0.2674	0.2741	0.2647
KMK	0.1477	0.2845	0.3661	0.2017
SMK	0.1108	0.328	0.3567	0.2044
SAR	0.0711	0.3268	0.3104	0.2917
LPL	0.2553	0.3537	0.2119	0.1791
DWF	0.0385	0.2645	0.5021	0.1949
MEN	0.0193	0.3437	0.4506	0.1864
PIN	0.0916	0.2999	0.3846	0.2239
MPL	0.0602	0.4461	0.2833	0.2105
SPL	0.213	0.2319	0.2276	0.3275
TIP	0.0405	0.3909	0.4526	0.1159
BEN	0.5	0.5	0	0
LGS	0.1308	0.2192	0.4067	0.2433
FIL	0.25	0.25	0.25	0.25
SMS	0.875	0.125	0	0
RAY	0.1577	0.2999	0.2839	0.2585
BSH	0.25	0.25	0.25	0.25
WSH	0.25	0.25	0.25	0.25
PSH	0.25	0.25	0.25	0.25
OSH	0.25	0.25	0.25	0.25
DBR	0.25	0.25	0.25	0.25
SBR	0.25	0.25	0.25	0.25
MAN	0.25	0.25	0.25	0.25
MYS	0.25	0.25	0.25	0.25
DOL	0.25	0.25	0.25	0.25
DDO	0.25	0.25	0.25	0.25
LOG	0.25	0.25	0.25	0.25
KMP	0.25	0.25	0.25	0.25
TUR	0.25	0.25	0.25	0.25
BCR	0.25	0.25	0.25	0.25
SCR	0.25	0.25	0.25	0.25
LOB	0.1283	0.009	0.4946	0.368
COR	0.25	0.25	0.25	0.25
CCA	0.25	0.25	0.25	0.25
OCT	0.25	0.25	0.25	0.25
SPG	0.25	0.25	0.25	0.25
CMB	0.25	0.25	0.25	0.25
INF	0.25	0.25	0.25	0.25
ECH	0.25	0.25	0.25	0.25
OYS	0.25	0.25	0.25	0.25
BIV	0.25	0.25	0.25	0.25
SES	0.25	0.25	0.25	0.25
EPI	0.25	0.25	0.25	0.25
GRS	0.25	0.25	0.25	0.25
ALG	0.25	0.25	0.25	0.25
MPB	0.25	0.25	0.25	0.25
LPP	0.25	0.25	0.25	0.25
SPP	0.25	0.25	0.25	0.25
DIN	0.25	0.25	0.25	0.25
PRO	0.25	0.25	0.25	0.25
JEL	0.25	0.25	0.25	0.25
SQU	0.25	0.25	0.25	0.25
LZP	0.25	0.25	0.25	0.25
SZP	0.25	0.25	0.25	0.25
PB	0.25	0.25	0.25	0.25
BB	0.25	0.25	0.25	0.25
DC	0.25	0.25	0.25	0.25
DL	0.25	0.25	0.25	0.25
DR	0.25	0.25	0.25	0.25

Table A.9: Seasonal Distribution of Atlantis Functional Group Harvested by Mexican Commercial Fleets

Group	Winter (Jan.-Mar.)	Spring (Apr.-Jun.)	Summer (Jul.-Sep.)	Fall (Oct. - Dec.)
GAG	0.25	0.25	0.25	0.25
RGR	0.2416	0.3179	0.2554	0.1852
SCM	0.25	0.25	0.25	0.25
SSR	0.2503	0.304	0.2499	0.1958
DSR	0.2367	0.3119	0.2687	0.1827
RSN	0.2943	0.2426	0.2109	0.2522
VSN	0.2292	0.2505	0.2831	0.2373
LUT	0.3093	0.241	0.2438	0.2059
BIO	0.25	0.25	0.25	0.25
LRF	0.2603	0.2477	0.2665	0.2255
SRF	0.8907	0.0782	0.0292	0.0019
BDR	0.25	0.25	0.25	0.25
RDR	0.396	0.2285	0.1357	0.2398
SEA	0.3624	0.2137	0.1756	0.2484
SCI	0.3231	0.2239	0.215	0.2379
LDY	0.25	0.25	0.25	0.25
MUL	0.2665	0.1746	0.2319	0.3269
POM	0.3561	0.2697	0.1863	0.188
SHP	0.25	0.25	0.25	0.25
SNK	0.2645	0.258	0.2431	0.2344
FLT	0.2384	0.1983	0.1427	0.4206
ODF	0.2306	0.2558	0.2648	0.2488
SDF	0.3932	0.2937	0.1585	0.1546
YTN	0.1904	0.275	0.2991	0.2356
BTN	0.7164	0.2027	0.0032	0.0777
LTN	0.2825	0.2657	0.2301	0.2217
OTN	0.1207	0.1706	0.3159	0.3929
SWD	0.2286	0.2019	0.2351	0.3344
WMR	0.2353	0.1759	0.2716	0.3172
BMR	0.1843	0.2385	0.3258	0.2514
BIL	0.0331	0.6081	0.2894	0.0694
AMB	0.25	0.25	0.25	0.25
JCK	0.2794	0.2916	0.2069	0.222
KMK	0.3421	0.2728	0.2133	0.1718
SMK	0.3753	0.1318	0.1321	0.3608
SAR	0.2559	0.2359	0.3233	0.1849
LPL	0.3519	0.1992	0.1737	0.2752
DWF	0.25	0.25	0.25	0.25
MEN	0.25	0.25	0.25	0.25
PIN	0.25	0.25	0.25	0.25
MPL	0.2948	0.2832	0.2194	0.2026
SPL	0.685	0.0956	0.042	0.1775
TIP	0.2752	0.2823	0.1807	0.2618
BEN	0.2752	0.2823	0.1807	0.2618
LGS	0.2924	0.2735	0.2054	0.2287
FIL	0.25	0.25	0.25	0.25
SMS	0.2752	0.2823	0.1807	0.2618
RAY	0.2855	0.2503	0.2382	0.226
BSH	0.1893	0.2428	0.264	0.304
WSH	0.1893	0.2428	0.264	0.304
PSH	0.1893	0.2428	0.264	0.304
OSH	0.1893	0.2428	0.264	0.304
DBR	0.25	0.25	0.25	0.25
SBR	0.25	0.25	0.25	0.25
MAN	0.25	0.25	0.25	0.25
MYS	0.25	0.25	0.25	0.25
DOL	0.25	0.25	0.25	0.25
DDO	0.25	0.25	0.25	0.25
LOG	0.25	0.25	0.25	0.25
KMP	0.25	0.25	0.25	0.25
TUR	0.25	0.25	0.25	0.25
BCR	0.2568	0.2567	0.237	0.2496
SCR	0.2568	0.2567	0.237	0.2496
LOB	0.1958	0.2816	0.3932	0.1294
COR	0.25	0.25	0.25	0.25
CCA	0.25	0.25	0.25	0.25
OCT	0.25	0.25	0.25	0.25
SPG	0.25	0.25	0.25	0.25
CMB	0.09	0.5917	0.302	0.0163
INF	0.25	0.25	0.25	0.25
ECH	0.25	0.25	0.25	0.25
OYS	0.1985	0.2176	0.2813	0.3026
BIV	0.2522	0.238	0.2324	0.2774
SES	0.25	0.25	0.25	0.25
EPI	0.25	0.25	0.25	0.25
GRS	0.25	0.25	0.25	0.25
ALG	0.25	0.25	0.25	0.25
MPB	0.25	0.25	0.25	0.25
LPP	0.25	0.25	0.25	0.25
SPP	0.25	0.25	0.25	0.25
DIN	0.25	0.25	0.25	0.25
PRO	0.25	0.25	0.25	0.25
JEL	0.25	0.25	0.25	0.25
SQU	0.0281	0.0264	0.3757	0.5698
LZP	0.25	0.25	0.25	0.25
SZP	0.25	0.25	0.25	0.25
PB	0.25	0.25	0.25	0.25
BB	0.25	0.25	0.25	0.25
DC	0.25	0.25	0.25	0.25
DL	0.25	0.25	0.25	0.25
DR	0.25	0.25	0.25	0.25

Table A.10: Proportion of Functional Group Landings Across U.S. Commercial Atlantis Fleets.

Group	GillnetEst	TwlShpEst	OytEst	PotCrbEst	TwlShpShf	PotCrbShf	PotLbtShf	HLReefShf	LLReefShf
GAG								0.672	0.244
RGR						0			0.991
SCM								0.48	0.507
SSR						0.01	0.001	0.525	0.281
DSR				0.013		0.373		0.121	0.493
RSN								0.961	0.033
VSN								0.997	0.002
LUT	0					0.003	0.001	0.919	0.065
BIO									
LRF	0.002	0.015			0.004	0.012	0.007	0.326	0.042
SRF	0.001							0.282	0.692
BDR	0.025	0.019		0.015	0.066			0.059	0.791
RDR								1	
SEA	0.095	0.003			0.091			0.783	
SCI	0.124	0.068		0.001	0.284			0.371	
LDY	0.688							0.042	
MUL	0.177			0	0			0	
POM	0.234							0.554	
SHP	0.078	0.134		0.002	0.176			0.405	0.037
SNK									
FLT	0.203	0.254		0.017	0.069	0.016		0.041	0.039
ODF	0.005			0.007		0.241	0.001	0.711	0.031
SDF		1							
YTN								0.012	
BTN									
LTN	0.087							0.913	
SWD								0.035	
AMB								0.961	0.014
JCK	0.048			0		0.012		0.645	0.015
KMK								0.792	
SMK	0.81	0						0.101	
SAR								0.088	
LPL	0.19	0.036						0.398	0.015
DWF									
MEN	0							0	
PIN						0.588		0.27	
MPL				0.001				0.311	
SPL	0								
TIP								0.919	
LGS	0.34	0.001			0			0.258	0.037
RAY	1								
BSH		0.193			0.807				
WSH		0.298			0.701				
PSH		0.002			0.998				
OSH		0.311			0.622	0			
BCR		0.002		0.997	0	0		0	0
SCR				0.984			0.016		
LOB				0	0		0.966		
SPG									
OYS			0.967						
BIV	0.003	0.003	0.002	0.001	0.937	0.037	0.004	0	0
SQU		0.266		0.115	0.429	0.14		0.049	

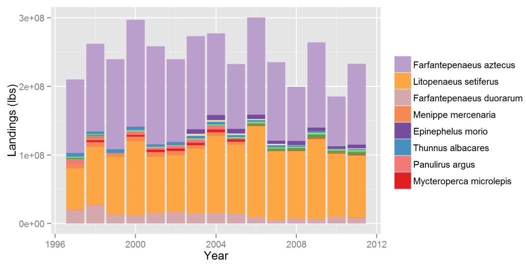
Table A.10: Continued

Group	SeineMenShf	LLShkShf	LLPelgc	RoyalRed	OtherUS
GAG					0.084
RGR					0.009
SCM					0.013
SSR					0.183
DSR					0
RSN					0.007
VSN					0.001
LUT					0.013
BIO					
LRF					0.591
SRF			0.003		0.021
BDR			0.02		0.004
RDR					
SEA					0.028
SCI					0.151
LDY					0.27
MUL	0.006				0.816
POM					0.212
SHP	0				0.168
SNK					
FLT			0.018		0.343
ODF					0.005
SDF					
YTN			0.988		
BTN			1		
LTN					
SWD			0.965		
AMB					0.025
JCK					0.28
KMK			0.208		
SMK	0.002		0.061		0.027
SAR					0.912
LPL	0.016		0.338		0.008
DWF					
MEN	1				0
PIN					0.142
MPL			0.003		0.685
SPL					1
TIP		0.081			
LGS	0	0.29	0.072		0.002
RAY					
BSH					0
WSH					0
PSH					
OSH				0.067	0
BCR					
SCR					
LOB					0.033
SPG					1
OYS					0.033
BIV			0		0.013
SQU					0.001

Table A.11: Distribution of Mexican Commercial Landings Amongst Atlantis Fleets.

Group	TwlShpMX	LLReefMX	LLShkMX	GillnetMackMX	OctpsMX	MixedMX
RGR		0.500				0.500
SSR		0.500				0.500
DSR		1.000				
RSN		0.500				0.500
VSN		0.500				0.500
LUT		0.500				0.500
LRF						1.000
SRF						1.000
RDR						1.000
SEA						1.000
SCI						1.000
LDY						1.000
MUL				0.500		0.500
POM						1.000
SHP	0.333			0.333		0.330
SNK						1.000
FLT	0.333			0.333		0.333
ODF						1.000
SDF						1.000
YTN			0.500			0.500
BTN			0.500			0.500
LTN			0.500			0.500
OTN			0.500			0.500
SWD			0.500			0.500
WMR			0.500			0.500
BMR			0.500			0.500
BIL			0.500			0.500
AMB			0.500			0.500
JCK			0.500			0.500
KMK			0.500	0.500		
SMK			0.500	0.500		
SAR						1.000
LPL				1.000		
PIN						1.000
MPL						1.000
SPL						1.000
TIP			1.000			
BEN	0.333		0.333			0.333
LGS			0.500			0.500
FIL						1.000
SMS	0.250		0.250	0.250		0.250
RAY	0.333		0.333			0.333
BSH	1.000					
WSH	0.500					0.500
PSH	1.000					
OSH	0.500					0.500
BCR						1.000
SCR						1.000
LOB						1.000
OCT					1.000	
CMB	0.500					0.500
OYS						1.000
BIV						1.000
SQU	0.500					0.500

A.6 Additional Results for Section 2.3.2



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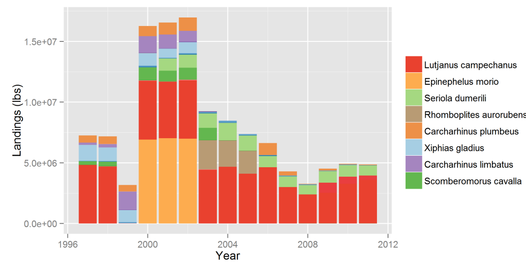

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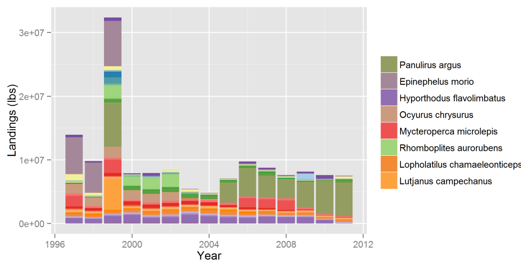

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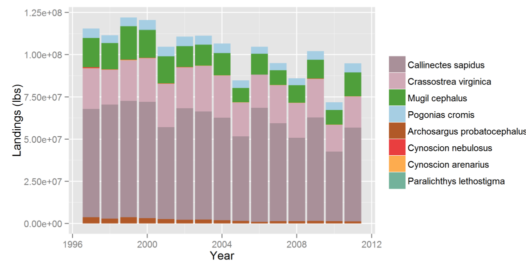

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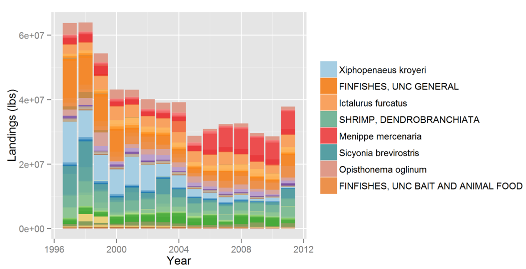
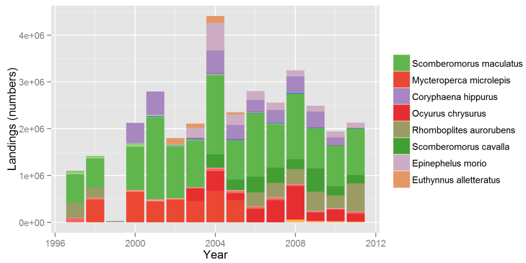


(e)

Figure A.17: Species Composition Time Series of United States Commercial Landings by Overfished Status. Legend shows only the eight most common species.



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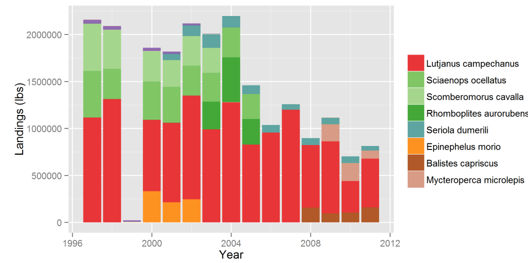

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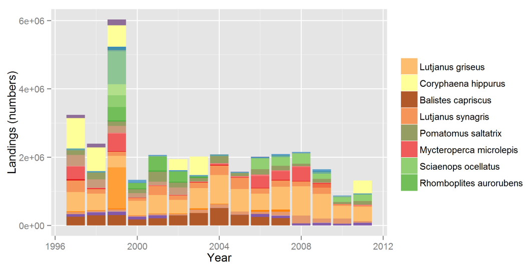

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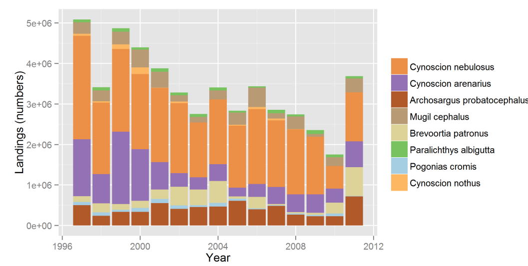

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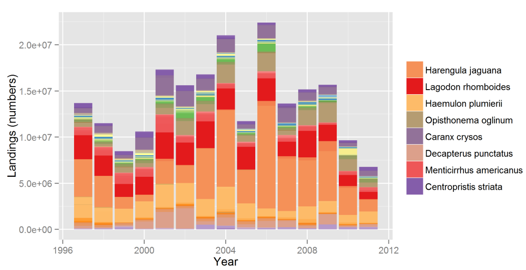
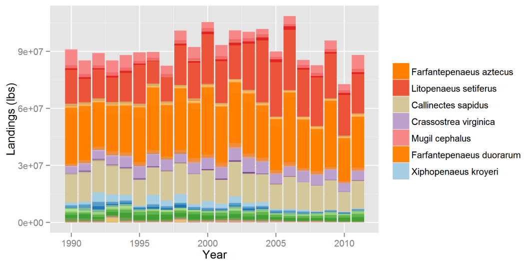


(e)

Figure A.18: Species Composition Time Series of United States Commercial Landings by Overfished Status. Legend shows only the eight most common species.



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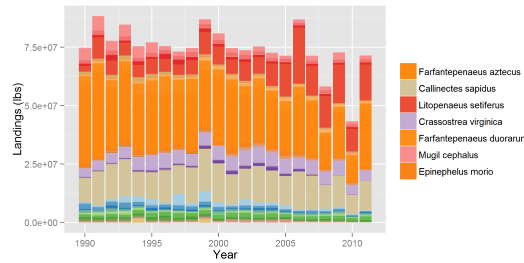

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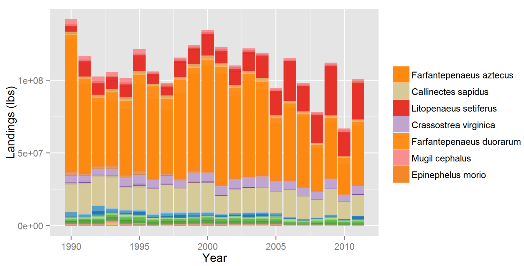

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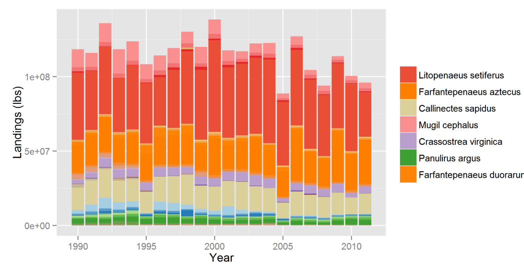
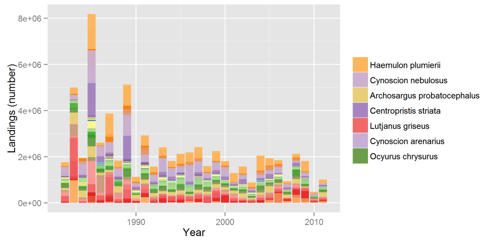
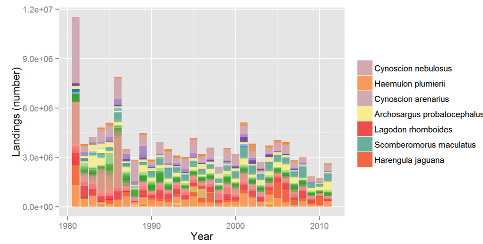


(d)

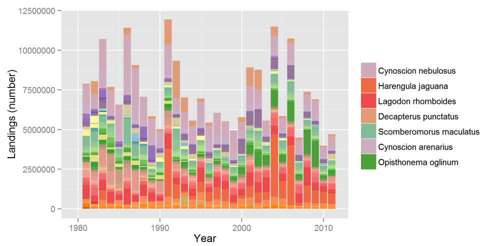
Figure A.19: Species Composition Time Series of United States Species-Specific Total Commercial Data (excluding menhaden). Data used to create these plots were also used to calculate U.S. commercial landings seasonal indicators. Species compositions are shown for winter, Jan. - Mar. (a), spring, Apr. - Jun. (b), summer, Jul. - Sep. (c), and fall, Oct. - Dec. (d). Legend shows only the seven most common species.



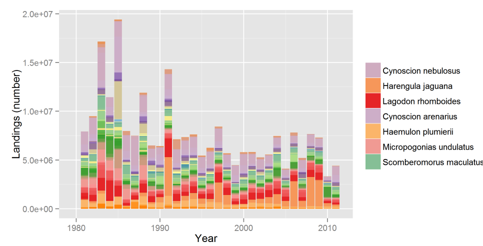
(a)



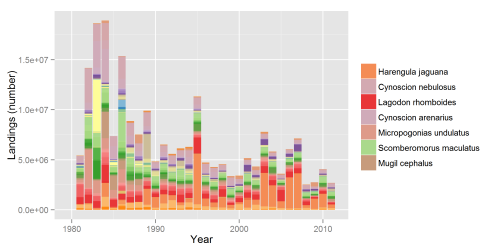
(b)



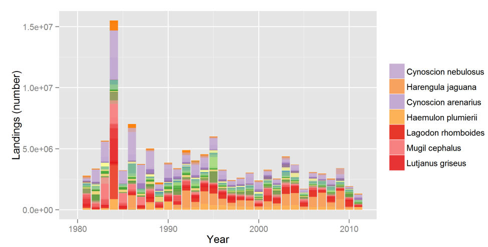
(c)



(d)

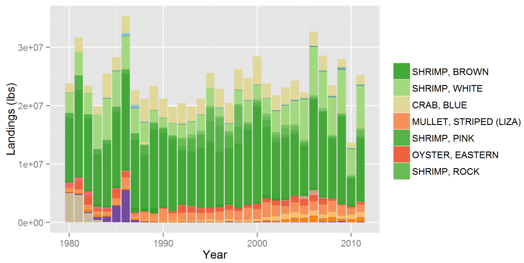


(e)

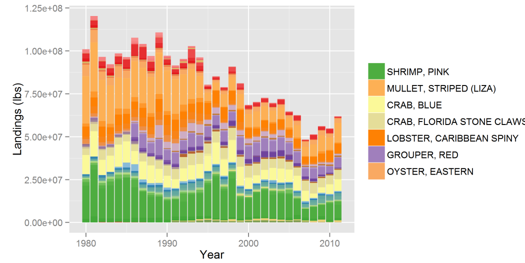


(f)

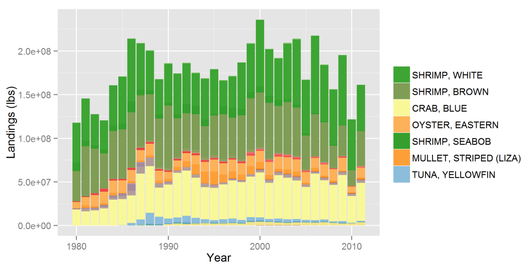
Figure A.20: Species Composition Time Series of Seasonal United States Species-Specific Recreational Landings. Data used to create these plots were also used to calculate U.S. recreational landings seasonal indicators. Species compositions are shown for wave 1, Jan. - Feb. (a), wave 2, Mar. - Apr. (b), wave 3, May. - Jun. (c), wave 4, Jul. - Aug. (d), wave 5, Sep. - Oct. (e), and wave 6, Nov. - Dec. (f). Legend shows only the seven most common species.



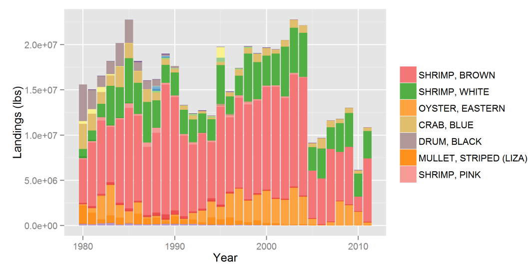
(a) Alabama



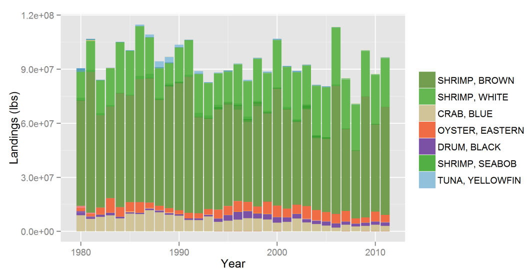
(b) Florida



(c) Louisiana

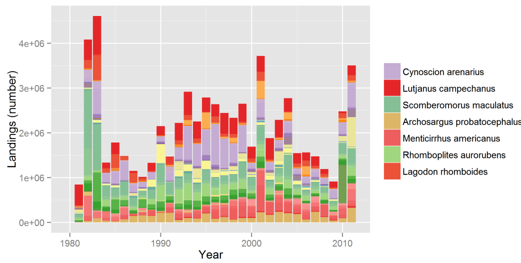


(d) Mississippi

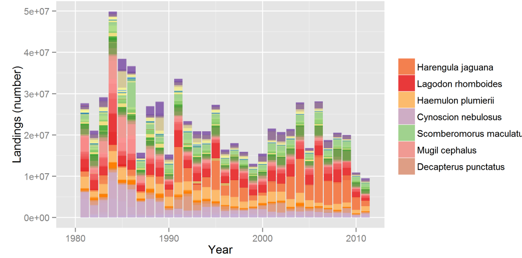


(e) Texas

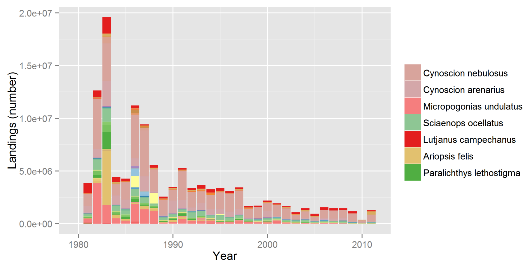
Figure A.21: Species Composition Time Series of United States Species-Specific Commercial Landings by State. Legend shows only the seven most common species.



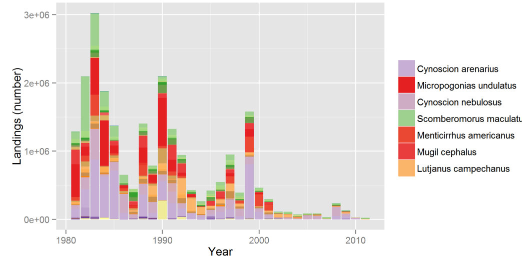
(a) Alabama



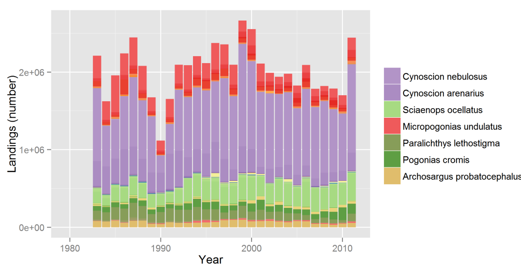
(b) Florida



(c) Louisiana



(d) Mississippi



(e) Texas

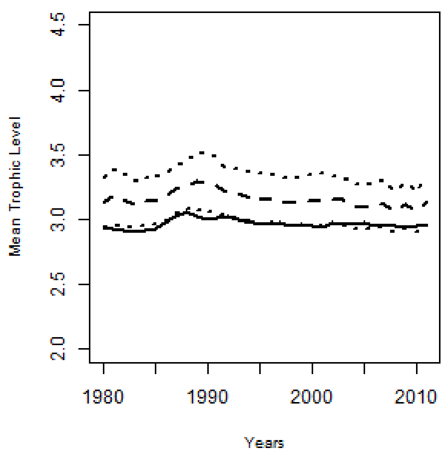
Figure A.22: Species Composition Time Series of United States Species-Specific Recreational Landings by State. Legend shows only the seven most common species.

A.6.1 Landings Mean Trophic Level Sensitivity Analysis

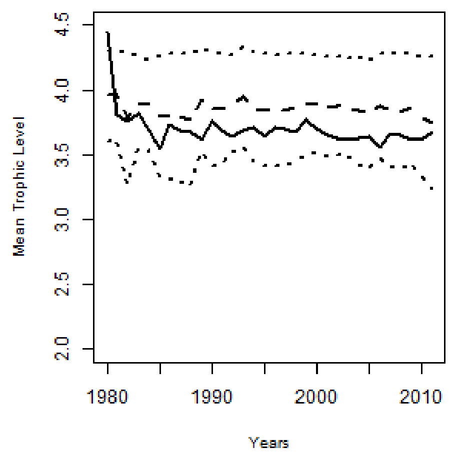
For commercial and recreational data, the trends in landings mean trophic level from both species-specific data and functional group-specific data are within the trends computed for the trophic level sensitivity analysis (Figure A.23a, A.23b). The sensitivity analysis suggests that the computation of landings mean trophic level is sensitive to trophic level. Thus, the aggregation into functional groups, and the averaging of species-specific trophic levels, could be causing the slight difference between functional group-specific and species-specific landings mean trophic level trends. The trends computed for the trophic level sensitivity analysis are wider for recreational data than commercial data because the trophic level standard errors considered here were only for some fish groups, and commercial landings have considerable amounts of invertebrate landings.

The computation of landings mean trophic level appears to be particularly sensitive to trophic level, thus the aggregation of data into functional groups, and the averaging of species-specific trophic levels, is likely having some impact on the value computed for landings mean trophic level. However, the difference observed here is small enough to be considered negligible.

The results from the sensitivity analysis indicating the computation of landings mean trophic level to be particularly sensitive to trophic level is not surprising considering that an organism's trophic level is not a constant value. Since an organism's trophic level is governed by the prey consumed, the trophic level of any one species can vary spatially, temporally, and as the organism ages (e.g., Jennings et al., 1997; Hussey et al., 2011; Yurkowski et al., 2016). A full sensitivity analysis on landings mean trophic level would be more informative for EBFM concerning the indicators robustness at various levels of species aggregation. Such an analysis should consider trophic level standard errors from laboratory studies, but if this information is not found in the literature than estimating trophic level standard errors may be necessary (e.g., Pauly and Christensen, 1995).



(a) U.S Commercial



(b) U.S Recreational

Figure A.23: Panels a and b show trends from the annual summaries of species-specific data (solid line), functional group-specific data (dashed line), and functional group-specific data with trophic level of multi-species functional groups being the average plus/minus the standard error across the multi-species functional groups (dotted lines).

APPENDIX B

Detailed Methodology and Additional Results for Chapter 3

B.1 Catch Data for Model Fitting

The Southeast Fisheries Science Center (SEFSC) conducts an annual bottom longline survey within the Gulf of Mexico and western Atlantic Ocean. Commercial-type longline gear is utilized so analyses based of this dataset can be related back to the commercial longline fisheries within the Gulf of Mexico. The mainline is suspended by two radar reflector high-flyers attached at each end, and held stationary with 5 kg weights located at the start, middle, and end of the mainline. The mainline consists of 100 gangions; each one is approximately 3.6 m in length and 18.3 m apart from one another. Gangions consist of 3 mm diameter monofilament line with #15 circle hook. Each hook is baited with atlantic mackerel (*Scomber scombrus*). Longline gear soaks for one hour after the set is complete. During the haul in organisms retained are processed immediately. Processing includes, but is not limited to, identifying species and recording length, weight, and sex. While smaller organisms (e.g. *Rhizoprionodon terraenovae*) are handled by hand, larger organisms (e.g. *Galeocerdo cuvier*) are held in a landing sling to facilitate processing. Organisms of concern (e.g., *Sphyrna lewini*) are also tagged. This survey operates along the continental shelf in depths between 9 - 366 meters, so Gulf-wide catch of pelagic species can not be represented by this dataset alone.

The Pelagic Observer Program, also managed by the SEFSC, provides longline catch and effort data within the Gulf of Mexico between 200m depth and the exclusive economic zone (EEZ). Since 1992, observers have monitored the mobile U.S. pelagic longline fleet operating in the western Atlantic Ocean. Pelagic longline gear consists of a mainline suspended mid-depth by a series of high-flyers. Longline sets can extend from 10 to 40 miles, fishing 200-1000 baited hooks spaced approximately 100 meters apart. Highly migratory species *Xiphias gladius*, *Thunnus albacares*, or *Thunnus obsess* are often the primary target. Harvesting methodology, area, and season changes based on the targeted species. For instance, pelagic longliners targeting *X. gladius* set hooks during the night while those targeting tunas set hooks during the day. Information retained by observers includes species, date, time, and location.

B.2 Supplementing Environmental Variables into Catch Datasets

Sea surface temperature is one of the few environmental variables monitored in both longline catch datasets. It is measured at multiple points during the setting and hauling of longline gear, so the mean of the reported measurements was used as final estimate of sea surface temperature for each catch record. Approximately 25% of the bottom longline records and 5% of the pelagic longline records were missing estimates of sea surface temperature. To retain these records for statistical analysis, estimates of sea surface temperature were generated by using *Interpolate PO.DAAC MODIS*

L3 SST at Points tool from the Marine Geospatial Ecology Tools (MGET) toolbox in *ArcGIS*, which extracts estimates of sea surface temperature from the Moderate Resolution Imaging Spectroradiometer (MODIS) dataset. The tool was set to draw daytime sea surface temperature values from the aqua satellite using a linear interpolation method. Different combinations of spatial resolution (4km grid or 9km grid) and temporal resolution (daily, 8 day, monthly) were used because a single combination could not extract estimates of sea surface temperature for all of the necessary catch records. This is likely due to the patchiness of MODIS data, due to cloud cover. Combinations with fine scale spatial and temporal resolutions were attempted first (4km, daily), followed by combinations with reduced temporal resolution. Then, the combination with reduced spatial resolution and fine scale temporal resolution (9km, daily). Again, this was followed by combinations with reduced temporal resolution. If a catch record was still missing an estimate of sea surface temperature, then a value was drawn from another catch record in the corresponding longline catch dataset. The chosen catch record was one with a similar harvest date and location as the record missing sea surface temperature.

Altimetry data was collected from the Archiving, Validation and Interpretation of Satellite Oceanographic (AVISO) dataset. AVISO gathers raw data from various satellite sources which are individually processed into estimates of altimetry then merged as described by Ducet et al. (2000). The resulting altimetry data are provided in 7-day increments, implying that measurements may have been taken up to 3 days before or after the date displayed in the dataset. Data are mapped to an equal angle grid 0.25 degrees latitude by 0.25 degrees longitude. Estimates of altimetry for catch records in the longline catch datasets were calculated as the mean of the four AVISO data points nearest to the catch location and corresponded to the date the catch occurred.

The routine for calculating an estimate of the minimum distance between a catch event and a frontal edge is dependent on work by Cayula and Cornillon (1992). Cayula and Cornillon presented an algorithm for detecting fronts in satellite-derived sea surface temperature fields. After the initial processing of the data input, there are three different stages focusing on the detection and removal of clouds (since they can cause erroneous edge detection). Next, the algorithm detects and verifies an edge (i.e., front) at the window level using a histogram analysis and cohesion algorithm, respectively. Then, the front is detected and verified at a local level using contour following. Lastly, the fronts are extracted. The MGET toolbox contains a tool that uses the algorithm presented by Cayula and Cornillon (1992) for the detection and extraction of fronts, call the *Cayula-Cornillon Fronts in ArcGIS Raster MGET* tool. Preliminary work executing this tool with sea surface temperature fields produced patchy and fragmented front profiles (Figure B.1a). Sea surface temperature fields collected from the Gulf of Mexico can have weak gradients (Legeckis, 1978) which make it difficult for the Cayula and Cornillon algorithm to detect a front. The dynamics of the Gulf of Mexico are mostly driven by the physical oceanography, which relates directly to altimetry. Executing the *Cayula-Cornillon Fronts in ArcGIS Raster MGET* tool with altimetry profiles produces smoother front profiles (Figure B.1b). Altimetry needed to be magnified to be on a similar scale as sea surface temperature, and a factor of 1000 produced the cleanest images.

B.3 Other Important Model Descriptors

Preliminary investigations selecting model descriptors identified variables capable of improving the fit of some models. Table B.1 highlights these results. Variables were used individually to fit generalized additive models with the bottom longline survey data. Some of these variables were not used as model descriptors primarily due to the lack of data available to make Gulf-wide data fishnets for model predictions.

B.3.1 Beam Transmission

Preliminary results showed beam transmission to be a statistically important descriptor for shark-based functional groups. Beam transmission (%), a measurement of the penetration of light through the water column, may influence the local density of an organism (e.g., fish residing in murky waters to evade predators), or it may relate to catchability (e.g., fish are more/less likely to strike a baited hook in waters with more/less light). However, beam transmission depends on many dynamic environmental processes (e.g., cloud cover, sediment, pollution, etc), thus developing seasonal, Gulf-wide estimates of beam transmission for model predictions would be inappropriate. However, CPUE modeling over a smaller temporal range should consider beam transmission as a descriptor.

B.3.2 Density

Sea bottom density was a statistically important descriptor for shark-based functional groups, however a dataset containing estimates of sea bottom density across the Gulf could not be found. Considering the amount of deviance explained, it could prove to be useful to include this variable into future modeling efforts. Especially if at a smaller spatial and temporal scale allowing for the possibility of collecting data for model predictions.

B.3.3 Latitude and Longitude

The incorporation of latitude and longitude as model descriptors helped fitted models explain more deviance. Latitude and longitude were not considered as model descriptors because preliminary predictions showed an obvious bias in the regions outside of the spatial range of the catch datasets (i.e., catch rates showed a unnaturally strong north-south gradient). If predictions efforts were restricted to the northern Gulf of Mexico than latitude and longitude should be considered as potential model descriptors to improve model fits. Geospatial models could also be considered.

B.3.4 Daytime

Daytime, a binomial factor indicating day or night, did not explain much model deviance when fitting bottom longline survey data. However, daytime would likely impact models fit with pelagic longline observer data since hooks are set differently during the day versus night due to the change in target organism. To see how daytime may influence model predictions, models presented in the chapter were re-fitted with daytime as a descriptor (spline basis dimensions were set to three and not adjusted, thus the prediction profiles without daytime in the fitted model were similar to the night time predictions). These fitted models were than predicted across the same fishnet grids, once with daytime identified as day and again with daytime identified as night (day and night measurements of other model descriptors are not available). The coastal models (fit with bottom longline data) did not show any major differences between day and night prediction profiles, however some functional group with pelagic models had noticeable differences between day and night prediction profiles (examples in Figure B.3). The discussion in the chapter on *large sharks* is not significantly impacted by not including daytime into models, but some functional groups should have daytime incorporated into future modeling efforts (e.g., *swordfish*, and *white marlin*).

B.4 Selecting the Error Structure of Models fitting Zero-Truncated Data

Although the longline datasets record catch as counts (which is commonly modeled with the poisson distribution) catch rates (CPUE) in this study are continuous, which are commonly modeled with the log-normal and gamma distributions. First, we wanted to assess the validity for assuming a log-normal or gamma error structure (Maunder and Punt, 2004). Dong and Restrepo (1996) and Punt et al. (2000) discussed evaluating assumed error structure by comparing catch rate average and variance. A relationship where the variance in catch rate is proportional to the square of the average catch rate suggests the log-normal or gamma distribution. The functional group-specific average catch rate and variance in catch rate for each unique date are shown in Figure B.2, and functional group-specific catch data support the use of either the log-normal or gamma distribution for the CPUE data error structure.

Myers and Pepin (1990) found lognormal-based estimators to be very sensitive to violations of model assumptions, which can lead to biases as well as reduced efficiency, and they encouraged assuming a log-normal distribution only in situations when repeated samples from the same population consistently showed the distribution to be log-normal. If a random variable follows a log-normal distribution, than the natural log of the random variable will follow a normal distribution. Log-transforming functional group-specific catch rates for both longline datasets (Figure B.4) fails to normalize catch rates for a majority of functional groups. Thus, the data are not lognormal. Other studies have achieved comparable, if not improved, model fits using the gamma distribution rather than the lognormal (Punt et al., 2000; Dick, 2004; Ortiz and Arocha, 2004).

The statistical software R has three link functions associated to the gamma distribution:identity, inverse, and log. Functional group-specific catch profiles (for both the bottom longline survey and the pelagic longline observer data) were used to fit GAMs for each of the three link functions. The generic setup of the statistical model was as follows:

$$\eta_Z = s(SSH, k=3) + s(WD, k=3) + f(y) + s(SST, k=3) + s(MDF, k=3) \quad \text{(B.1)}$$

where η_Z is the abundance index, SSH is altimetry [m], WD is bottom depth [m], y is year, SST is sea surface temperature [°C], MDF is minimum distance from a front [m], $s()$ indicates a smooth function, k indicates a smoother's basis dimension, and $f()$ indicates a factor. All basis dimensions were set to three, the default value. Table B.2 displays the GCV and deviance explained for all of the model fits. Often, the best fit corresponds to models that used the inverse link function. This makes sense since the inverse link corresponds to the zero inflated nature of the cate rate data. Thus, this study assumes a gamma error structure with inverse link function for GAMs fitted with zero-truncated data.

B.5 Verification of Routine Setting Smoother Basis Dimension

Fit statistics for models fitted with *training* datasets for cross validation were recorded before and after to application of the basis dimension setting routine (Table B.3). Basis dimensions for smoothers in binomial data models were often unchanged after the application of the basis dimension setting routine, thus fit statistics didn't improve. However, basis dimensions for smoothers in zero-truncated data models were often increased thus improving model fits.

B.6 Forward Model Selection

During the forward model selection process for determining the order of model descriptors, a correlation analysis was conducted to determine if the environmental variable selected to be a model descriptor was highly correlated with selected model descriptors. A variable highly correlated with model descriptors (i.e., producing a correlation coefficient greater than 0.80) was not used as a model descriptor. Correlation coefficients for environmental variables considered for models fit with pelagic longline observer data (i.e., year, season, sea surface temperature, altimetry, and minimum distance from a front) are summarized in Table B.4. None of the variables were highly correlated, thus all of the considered variables were used as model descriptors for both parts of the delta framework.

Models fit with bottom longline survey data had a variety of environmental variables applicable as model descriptors, making overparameterization a concern, so the forward model selection process stopped (i.e., model descriptors were no longer added) once the deviance explained from model fits were not improved by more than 5%. The forward model selection process is presented for *large pelagic fish* (Table B.5), *large sharks* (Table B.6), *skates and rays* (Table B.7), and *blacktip sharks* (Table B.8). These tables also display correlation coefficients between environmental variables and model descriptors. If a model gains the most improvement from an environmental variable that is highly correlated to current model descriptors, than the variable providing the next best fit is considered for incorporation as a model descriptor instead. For example, consider the forward model selection results for the *large pelagic fish* zero-truncated data model (Table B.5). During the third iteration it is apparent that adding sea surface oxygen saturation to the model $do + ssh$ produced the most improved model (57.6% to 64.9% deviance explained). Although sea surface oxygen saturation and altimetry are not highly correlated (0.138 correlation coefficient), the previous iteration revealed that sea surface dissolved oxygen and sea surface oxygen saturation are highly correlated (0.814 correlation coefficient). Thus, year was added as a model descriptor since it provided the second-best improvement to the model's fit (62.3% deviance explained) and is not correlated with any of the the current model descriptors (0.034 correlation coefficient with sea surface dissolved oxygen and 0.468 correlation coefficient with altimetry).

B.7 Cross Validation Results

Cross validation results for all fitted delta models are displayed in Figure B.5.

B.8 Developing Seasonal Fishnet Grids for Model Predictions

The development of seasonal, spatial biomass distribution profiles for each functional group was dependent on using the fitted GAMs to predict across grids of data representing hypothetical values of model descriptors. These grids were developed in *ArcGIS*. First, a 0.1° latitude by 0.1° longitude grid of geographic coordinates spanning the entire Gulf of Mexico was created using the *Fishnet* tool. Four versions of the grid were generated, one for each season. Next, coordinates within the grids were assigned estimates of all model descriptors.

B.8.1 Environmental Data

To assign estimates of model descriptors to fishnets, environmental point data files needed to be converted to rasters. Bathymetry data, a polyline file, was first converted to a point file using the *Feature to Point* tool. Also, NCEI data (Table 3.1) was clipped to only contain points within the marine environment (i.e., removed the points representing Lake Okeechobee). Lastly, AVISO point data was split into seasonal datasets using the *Select* tool. Interpolation of point files to raster files was accomplished using the *Kriging* tool (all attributes remained set to default values). Rasters representing Gulf-wide seasonal averages were created for bathymetry (Figure B.6; assumed to not change seasonally), altimetry (Figure B.7), sea surface temperature (Figure B.8), sea bottom temperature (Figure B.9), sea bottom oxygen saturation (Figure B.10), sea surface dissolved oxygen (Figure B.11), sea bottom dissolved oxygen (Figure B.12), sea surface salinity (Figure B.13), and sea bottom salinity (Figure B.14).

Assigning values of environmental descriptors to seasonal Gulf-wide fishnet grids was done with the *Extract Values to Points* tool (set to bilinear interpolation). First, points in the Gulf-wide fishnet were assigned estimates of bathymetry. This allows the division of the Gulf-wide fishnet along the 250m isobath - creating coastal and pelagic seasonal fishnets. Seasonal, environmental data were then assigned to appropriate fishnets.

B.8.2 Minimum Distance From a Front

Fishnet grids were assigned estimates of minimum distance from a front using the routine described in Figure 3.2. The seasonal front polyline files created by seasonal AVISO averages (the point files) for calculating minimum distance from a front are shown in Figure B.15.

B.9 Gulf-wide Abundance Distribution Profiles

Seasonal, spatial abundance distribution profiles spanning the entire Gulf of Mexico were developed for each functional group based on predicted abundance indices generated by the fitted statistical models. First, grids describing hypothetical seasonal conditions in the Gulf of Mexico were developed (see B.8). Fitted models were used to predict across fishnet grids to create seasonal, spatial distribution profiles.

Seasonal, Gulf-wide biomass distribution profiles were developed to improve the spatial representation of pelagic functional groups in the Gulf of Mexico Atlantis model. These profiles were developed for each functional group by 1) averaging the spatial catch rate profiles across overlapping polygons in the Gulf of Mexico Atlantis map, 2) extrapolating average catch rates for the remaining Gulf of Mexico polygon map, then 3) calculating the proportion of catch rates in each polygon. Statistical software R was used to calculate the median catch rate for polygons overlapping the seasonal, spatial profiles of catch rates for each functional group. Median was used to prevent extreme catch rate predictions from having too much of an influence on the computed average. Two different methodologies were executed for extrapolating average catch rates across the remaining Atlantis polygon map.

Functional groups *large pelagic fish*, *skates and rays*, and *large sharks* were caught in both the survey and observer longline datasets, thus have GAMs for predicting across both pelagic and coastal areas in the Gulf of Mexico. Model predictions for *large sharks* are shown in the main paper, and the model predictions for *large pelagic fish* and *skates and rays* can be seen in Figure B.16 and Figure B.18, respectively. Due to the difference in bottom longline and pelagic longline functional group catchability, the coastal and pelagic profiles must be converted to a common scale before they can be combined. Statistical models were developed to standardize the two longline datasets. Data used to fit these models contained both bottom and pelagic longline catch, but only data from similar spatial and temporal ranges where the two datasets overlapped. *ArcGIS* was used to create this data subset by selecting all the longline catch events that occurred in off the coast of Louisiana, an area where the two longline datasets intersect (Figure 3.1). Species from the *large pelagic fish* functional group were not retained in both of the longline datasets throughout the data subset, so another method had to be taken for extrapolating the average catch rates across the remaining Atlantis polygon map. The setup of the statistical model solving for the abundance index (η_Z) was similar to Equation 3.1. The numerical descriptors include bottom depth [m], sea surface temperature [°C], altimetry [m[, and minimum distance from a front [m]. The categorical descriptors include year (2005-2010), season (1-4), and longline type (bottom or pelagic). Forward model selection was conducted to determine the best model for η_Z, for both functional groups (Table B.9). A standardization factor was calculated for average catch rates in pelagic polygons by dividing the median fitted CPUE of pelagic data by the median fitted CPUE of survey data. For *large sharks* the pelagic catch rate standardization factor is 0.522, and for *skates and rays* it is 0.061. Average catch rates for pelagic polygons were standardized by dividing the value by the standardization factor, thus allowing the pelagic and coastal profiles to be merged. The calculated standardization factors were used for all of the functional group's seasonal profiles.

For the remaining functional groups general assumptions were made for extrapolating estimates of the average catch rate to the remaining polygons. Online sources Fishbase (Froese and Pauly, 2016) and GulfBase (Moretzsohn et al., 2016), specifically the the Biodiversity of the Gulf of Mexico Database (Moretzsohn et al., 2011), were used to help gather information concerning species spatial distribution.

- BIL (*other billfish*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.20. Catch in this group is primarily sailfish (*Istiophorus albicans*, but some identify *I. platypterus* as a world-wide species). Sailfish are known to be oceanic, spending much of the time oceanic environments (Riede, 2004). Kerstetter et al. (2010) used satellite tag data to discuss vertical and die distributions, but did not address Gulf-wide horizontal movements. To keep assumption general, polygons with depths defined as 10, 20, or 50 m were assigned a average catch rate of zero, and polygons with depths defined as 200 m were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons. This was done for each seasonal profile.

- BMR (*blue marlin*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.21. Comparing the results presented by Kraus et al. (2011) to polygons defined for the Gulf of Mexico Atlantis model, polygons with depths defined as 10, 20, or 50 m were assigned a average catch rate of zero, and polygons with depths defined as 200 m were assigned the smallest medium catch rate calculated when averaging across polygons. This was done for each seasonal profile.

- BTN (*bluefin tuna*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.22. Considering results presented by Teo et al. (2007) polygons with depths defined as 10 or 20 m were assigned a average catch rate of zero, and polygons with depths defined as 50 or 200 m were assigned the smallest medium catch rate calculated when averaging across polygons. This was done for each seasonal profile. Bluefin tuna catch during the months of season 3 (Jul. - Sep.) are not present in the longline observer dataset, thus a catch rate profile could not be computed for this season. According to work by Block et al. (2005) bluefin tuna are found within Gulf of Mexico waters during this time. To develop a season 3 stock distribution profile for the Gulf of Mexico Atlantis model, the distribution of bluefin tuna were evenly distributed across polygons overlapping adult bluefin tuna hotspots reported by Block et al..

- DWF (*deep water fish*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.23. Catch in this group consist of various species, many of the *Cubiceps* genus. Many of the DWF species are not coastal but rather oceanic (e.g.,*Cubiceps capensis* (Riede, 2004)) and/or bathypelagic (e.g., *Cubiceps pauciradiatus* (Cervigón, 1994), *Trachipterus arcticus* (Muus et al., 1999)). Many of these species are concentrated around the slope Moretzsohn et al. (2011). All coastal polygons were assigned the smallest medium catch rate calculated when averaging across polygons (this was done for each seasonal profile). This aims to satisfy both observations: i) distributing DWF along the continental shelf, and ii) putting a slight emphasis on the slope, since GAMs estimates small catch rates for deep, oceanic polygons.

- FIL (*filter feeding sharks*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.24. Catch in this group consist of mantas (of the family *Mobulidae*). Many of these species are epipelagic, centering around the slope Moretzsohn et al. (2011). All coastal polygons were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons (this was done for each seasonal profile). This encourages a strong emphasis on the slope since the GAM predicts small catch rates for deep, oceanic polygons.

- LPL (*large pelagic fish*) - extrapolate across coastal polygons

  LPL species are retained in the bottom longline survey but after i) studying these catch records and ii) considering the coastal GAM predictions, the coastal model for LPL was not considered. The catch rate spatial profiles indicate a strong seasonal flux, which we know is not part of the life histories of species in the LPL functional group. This flux is likely influenced by the fact that the survey operates primarily during summer and fall months. This signal is easier for the LPL model to pick up since there are very few instances of LPL species being caught in the bottom longline survey (barely enough to fit a statistical model). LPL catch records mostly consist of *Remora* sp. and *Sphyraena barracuda*, neither of which are benthic species. Thus, LPL catch records are likely incidental catch occurring when hooks are being set/hauled (i.e., traversing through the water column). Although it is clear that LPL species are within Gulf of Mexico coastal waters, the bottom longline survey is an inappropriate dataset for extrapolating information regarding the coastal distribution. Species identified in both longline catch datasets are known to use coastal waters (e.g., *Remora remora* (Fricke et al., 2011), *Sphyraena barracuda* (de Sylva, 1990), *Pomatomus saltatrix* (Claro, 1994)). All coastal polygons were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons. This was done for each seasonal profile.

- MPL (*medium pelagic fish*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.25. Catch in this group consist of various species (e.g., *Brama* sp. and *Megalops atlanticus*). Many of these species have been found in coastal waters (e.g., *Brama brama* (May and Maxwell, 1986), *Megalops atlanticus* (Whitehead and Vergara, 1978)). For each seasonal profile, when calculating the median catch rate within polygons the median of those catch rates was also calculated. The median catch rate, for each season, were assigned to all coastal polygons as the average catch rate.

- SMK (*spanish mackerel*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.26. Two species dominate this catch: *Lepidocybium flavobrunneum* and *Ruvettus pretiosus*. Both species are benthopelagic and oceanic (Riede, 2004), as well as occupying the slope (Nakamura and Parin, 1993; Nakamura, 1995). Thus, polygons with depths defined as 10, 20, or 50 m were assigned a average catch rate of zero, and polygons with depths defined as 200 m were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons. This was done for each seasonal profile. Using the medium of catch rates will encourage a slight concentration of the functional group around the slope.

- SMS (*small sharks*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.27. Some SMS species use the entire coast (*Isistius brasiliensis* (Kiraly et al., 2003)), and some are usually meso- and/or bathypelagic (e.g. *Zameus squamulosus* (Kiraly et al., 2003), *Somniosus microcephalus* (Muus et al., 1999; Moretzsohn et al., 2011), *Squalus acanthias* (Cox and Francis, 1997; Compagno, 2002)). Thus, polygons with depths defined as 10, 20, or 50 m were assigned an average catch rate of zero, and polygons with depths defined as 200 m were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons. This was done for each seasonal profile.

- SWD (*swordfish*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.28. There is limited information discussing the horizontal distribution of swordfish, especially within the Gulf of Mexico. Dewar et al. (2011) presented data collected from swordfish tagged with PSAT tags, but the relatively low sample size and short deployment durations limit the utility for examining migratory patterns or stock structure. Nakamura (1985) generalizes that the stock is mostly pelagic with some instances of being in coastal habitats. Polygons with depths defined as 10, 20, or 50 m were assigned a average catch rate of zero, and polygons with depths defined as 200 m were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons. This was done for each seasonal profile.

- TIP (*blacktip sharks*) - extrapolate across pelagic polygons

  Model predictions can be seen in Figure B.29. Blacktip sharks are primarily coastal, rarely moving through deep, oceanic waters (Compagno, 1984). All pelagic polygons were assigned an average catch rate equal to zero.

- TUR (*other turtles*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.30. The TUR species identified in the catch records are known to be coastal (e.g., *Chelonia mydas*, *Dermochelys coriacea*, *Eretmochelys imbricata* (Moretzsohn et al., 2011)). All coastal polygons were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons. This was done for each seasonal profile.

- WMR (*white marlin*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.31. White marlin generally prefer water deeper than 100 m (ICCAT, 2012). Polygons with depths defined as 10, 20, or 50 m were assigned a average catch rate of zero, and polygons with depths defined as 200 m were assigned the smallest medium catch rate calculated when averaging across polygons. This was done for each seasonal profile.

- YTN (*yellowfin tuna*) - extrapolate across coastal polygons

  Model predictions can be seen in Figure B.32. Yellowfin tuna are known to be oceanic, spending much of the time oceanic environments (Riede, 2004). Polygons with depths defined as 10, 20, or 50 m were assigned a average catch rate of zero, and polygons with depths defined as 200 m were assigned an average catch rate equal to the medium of all the catch rates calculated when averaging across polygons. This was done for each seasonal profile.

B.10 Spatial Predications from Updated Pelagic Models: *Large Sharks*

Forward selection of pelagic models was originally done with training datasets for cross validation. This should have been done with the entire dataset (data for forecasting fitting). Forward selection of pelagic models was done with data for forecasting fitting, and these models were used to compute predictions. While for many functional groups predictions were the similar as those from pelagic models selected from training data, predictions for *large sharks* were quite different (Figure B.33). This is because the pelagic delta model selected with data for forecasting fitting

(Eqn. B.2) selected bottom depth as the variable providing the most improvement to AIC, so bottom depth was the first descriptor to have the basis dimension adjusted. This resulted in a smoothing spline for bottom depth to be more 'wiggly' than the smoothing spline reported in the chapter (Figure B.33). Predictions for *large sharks* presented in the chapter seem to make more ecological sense than predictions for *large sharks* from the model selected with data for forecasting fitting, and thus were selected to be used to parameterize the Gulf of Mexico Atlantis model. This is likely due to the smoothing spline for bottom depth being excessively 'wiggly' from the model selected with data for forecasting fitting. This highlights the limitations of using an automated routine for basis dimension setting.

$$g(\eta_B) = s(BD, 9) + f(yr) + f(sn) + s(MDF, 3) + s(SSH, 3) \tag{B.2}$$

$$g(\eta_Z) = s(BD, 21) + f(yr) + f(sn) + s(SST, 9) + s(SSH, 25) + s(MDF, 18)$$

Table B.1: The deviance explained when bottom longline data was fit individually with the environmental and temporal variables considered to be model descriptors. Variables include year, daytime, latitude (LAT.DEG.N), longitude (LON.DEG.W), sea bottom depth (WATER.DEPTH), sea surface temperature (SST), sea surface height (SSH), minimum distance from a front (NEAR.DIST), beam transmission (XMISS), dissolved oxygen (OXY.MG), oxygen saturation (OXSAT), density, salinity, and some of these variables measured from the sea bottom (indicated by CTD.BT).

	Bernoulli Models				Gamma models			
	LGS	TIP	RAY	LPL	LGS	TIP	RAY	LPL
YEAR	0.0268	0.0076	0.0162	0.0044	0.0408	0.1094	0.0628	0.1857
DAYTIME	3.13E-07	0.0018	0.0028	0.0005	0.0002	0.0181	4.14E-05	0.0134
LAT.DEG.N	0.0140	0.0138	0.0217	0.0714	0.0249	0.1422	0.0762	0.1592
LON.DEG.W	0.0099	0.0420	0.0779	0.0752	0.1532	0.2369	0.1930	0.0594
WATER.DEPTH	0.4486	0.3026	0.1032	0.0780	0.1224	0.1710	0.1659	0.0710
SST	0.0071	0.0332	0.0068	0.0441	0.0425	0.0742	0.1202	0.0420
SSH	5.62E-08	0.0274	0.0213	0.0179	0.1253	0.1111	0.0184	0.1036
NEAR.DIST	0.0120	0.0441	0.0249	0.0344	0.0012	0.0392	0.0306	4.82E-07
XMISS	0.0118	0.1820	0.0017	0.0326	0.0093	0.0636	0.0226	1.91E-06
OXY.MG	0.0031	0.0156	0.0042	0.0592	5.91E-08	0.0470	8.76E-07	0.3034
OXSAT	0.0034	0.0123	0.0086	0.0471	0.0002	0.0881	2.82E-07	0.1401
DENSITY	3.74E-07	0.0995	8.84E-08	0.0409	0.0276	0.2174	0.0267	0.0573
SALINITY	0.0047	0.1009	7.03E-07	0.0097	0.0373	0.2418	0.0386	0.0556
CTD.BT.Temp	0.4260	0.2431	0.1104	0.0529	0.1609	0.1714	0.2169	2.23E-06
CTD.BT.XMISS	0.0048	0.1612	0.0071	0.0593	0.2034	0.3179	0.2226	0.0759
CTD.BT.OXY.MG	0.0807	0.0334	0.0349	0.0725	0.0488	0.0683	0.0704	0.0547
CTD.BT.OXSAT	0.1778	0.0578	0.0579	0.0894	0.0335	0.0592	0.0926	0.1108
CTD.BT.DENSITY	0.4683	0.2546	0.0864	0.0247	0.0704	0.3057	0.1429	4.57E-06
CTD.BT.SAL	0.0126	0.0716	0.0223	0.0046	1.47E-07	0.3142	0.1141	0.0251

Table B.2: Comparing Statistical Fits of Gamma Link Functions. The three gamma link functions (identity, inverse, and log) are being compared with the fit statistics generalized cross validation (GCV) and deviance explained. Bolded values indicated the best fit. The results for starred functional groups are derived from bottom longline survey data, and all other results are derived from pelagic longline observer data.

Functional Group	Fit Statistic	Identity	Inverse	Log
BIL (*other billfish*)	GCV	0.428	**0.394**	0.406
	Deviance Explained	0.244	**0.304**	0.284
BMR (*blue marlin*)	GCV	0.337	**0.327**	0.334
	Deviance Explained	0.188	**0.215**	0.194
BTN (*bluefin tuna*)	GCV	**0.357**	0.359	0.358
	Deviance Explained	**0.076**	0.072	0.074
DWF (*deep water fish*)	GCV	0.068	**0.062**	0.065
	Deviance Explained	0.386	**0.436**	0.412
FIL (*filter feeding sharks*)	GCV	0.161	**0.147**	0.156
	Deviance Explained	0.213	**0.296**	0.243
LGS (*large sharks*)	GCV	0.790	0.626	**0.594**
	Deviance Explained	0.536	0.633	**0.652**
LGS (*large sharks*)⋆	GCV	0.998	**0.916**	0.968
	Deviance Explained	0.190	**0.259**	0.216
LPL (*large pelagic fish*)	GCV	0.993	0.966	**0.966**
	Deviance Explained	0.212	0.234	**0.234**
LPL (*large pelagic fish*)⋆	GCV	0.206	**0.189**	0.200
	Deviance Explained	0.270	**0.366**	0.309
MPL (*medium pelagic fish*)	GCV	0.252	**0.251**	0.252
	Deviance Explained	0.048	**0.056**	0.052
RAY (*skates and rays*)	GCV	0.499	**0.485**	0.490
	Deviance Explained	0.139	**0.164**	0.154
RAY (*skates and rays*)⋆	GCV	0.823	**0.692**	0.751
	Deviance Explained	0.290	**0.412**	0.353
SMK (*spanish mackerel*)	GCV	0.661	**0.659**	0.660
	Deviance Explained	0.064	**0.068**	0.067
SMS (*small sharks*)	GCV	0.474	**0.398**	0.424
	Deviance Explained	0.405	**0.503**	0.469
SWD (*swordfish*)	GCV	0.738	**0.662**	0.665
	Deviance Explained	0.349	**0.417**	0.413
TIP (*blacktip sharks*)⋆	GCV	0.696	0.685	**0.683**
	Deviance Explained	0.159	0.169	**0.174**
TUR (*other turtles*)	GCV	0.208	**0.138**	0.169
	Deviance Explained	0.511	**0.673**	0.601
WMR (*white marlin*)	GCV	0.303	**0.293**	0.299
	Deviance Explained	0.187	**0.218**	0.202
YTN (*yellowfin tuna*)	GCV	0.669	**0.663**	0.665
	Deviance Explained	0.104	**0.112**	0.108

Table B.3: Evaluating Basis Dimension Estimation Routine. This table displays the deviance explained for functional group-specific GAMs before and after the execution of the basis dimension estimation routine. Results for starred functional groups are derived from bottom longline survey data, and all other results are derived from pelagic longline observer data. All results come from models fit with *training* datasets developed for the cross validation.

Functional	Binomial Data Model		Zero-Truncated Data Model	
Group	Pre-Routine	Post-Routine	Pre-Routine	Post-Routine
other billfish	0.305	0.305	0.277	0.352
blue marlin	0.207	0.207	0.192	0.245
bluefin tuna	0.431	0.431	0.088	0.088
deep water fish	0.117	0.117	0.671	0.671
filter feeding sharks	0.088	0.088	0.446	0.446
large sharks	0.197	0.197	0.648	0.702
large sharks*	0.474	0.603	0.302	0.382
large pelagic fish	0.150	0.150	0.227	0.321
large pelagic fish*	0.474	0.485	0.445	0.467
medium pelagic fish	0.101	0.101	0.179	0.179
skates and rays	0.221	0.221	0.359	0.399
skates and rays*	0.165	0.264	0.294	0.582
spanish mackerel	0.105	0.136	0.152	0.221
small sharks	0.225	0.225	0.520	0.604
swordfish	0.238	0.261	0.413	0.479
blacktip sharks	0.227	0.676	0.628	0.628
other turtles	0.085	0.085	0.724	0.724
white marlin	0.212	0.228	0.216	0.216
yellowfin tuna	0.310	0.310	0.119	0.138

Table B.4: Summary of Correlations Among Environmental Variables for Models Fit with Pelagic Longline Observer Data. Presented are the correlation coefficients for both components of the Delta framework: models fit with binomial data and models fit with zero-truncated data. Model descriptors include year, season, sea surface temperature (SST), altimetry (SSH), bottom depth (BD), and minimum distance from a front (MDF). Functional group-specific binomial data models produce the same correlation matrix since models are fitted with the entire longline set data, but zero-truncated data models produce different correlation matrices since fitted datasets only include functional group-specific catch events. The correlation matrices are summarized here with the table below displaying the average, minimum, and maximum.

Binomial Data Models						
Descriptors	year	season	SST	SSH	BD	MDF
year	-	-	-	-	-	-
season	-0.14	-	-	-	-	-
SST	-0.16	0.51	-	-	-	-
SSH	-0.10	0.29	0.37	-	-	-
BD	0.08	0.03	0.12	-0.08	-	-
MDF	0.20	0.03	0.00	-0.09	-0.02	-
Zero-Truncated Data Models						
Descriptors	year	season	SST	SSH	BD	MDF
year	-	-	-	-	-	-
season	-0.13(-0.25 - 0.06)	-	-	-	-	-
SST	-0.14(-0.23 - -0.02)	0.44(0.2 - 0.53)	-	-	-	-
SSH	-0.06(-0.16 - 0.14)	0.27(0.08 - 0.44)	0.35(0.09 - 0.56)	-	-	-
BD	0.08(0 - 0.18)	0.01(-0.15 - 0.08)	0.1(-0.17 - 0.29)	-0.07(-0.23 - 0.16)	-	-
MDF	0.18(-0.15 - 0.26)	-0.01(-0.1 - 0.05)	-0.02(-0.16 - 0.12)	-0.1(-0.35 - 0.11)	0.01(-0.12 - 0.17)	-

Table B.5: Forward model selection results for GAMs fitted with *large pelagic fish* bottom longline survey data. Model descriptors included year, bottom depth, sea surface temperature (sst), sea bottom temperature (sbt), altimetry (ssh), minimum distance from a front (mdf), sea surface dissolved oxygen (do), sea bottom dissolved oxygen (sbdo), sea surface oxygen saturation (oxsat), sea bottom oxygen saturation (sboxsat), sea surface salinity (salinity), and sea bottom salinity (sbsalinity). Forward model selection ceased when descriptors failed to improve the deviance explained (d) more than 5%. The displayed correlation coefficient (c) is calculated based on the last two model descriptors. Bold-faced indicates selected models.

Binomial Data Model	d	c	Zero-Truncated Data Model	d	c
year	0.004	-	year	0.200	-
depth	0.086	-	depth	0.140	-
sst	0.032	-	sst	0.059	-
ssh	0.021	-	ssh	0.180	-
mdf	0.027	-	mdf	2.7E-7	-
do	0.042	-	**do**	**0.332**	-
oxsat	0.032	-	oxsat	0.164	-
salinity	0.011	-	salinity	0.052	-
sbt	0.070	-	sbt	0.040	-
sbdo	0.080	-	sbdo	0.063	-
sboxsat	**0.106**	-	sboxsat	0.158	-
sbsalinity	1.4E-6	-	sbsalinity	0.058	-
sboxsat + year	0.112	-0.187	do + year	0.466	0.034
sboxsat + depth	0.124	-0.500	do + depth	0.348	-0.168
sboxsat + sst	**0.144**	-0.263	do + sst	0.332	-0.306
sboxsat + ssh	0.114	-0.301	**do + ssh**	**0.576**	0.262
sboxsat + mdf	0.122	0.454	do + mdf	0.332	-0.083
sboxsat + do	0.131	0.433	do + oxsat	0.379	0.814
sboxsat + oxsat	0.121	0.433	do + salinity	0.453	-0.254
sboxsat + salinity	0.122	0.192	do + sbt	0.332	0.305
sboxsat + sbt	0.131	0.529	do + sbdo	0.351	-0.135
sboxsat + sbdo	0.148	0.965	do + sboxsat	0.391	0.008
sboxsat + sbsalinity	0.106	-0.037	do + sbsalinity	0.332	-0.362
sboxsat + sst + year	0.147	0.133	**do + ssh + year**	**0.623**	0.468
sboxsat + sst + depth	0.144	-0.033	do + ssh + depth	0.576	-0.132
sboxsat + sst + ssh	0.144	-0.019	do + ssh + sst	0.576	-0.116
sboxsat + sst + mdf	0.154	-0.226	do + ssh + mdf	0.576	-0.096
sboxsat + sst + do	**0.172**	-0.511	do + ssh + oxsat	0.649	0.138
sboxsat + sst + oxsat	0.157	-0.404	do + ssh + salinity	0.576	0.200
sboxsat + sst + salinity	0.146	0.300	do + ssh + sbt	0.576	0.242
sboxsat + sst + sbt	0.156	0.048	do + ssh + sbdo	0.597	0.297
sboxsat + sst + sbdo	0.159	-0.328	do + ssh + sboxsat	0.617	0.326
sboxsat + sst + sbsalinity	0.144	0.216	do + ssh + sbsalinity	0.576	0.017
sboxsat + sst + do + year	0.177	-0.443	do + ssh + year + depth	0.626	-0.389
sboxsat + sst + do + depth	**0.189**	0.031	do + ssh + year + sst	0.623	-0.351
sboxsat + sst + do + ssh	0.174	-0.194	do + ssh + year + mdf	0.623	-0.075
sboxsat + sst + do + mdf	0.183	0.361	do + ssh + year + salinity	0.628	0.070
sboxsat + sst + do + oxsat	0.180	0.990	do + ssh + year + sbt	0.623	0.397
sboxsat + sst + do + salinity	0.177	0.094	do + ssh + year + sbdo	0.640	0.416
sboxsat + sst + do + sbt	0.182	-0.056	**do + ssh + year + sboxsat**	**0.659**	0.462
sboxsat + sst + do + sbdo	0.175	0.533	do + ssh + year + sbsalinity	0.623	-0.089
sboxsat + sst + do + sbsalinity	0.172	-0.105			
sboxsat + sst + do + depth + year	0.177	-0.021			
sboxsat + sst + do + depth + ssh	0.189	0.111			
sboxsat + sst + do + depth + mdf	0.202	-0.210			
sboxsat + sst + do + depth + oxsat	0.197	0.033			
sboxsat + sst + do + depth + salinity	0.177	0.071			
sboxsat + sst + do + depth + sbt	0.189	-0.878			
sboxsat + sst + do + depth + sbdo	0.197	-0.314			
sboxsat + sst + do + depth + sbsalinity	**0.203**	0.049			

Table B.6: Forward model selection results for GAMs fitted with *large sharks* bottom longline survey data. Model descriptors considered include year, bottom depth, sea surface temperature (sst), sea bottom temperature (sbt), altimetry (ssh), minimum distance from a front (mdf), sea surface dissolved oxygen (do), sea bottom dissolved oxygen (sbdo), sea surface oxygen saturation (oxsat), sea bottom oxygen saturation (sboxsat), sea surface salinity (salinity), and sea bottom salinity (sbsalinity). Forward model selection ceased when descriptors failed to improve the deviance explained (d) more than 5%. The displayed correlation coefficient (c) is calculated based on the last two model descriptors. Bold-faced indicates selected models.

Binomial Data Model	d	c	Zero-Truncated Data Model	d	c
year	0.008	-	year	0.037	-
depth	**0.505**	-	depth	0.144	-
sst	0.007	-	sst	0.070	-
ssh	0.017	-	ssh	0.146	-
mdf	0.031	-	mdf	0.004	-
do	0.010	-	do	0.002	-
oxsat	0.008	-	oxsat	0.004	-
salinity	0.006	-	salinity	0.037	-
sbt	0.454	-	**sbt**	**0.168**	-
sbdo	0.201	-	sbdo	0.050	-
sboxsat	0.198	-	sboxsat	0.036	-
sbsalinity	0.232	-	sbsalinity	1.9E-7	-
			sbt + year	0.205	0.030
			sbt + depth	0.190	-0.837
			sbt + sst	0.223	0.030
			sbt + ssh	**0.291**	-0.050
			sbt + mdf	0.176	0.193
			sbt + do	0.183	-0.016
			sbt + oxsat	0.183	-0.016
			sbt + salinity	0.208	-0.078
			sbt + sbdo	0.244	0.235
			sbt + sboxsat	0.237	0.427
			sbt + sbsalinity	0.168	-0.382
			sbt + ssh + year	**0.321**	0.288
			sbt + ssh + depth	0.328	0.115
			sbt + ssh + sst	0.310	-0.044
			sbt + ssh + mdf	0.299	-0.241
			sbt + ssh + do	0.297	-0.147
			sbt + ssh + oxsat	0.297	-0.177
			sbt + ssh + salinity	0.297	-0.338
			sbt + ssh + sbdo	0.314	-0.389
			sbt + ssh + sboxsat	0.312	-0.377
			sbt + ssh + sbsalinity	0.293	-0.164

Table B.7: Forward model selection results for GAMs fitted with *skates and rays* bottom longline survey data. Model descriptors considered include year, bottom depth, sea surface temperature (sst), sea bottom temperature (sbt), altimetry (ssh), minimum distance from a front (mdf), sea surface dissolved oxygen (do), sea bottom dissolved oxygen (sbdo), sea surface oxygen saturation (oxsat), sea bottom oxygen saturation (sboxsat), sea surface salinity (salinity), and sea bottom salinity (sbsalinity). Forward model selection ceased when descriptors failed to improve the deviance explained (d) more than 5%. The displayed correlation coefficient (c) is calculated based on the last two model descriptors. Bold-faced indicates selected models.

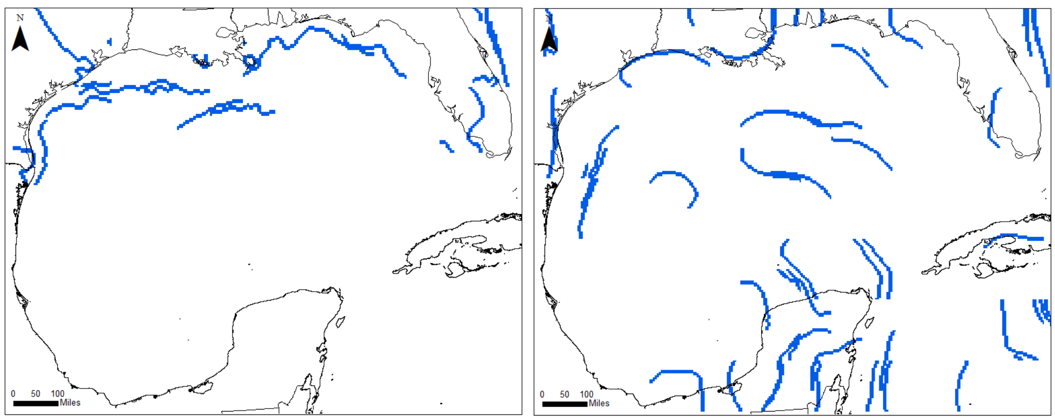
Binomial Data Model	d	c	Zero-Truncated Data Model	d	c
year	0.006	-	year	0.025	-
depth	**0.127**	-	depth	0.155	-
sst	1.5E-7	-	sst	0.101	-
ssh	0.015	-	ssh	3.E-6	-
mdf	0.027	-	mdf	0.015	-
do	0.003	-	do	0.003	-
oxsat	0.005	-	oxsat	1.2E-6	-
salinity	2.5E-7	-	salinity	0.034	-
sbt	0.126	-	**sbt**	**0.210**	-
sbdo	0.090	-	sbdo	0.056	-
sboxsat	0.110	-	sboxsat	0.098	-
sbsalinity	0.022	-	sbsalinity	0.092	-
depth + year	0.131	0.243	sbt + year	0.250	-0.024
depth + sst	0.134	0.244	sbt + depth	0.231	-0.830
depth + ssh	0.132	0.239	**sbt + sst**	**0.328**	0.062
depth + mdf	0.132	-0.259	sbt + ssh	0.210	0.043
depth + do	0.129	0.031	sbt + mdf	0.210	0.089
depth + oxsat	**0.132**	0.032	sbt + do	0.229	-0.009
depth + salinity	0.137	0.071	sbt + oxsat	0.216	-0.004
depth + sbt	0.142	-0.877	sbt + salinity	0.325	-0.045
depth + sbdo	0.146	-0.314	sbt + sbdo	0.237	0.277
depth + sboxsat	0.150	-0.500	sbt + sboxsat	0.221	0.508
depth + sbsalinity	0.127	0.049	sbt + sbsalinity	0.210	-0.021
			sbt + sst + year	0.342	0.339
			sbt + sst + depth	0.337	-0.011
			sbt + sst + ssh	0.328	0.245
			sbt + sst + mdf	0.328	-0.136
			sbt + sst + do	0.336	-0.468
			sbt + sst + oxsat	0.331	-0.369
			sbt + sst + salinity	**0.418**	0.144
			sbt + sst + sbdo	0.329	-0.302
			sbt + sst + sboxsat	0.329	-0.252
			sbt + sst + sbsalinity	0.328	0.241

Table B.8: Forward model selection results for GAMs fitted with *blacktip sharks* bottom longline survey data. Model descriptors considered include year, bottom depth, sea surface temperature (sst), sea bottom temperature (sbt), altimetry (ssh), minimum distance from a front (mdf), sea surface dissolved oxygen (do), sea bottom dissolved oxygen (sbdo), sea surface oxygen saturation (oxsat), sea bottom oxygen saturation (sboxsat), sea surface salinity (salinity), and sea bottom salinity (sbsalinity). Forward model selection ceased when descriptors failed to improve the deviance explained (d) more than 5%. The displayed correlation coefficient (c) is calculated based on the last two model descriptors. Bold-faced indicates selected models.

Binomial Data Model	d	c	Zero-Truncated Data Model	d	c
year	0.007	-	year	0.106	-
depth	**0.307**	-	depth	0.181	-
sst	0.033	-	sst	0.141	-
ssh	0.027	-	ssh	0.130	-
mdf	0.048	-	mdf	0.027	-
do	0.017	-	do	0.088	-
oxsat	0.010	-	oxsat	0.100	-
salinity	0.115	-	salinity	0.246	-
sbt	0.245	-	sbt	0.211	-
sbdo	0.023	-	sbdo	0.172	-
sboxsat	0.034	-	sboxsat	0.164	-
sbsalinity	0.066	-	**sbsalinity**	**0.345**	-
depth + year	0.315	0.243	sbsalinity + year	0.380	0.075
depth + sst	0.320	0.244	sbsalinity + depth	0.388	0.381
depth + ssh	0.357	0.239	sbsalinity + sst	0.382	0.191
depth + mdf	0.319	-0.259	sbsalinity + ssh	0.351	-0.287
depth + do	0.325	0.031	sbsalinity + mdf	0.356	-0.123
depth + oxsat	0.323	0.032	sbsalinity + do	0.367	-0.050
depth + salinity	**0.364**	0.071	sbsalinity + oxsat	0.370	0.013
depth + sbt	0.313	-0.877	sbsalinity + salinity	0.365	0.584
depth + sbdo	0.344	-0.314	sbsalinity + sbt	0.394	-0.225
depth + sboxsat	0.345	-0.500	**sbsalinity + sbdo**	**0.403**	0.059
depth + sbsalinity	0.324	0.049	sbsalinity + sboxsat	0.398	0.062
depth + salinity + year	0.375	0.029	sbsalinity + sbdo + year	0.422	-0.457
depth + salinity + sst	0.378	0.298	**sbsalinity + sbdo + depth**	**0.475**	-0.060
depth + salinity + ssh	**0.395**	-0.179	sbsalinity + sbdo + sst	0.410	-0.424
depth + salinity + mdf	0.380	0.056	sbsalinity + sbdo + ssh	0.403	-0.528
depth + salinity + do	0.373	0.094	sbsalinity + sbdo + mdf	0.403	0.506
depth + salinity + oxsat	0.372	0.164	sbsalinity + sbdo + do	0.406	0.594
depth + salinity + sbt	0.367	-0.100	sbsalinity + sbdo + oxsat	0.407	0.615
depth + salinity + sbdo	0.384	0.237	sbsalinity + sbdo + salinity	0.406	0.397
depth + salinity + sboxsat	0.387	0.192	sbsalinity + sbdo + sbt	0.470	-0.043
depth + salinity + sbsalinity	0.373	0.407	sbsalinity + sbdo + sboxsat	0.458	0.992
depth + salinity + ssh + year	0.407	0.374			
depth + salinity + ssh + sst	0.410	-0.018			
depth + salinity + ssh + mdf	0.409	-0.254			
depth + salinity + ssh + do	0.405	-0.194			
depth + salinity + ssh + oxsat	0.404	-0.220			
depth + salinity + ssh + sbt	0.400	-0.029			
depth + salinity + ssh + sbdo	0.413	-0.329			
depth + salinity + ssh + sboxsat	**0.415**	-0.301			
depth + salinity + ssh + sbsalinity	0.406	-0.121			

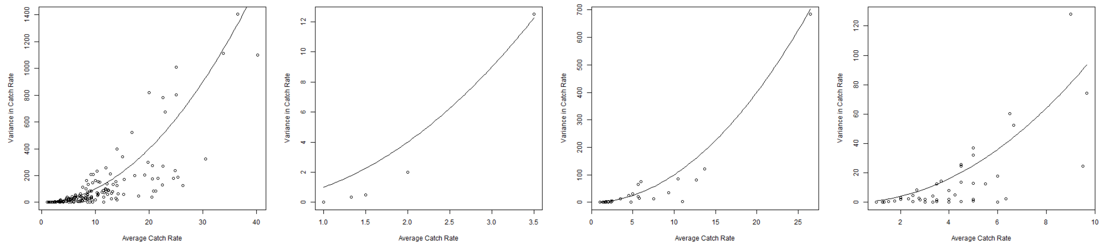
Table B.9: Forward Model Selection results for GAMs solving for catch-per-unit-effort to be used to standardize coastal and pelagic predictions of *large sharks* (left) and *skates and rays* (right). Model descriptors considered include year, season, longline type (title), bottom depth, sea surface temperature (sst), altimetry (ssh), and minimum distance from a front (mdf). Descriptors were selected based on model deviance explained (d). Forward model selection ceased when descriptors provided no improvement to model fits. Bold-faced indicates selected models.

large sharks	d	*skates and rays*	d
year	0.199	year	0.187
season	0.25	**season**	**0.303**
title	0.212	title	0.235
depth	**0.377**	depth	0.192
sst	0.167	sst	0.221
ssh	0.252	ssh	0.011
mdf	3.23E-7	mdf	0.209
depth + year	**0.518**	season + year	0.451
depth + season	0.46	season + title	0.31
depth + title	0.451	season + depth	0.447
depth + sst	0.444	season + sst	0.349
depth + ssh	0.456	season + ssh	0.303
depth + mdf	0.377	**season + mdf**	**0.472**
depth + year + season	**0.57**	**season + mdf + year**	**0.602**
depth + year + title	0.55	season + mdf + title	0.475
depth + year + sst	0.542	season + mdf + depth	0.534
depth + year + ssh	0.553	season + mdf + sst	0.472
depth + year + mdf	0.537	season + mdf + ssh	0.482
depth + year + season + title	0.57	**season + mdf + year + title**	**0.611**
depth + year + season + sst	0.57	season + mdf + year + depth	0.603
depth + year + season + ssh	0.57	season + mdf + year + sst	0.602
depth + year + season + mdf	**0.588**	season + mdf + year + ssh	0.602
depth + year + season + mdf + title	0.589		
depth + year + season + mdf + sst	**0.597**		
depth + year + season + mdf + ssh	0.588		
depth + year + season + mdf + sst + title	**0.598**		
depth + year + season + mdf + sst + ssh	0.597		

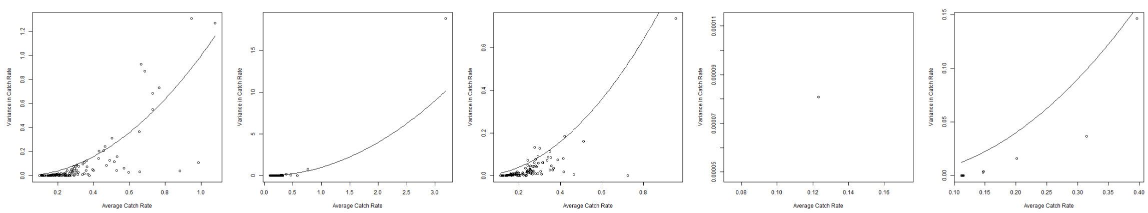


(a) (b)

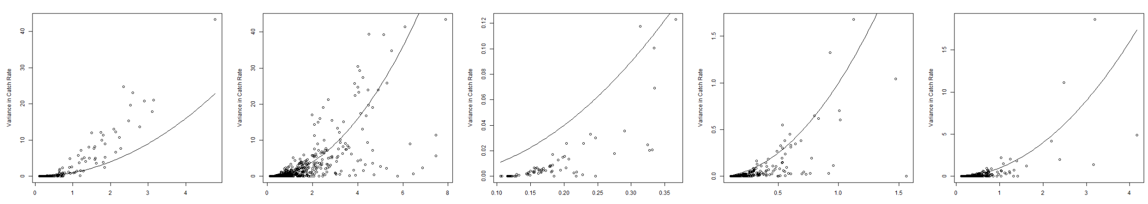
Figure B.1: Fronts, indicated by blue lines, produced by the *Cayula-Cornillon Fronts in ArcGIS Raster MGET* tool in *ArcGIS*. Panel (a) displays the results produced when 2006 sea surface temperature data from January, February, and March (season 1) are processed. Panel (b) displays the results produced with 2006 altimetry data from season 1, scaled by 1000, are processed.



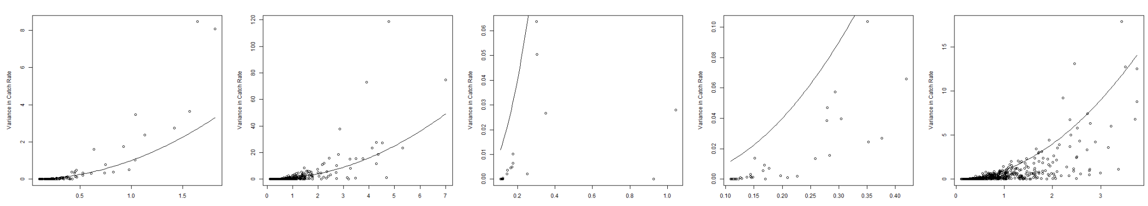
(a) *large sharks* (b) *large pelagic fish* (c) *skates and rays* (d) *blacktip sharks*



(e) *other billfish* (f) *blue marlin* (g) *bluefin tuna* (h) *deep water fish* (i) *filter feeding sharks*

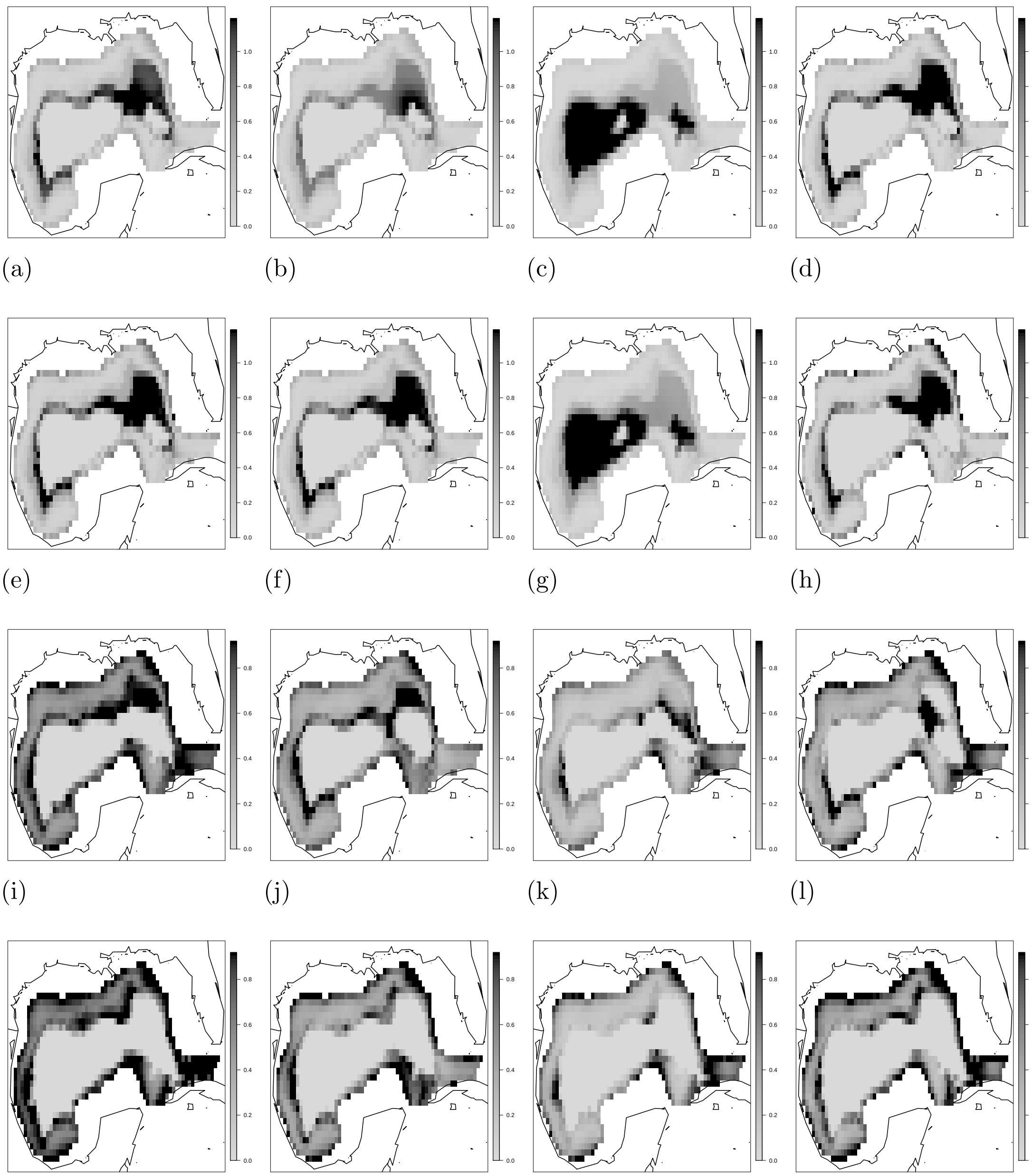


(j) *large sharks* (k) *large pelagic fish* (l) *medium pelagic fish* (m) *skates and rays* (n) *spanish mackerel*



(o) *small sharks* (p) *swordfish* (q) *other turtles* (r) *white marlin* (s) *yellowfin tuna*

Figure B.2: The variance in catch rate is plotted against the mean catch rate. Panels (a) - (d) are derived from bottom longline survey data and panels (e) - (s) are derived from pelagic longline observer data. For all images the black line displays the square of the average catch rate curve.



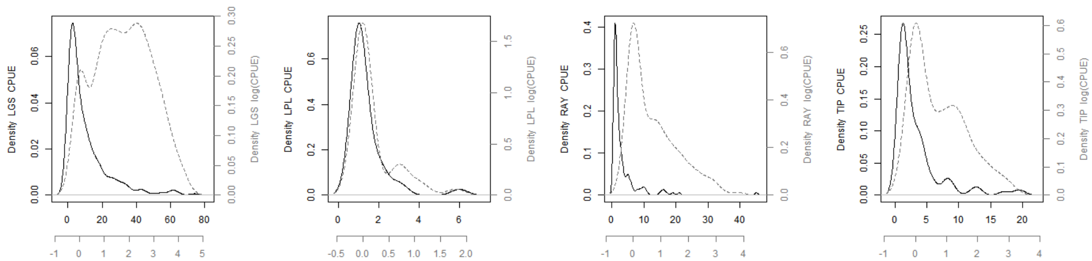
(a) (b) (c) (d)

(e) (f) (g) (h)

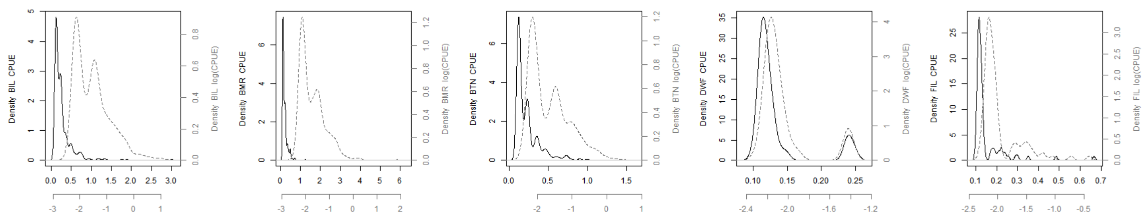
(i) (j) (k) (l)

(m) (n) (o) (p)

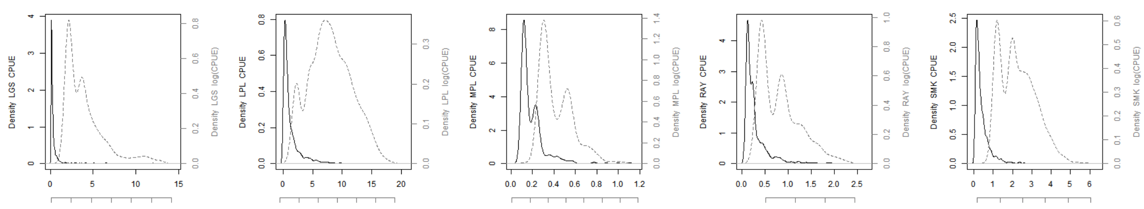
Figure B.3: The *large sharks* seasonal predictions for day (a - d) are similar to the predictions for night (e - h). The *swordfish* seasonal predictions for day (i - l) are slightly different than the corresponding predictions for night (m - p). Columns correspond to seasons.



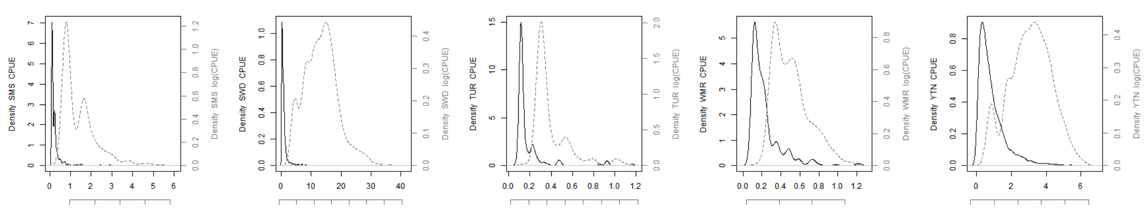
(a) *large sharks* (b) *large pelagic fish* (c) *skates and rays* (d) *blacktip sharks*



(e) *other billfish* (f) *blue marlin* (g) *bluefin tuna* (h) *deep water fish* (i) *filter feeding sharks*

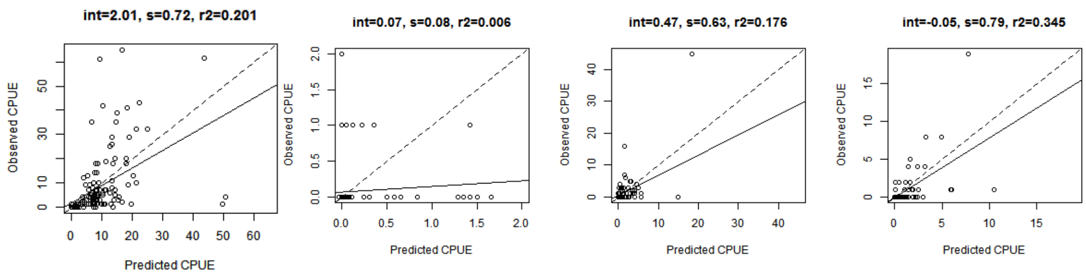


(j) *large sharks* (k) *large pelagic fish* (l) *medium pelagic fish* (m) *skates and rays* (n) *spanish mackerel*

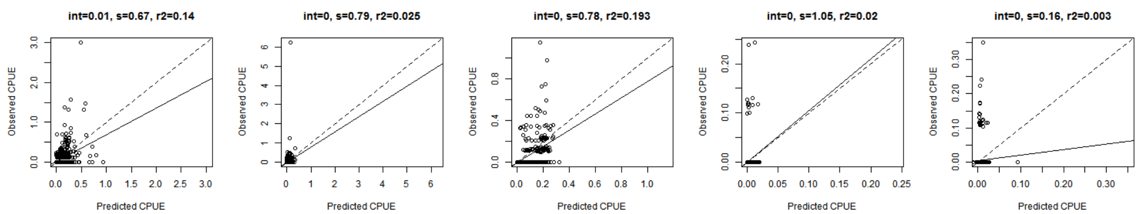


(o) *small sharks* (p) *swordfish* (q) *other turtles* (r) *white marlin* (s) *yellowfin tuna*

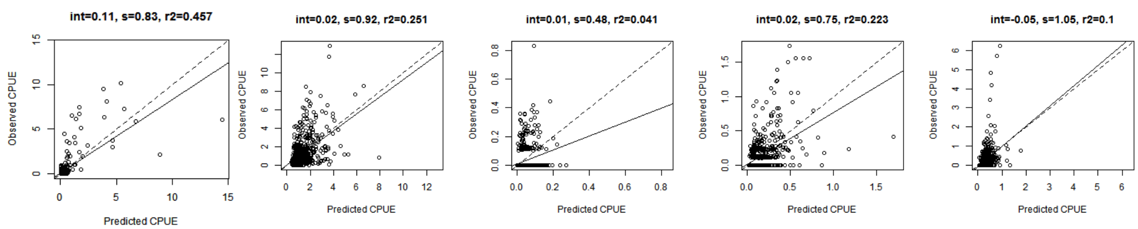
Figure B.4: The distribution plots of normal-scale catch rates (black lines; corresponding to the primary axis) and log-transformed catch rates (grey lines; corresponding to the secondary axis). Panels (a) - (d) are derived from bottom longline survey data while panels (e) - (s) are derived from pelagic longline observer data.



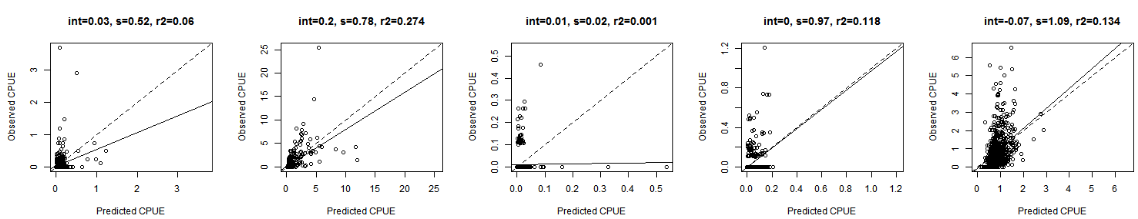
(a) *large sharks* (b) *large pelagic fish* (c) *skates and rays* (d) *blacktip shark*



(e) *other billfish* (f) *blue marlin* (g) *bluefin tuna* (h) *deepwater fish* (i) *filter feeding sharks*



(j) *large sharks* (k) *large pelagic fish* (l) *medium pelagic fish* (m) *skates and rays* (n) *spanish mackerel*



(o) *small sharks* (p) *swordfish* (q) *other turtles* (r) *white marlin* (s) *yellowfin tuna*

Figure B.5: Observed catch rates against predicted catch rates for coastal models (a - d), and pelagic models (e - s). Solid lines indicate the fitted linear regression and the dashed line indicates the 1:1 line. The plot title states the intercept, slope, and adjusted r-square value.

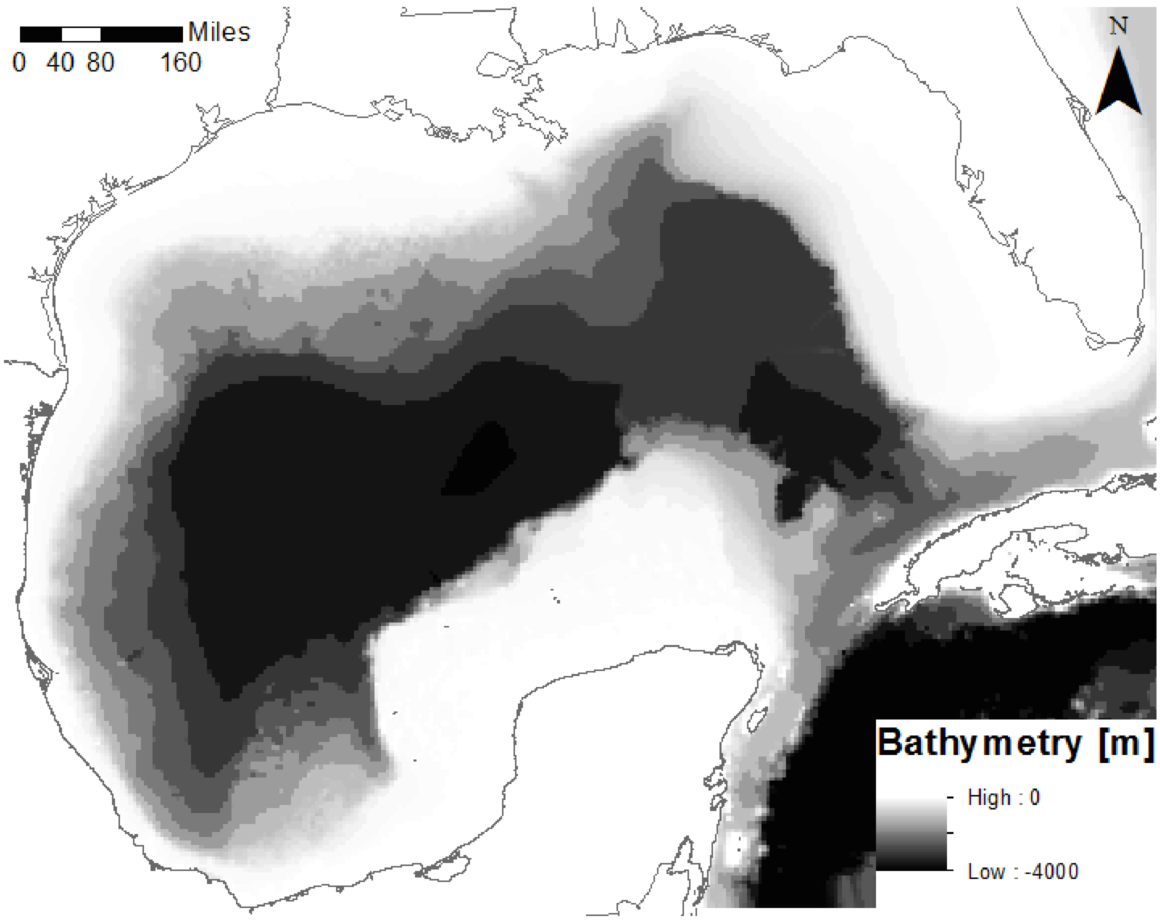


Figure B.6: Bathymetry [m] estimates across the Gulf of Mexico. The raster was developed in *ArcGIS* by processing bathymetry data (Table 3.1) with the *Kriging* tool (default settings).

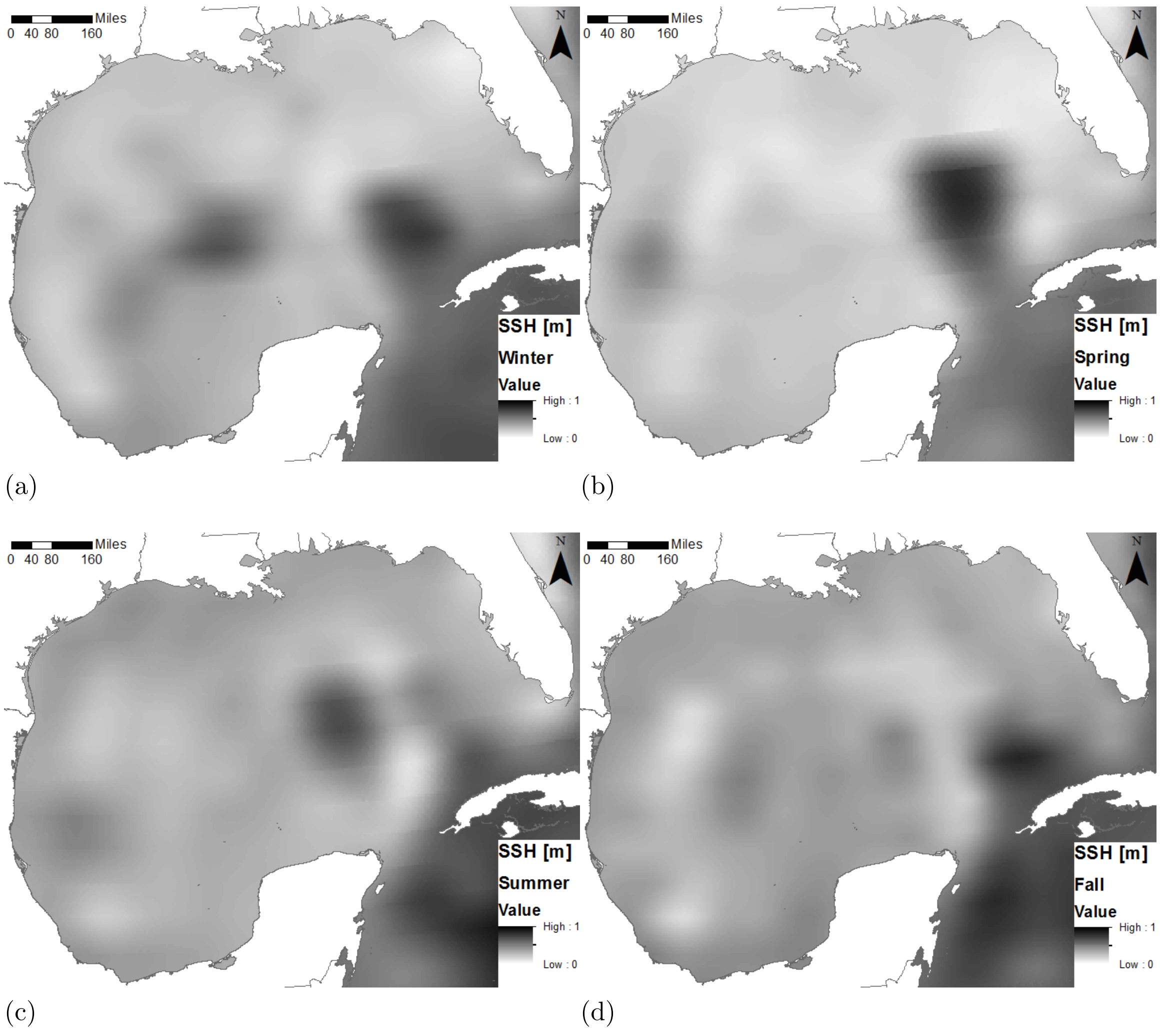


Figure B.7: Seasonal average estimates of sea surface height [m] across the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea surface height data (Table 3.1) with the *Kriging* tool (default settings).

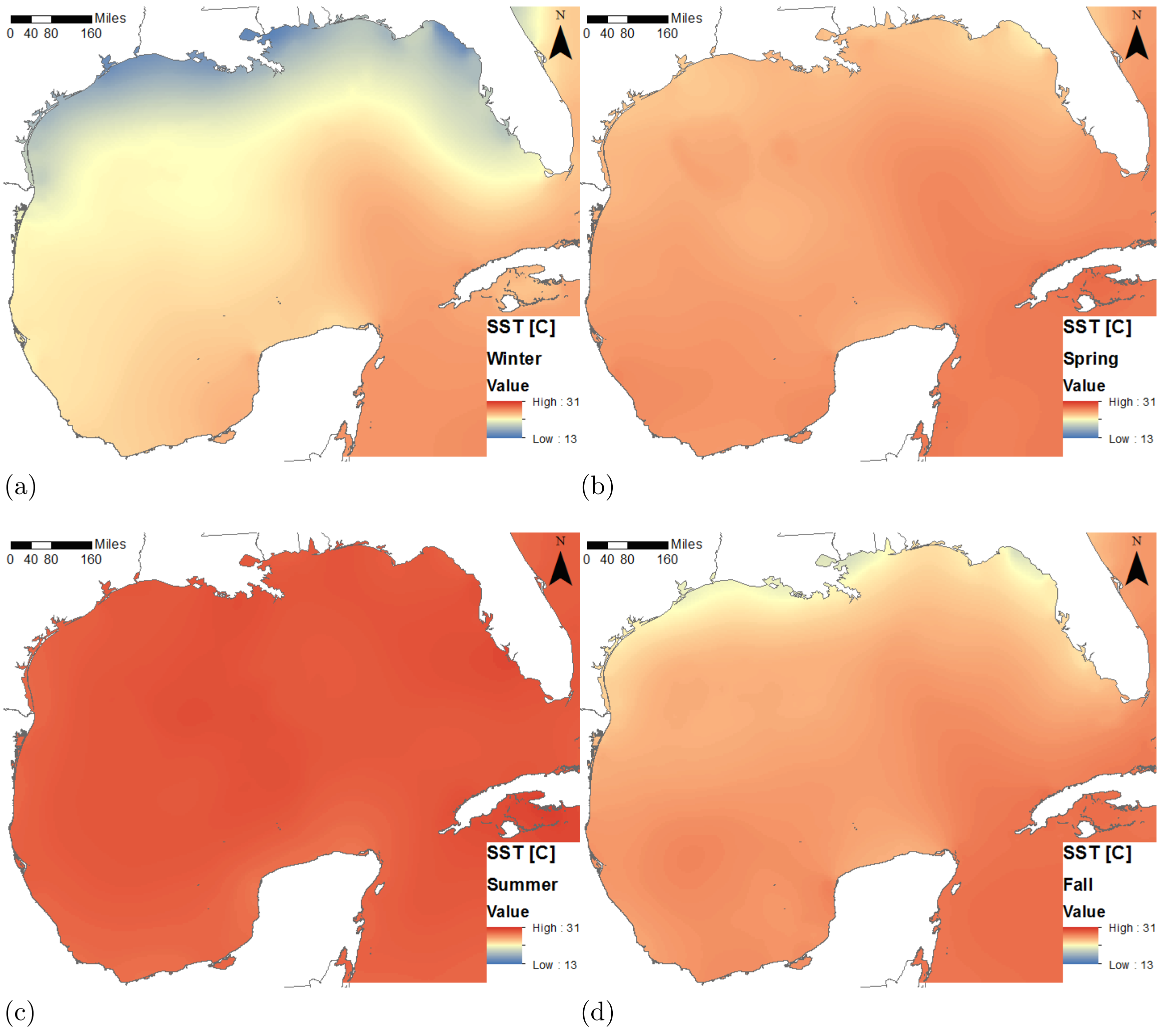


Figure B.8: Seasonal average estimates of sea surface temperature [C°] across the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea surface temperature data (Table 3.1) with the *Kriging* tool (default settings).

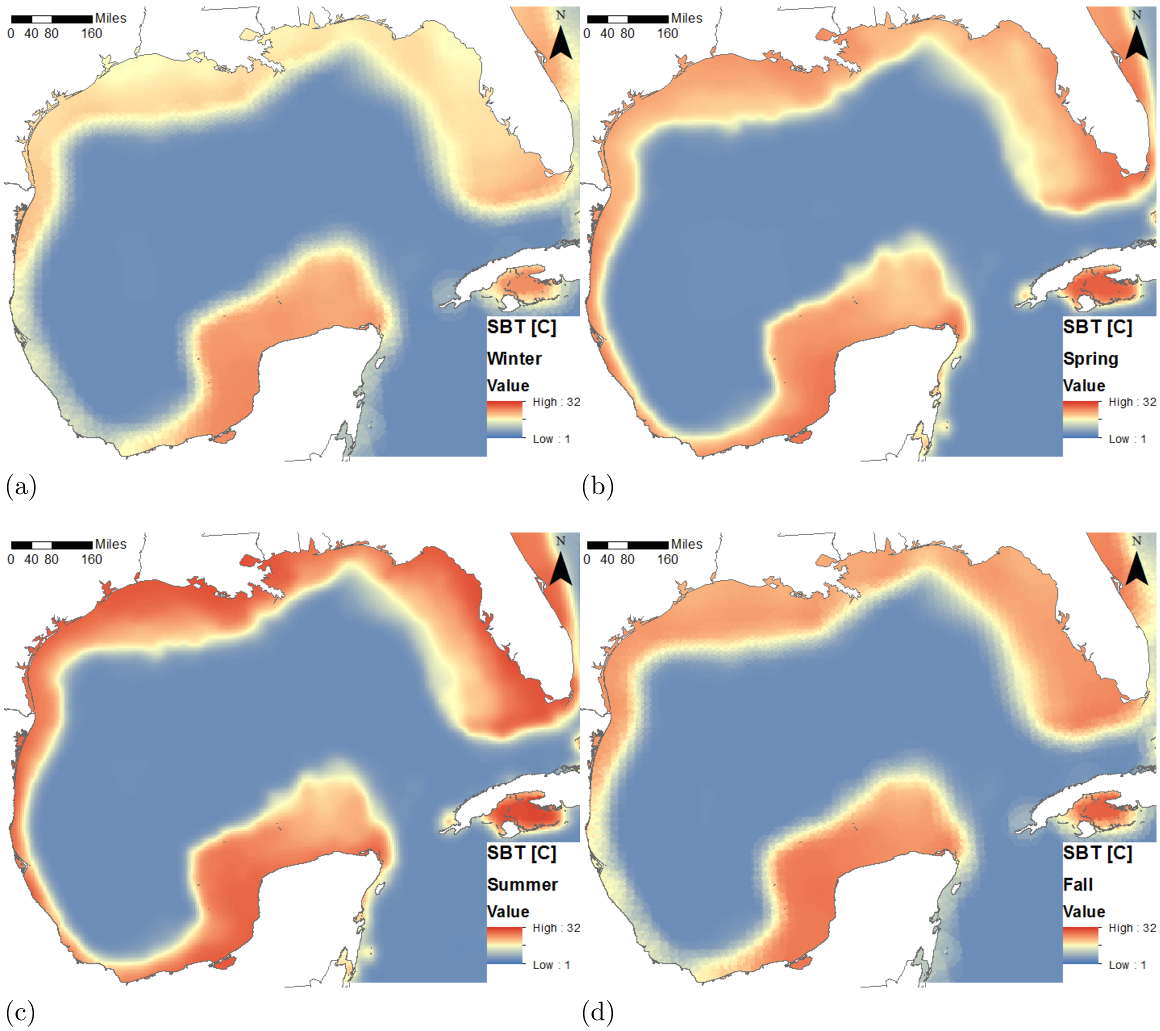


Figure B.9: Seasonal average estimates of sea bottom temperature [C°] across the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea bottom temperature data (Table 3.1) with the *Kriging* tool (default settings).

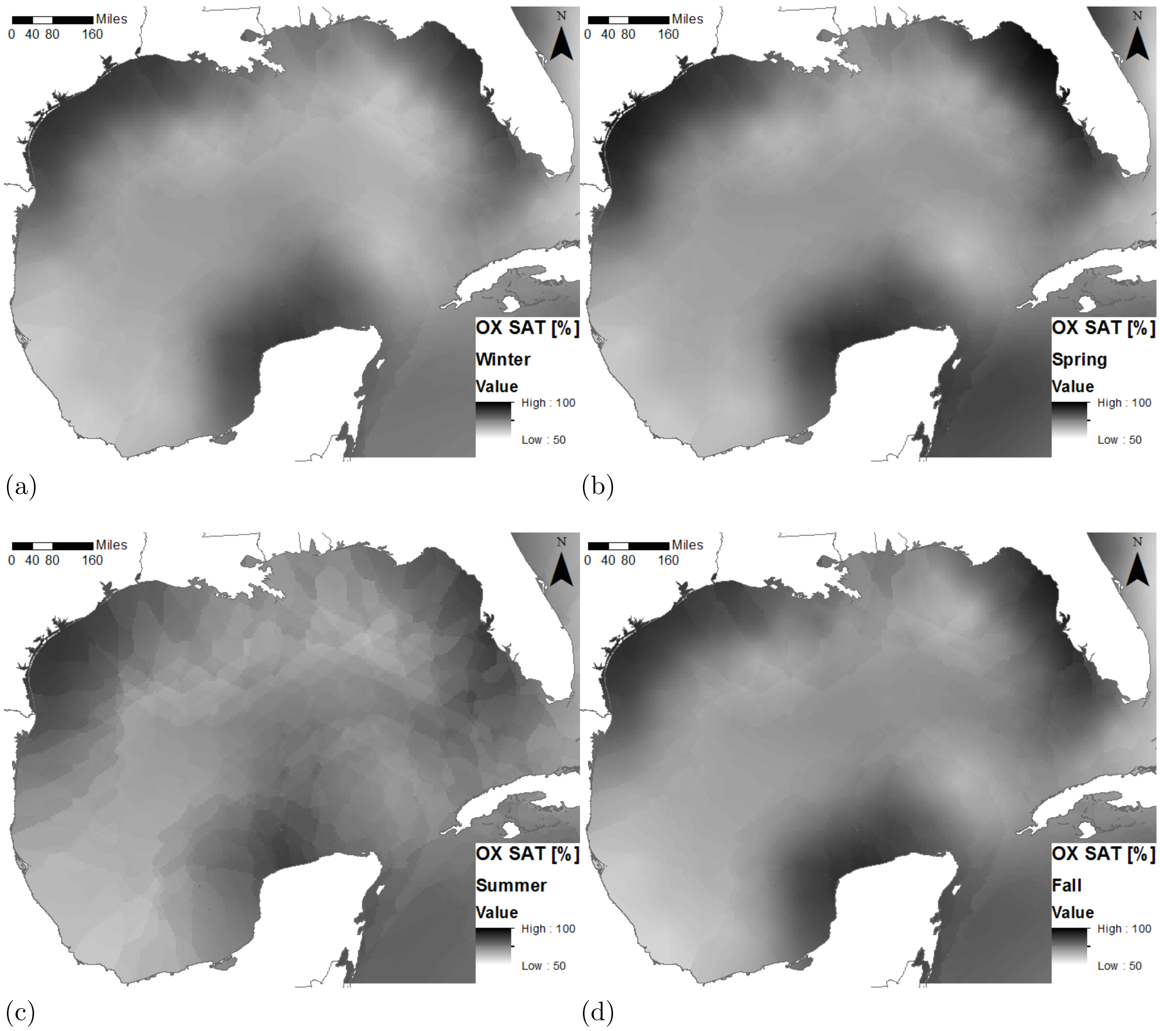


Figure B.10: Seasonal average estimates of sea bottom oxygen saturation [%] across the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea bottom oxygen saturation data (Table 3.1) with the *Kriging* tool (default settings).

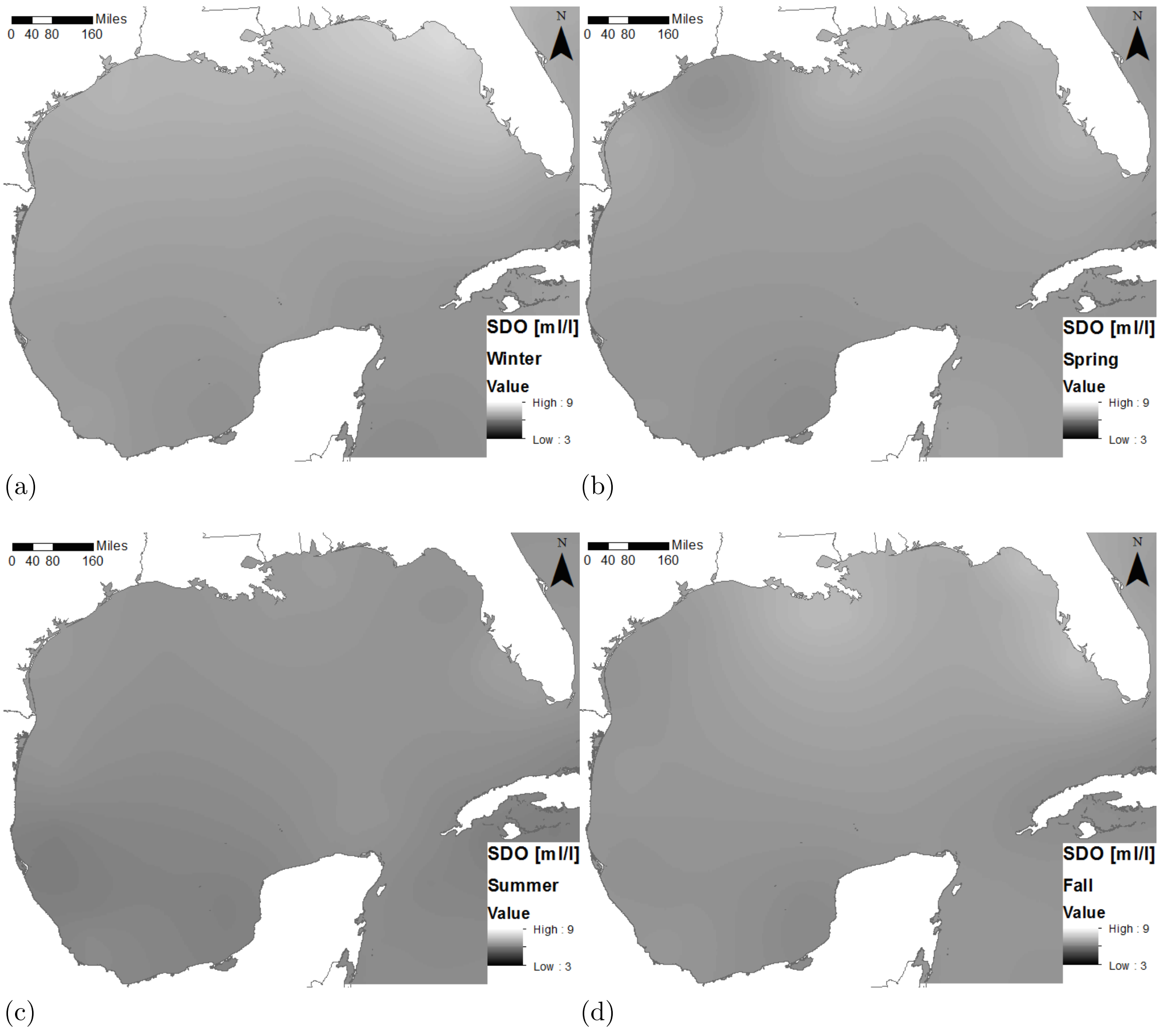


Figure B.11: Seasonal average estimates of sea surface dissolved oxygen [ml/l] across the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea surface dissolved oxygen data (Table 3.1) with the *Kriging* tool (default settings).

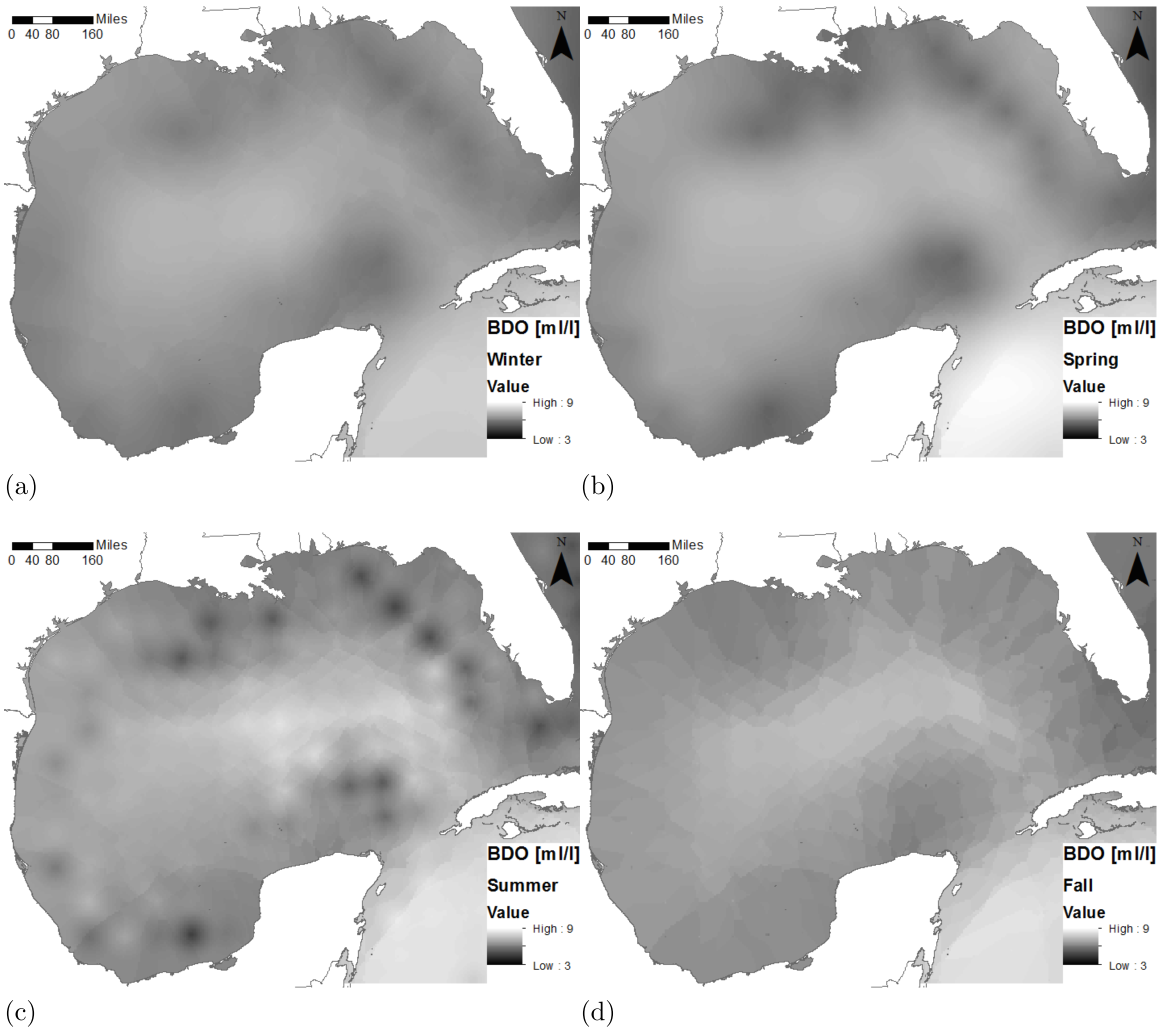


Figure B.12: Seasonal average estimates of the sea bottom dissolved oxygen [ml/l] across the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea bottom dissolved oxygen data (Table 3.1) with the *Kriging* tool (default settings).

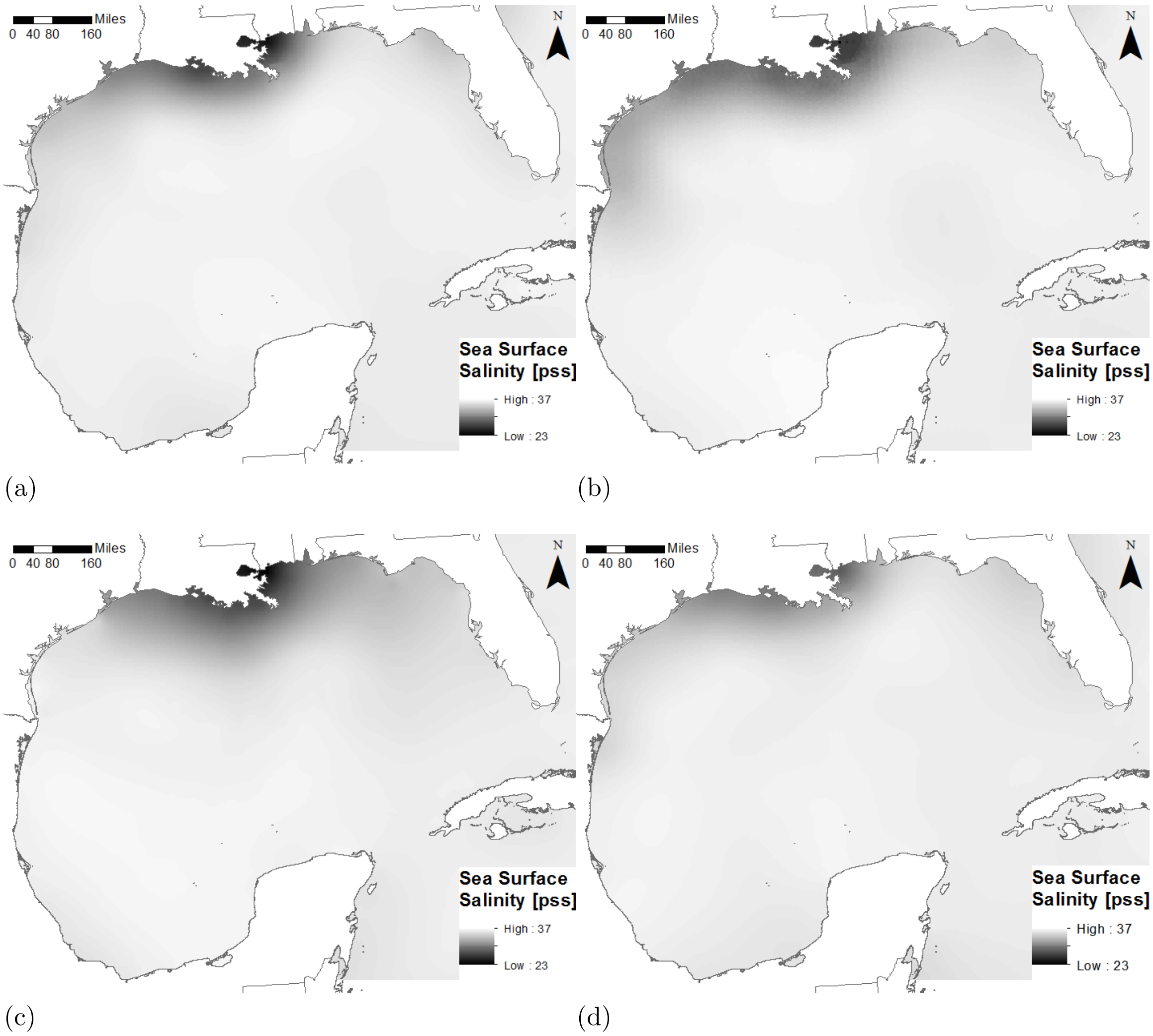


Figure B.13: Seasonal average estimates of sea surface salinity [pss] the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea surface salinity data (Table 3.1) with the *Kriging* tool (default settings).

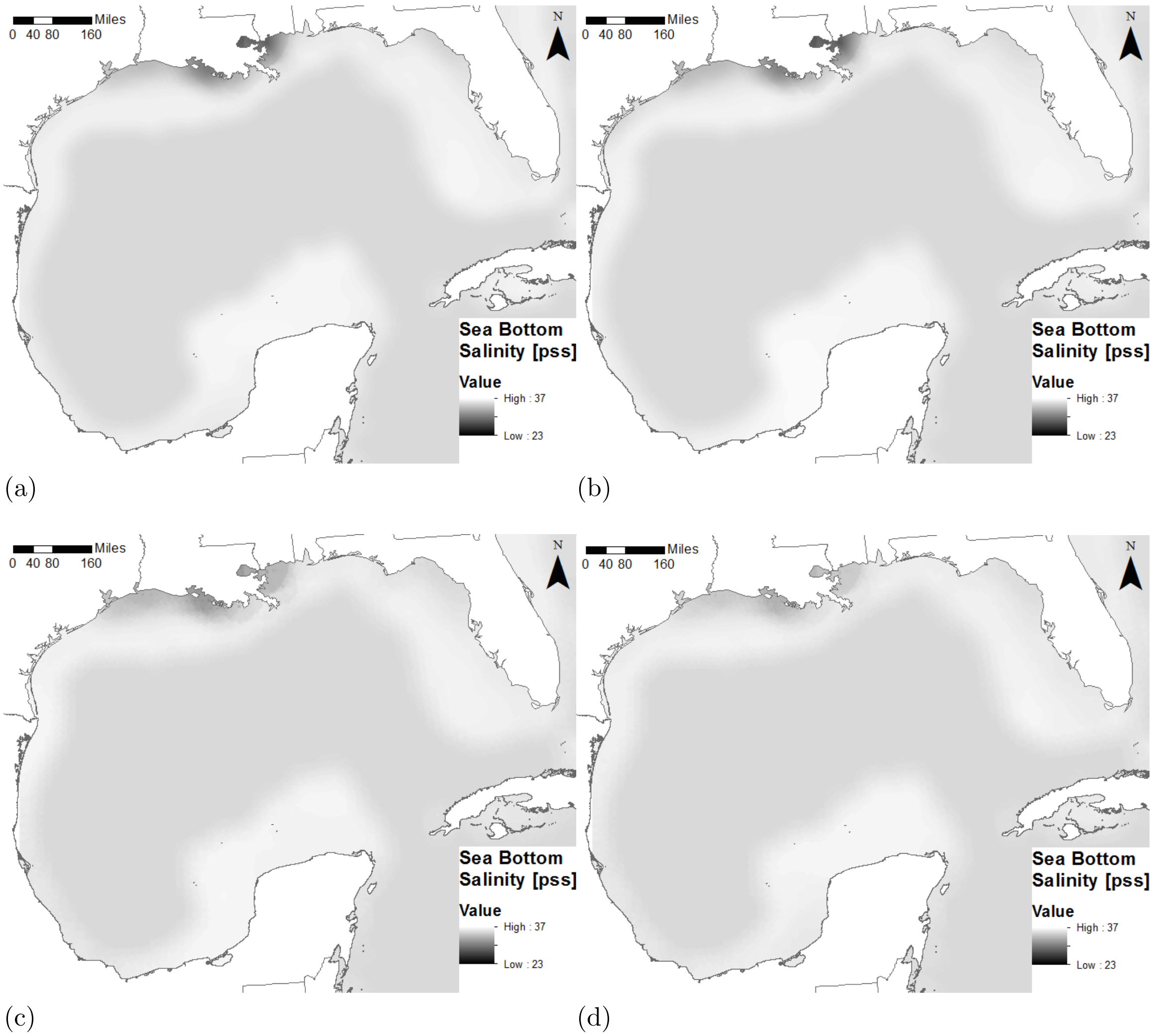


Figure B.14: Seasonal average estimates of sea bottom salinity [pss] the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Rasters were created in *ArcGIS* by processing seasonal sea bottom salinity data (Table 3.1) with the *Kriging* tool (default settings).

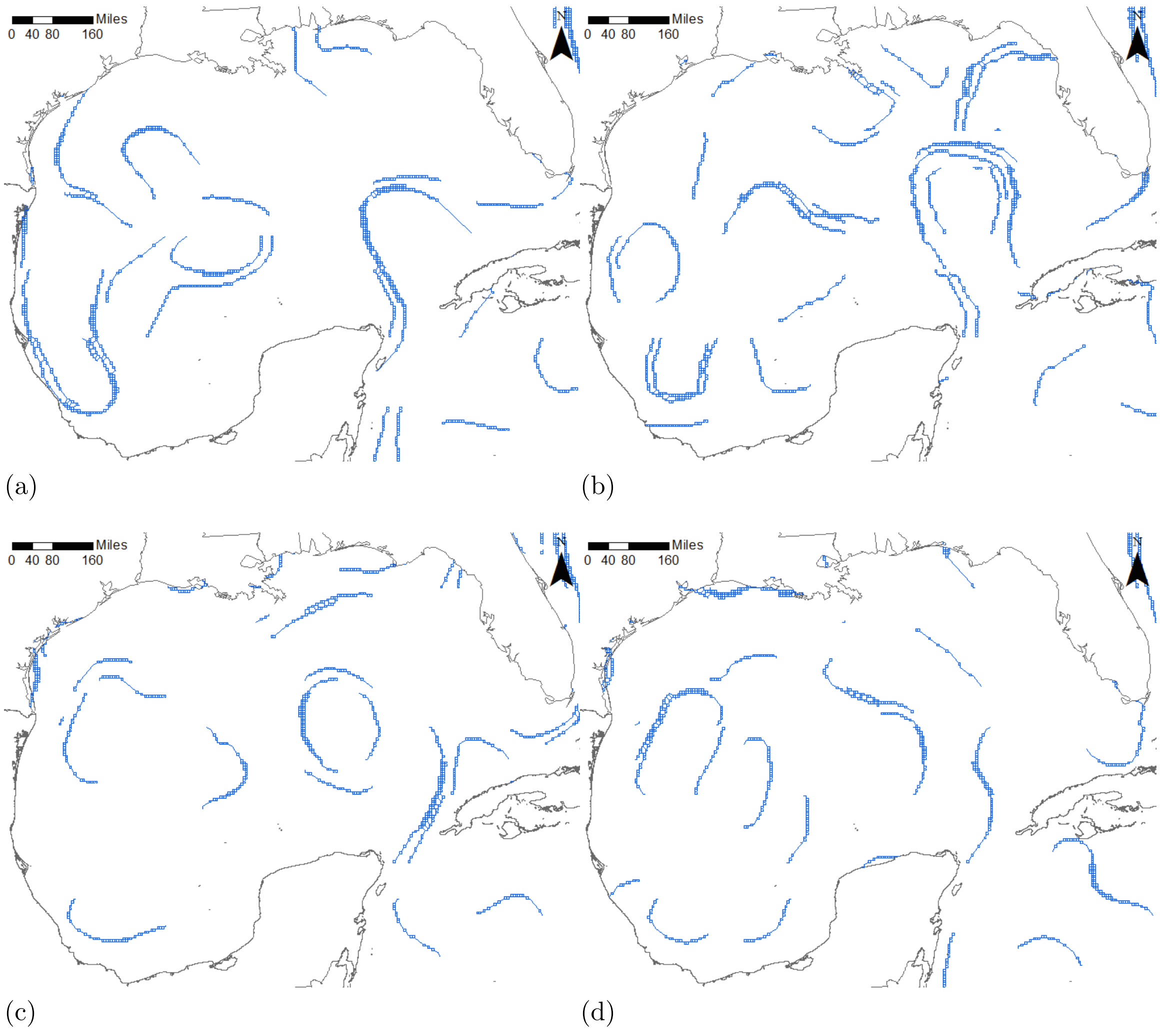
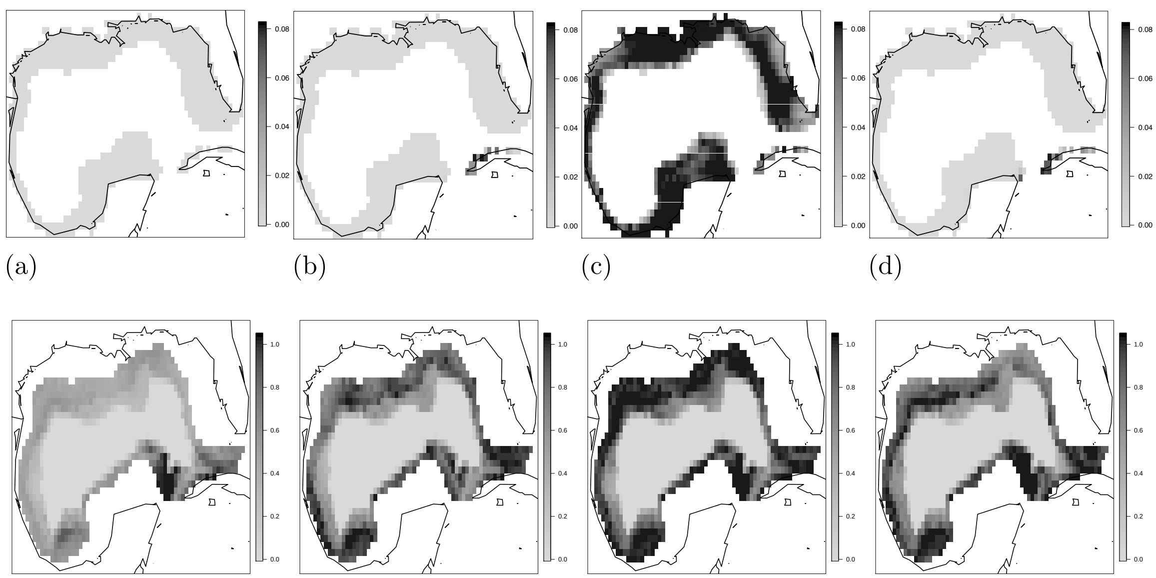


Figure B.15: Seasonal estimates of the average front locations within the Gulf of Mexico during the winter (a), spring (b), summer (c), and fall (d). Front polyline files were created by processing AVISO point data, separated by season, by the routine described in Figure 3.2 for calculating minimum distance from a front.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure B.16: Catch rates of *large pelagic fish* predicted by GAMs fitted with bottom longline survey data (a - d), and GAMs fitted with pelagic longline observer data (e - h). Columns correspond to season.

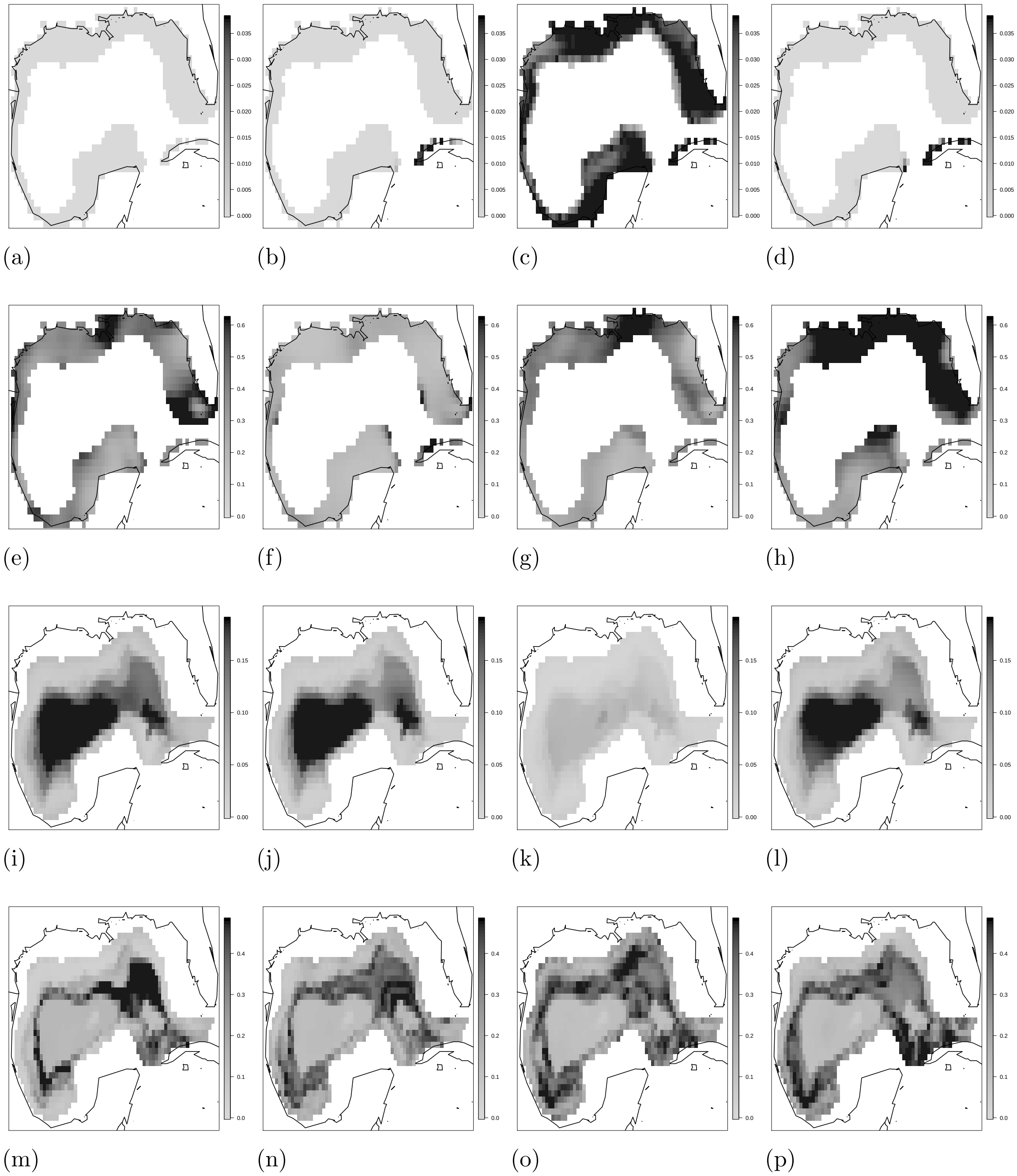


Figure B.17: Standard error of seasonal predictions from the *large pelagic fish* coastal logistic model (a - d), coastal Gamma model (e - h), pelagic logistic model (i - l), and pelagic Gamma model (m - p). Columns correspond to season.

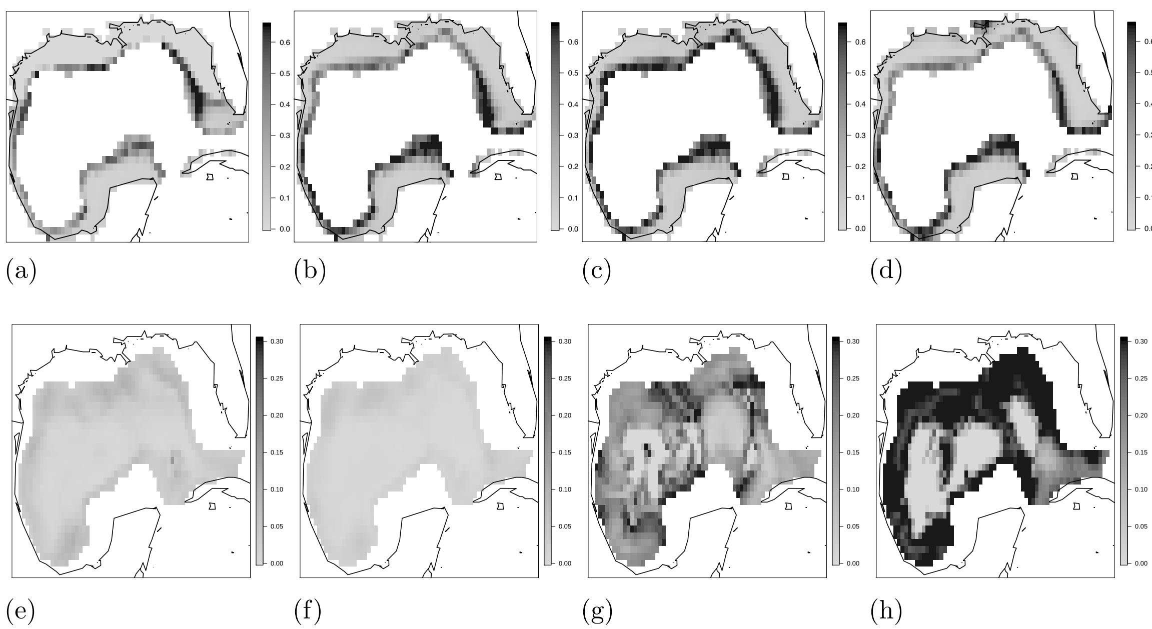


Figure B.18: Catch rates of *skates and rays* predicted by GAMs fitted with bottom longline survey data (a - d), and GAMs fitted with pelagic longline observer data (e - h). Columns correspond to season.

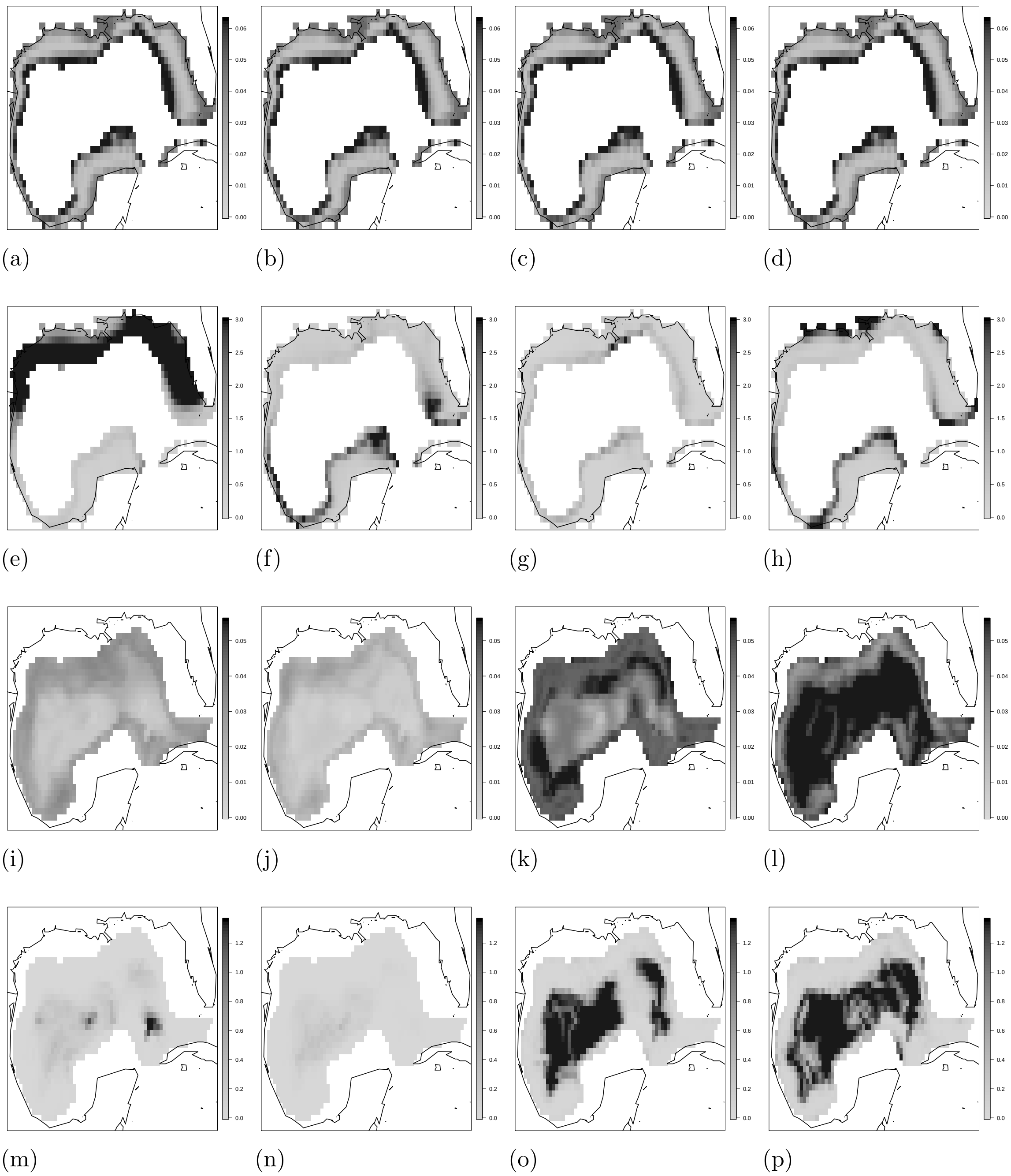


Figure B.19: Standard error of seasonal predictions from the *skates and rays* coastal logistic model (a - d), coastal Gamma model (e - h), pelagic logistic model (i - l), and pelagic Gamma model (m - p). Columns correspond to season.

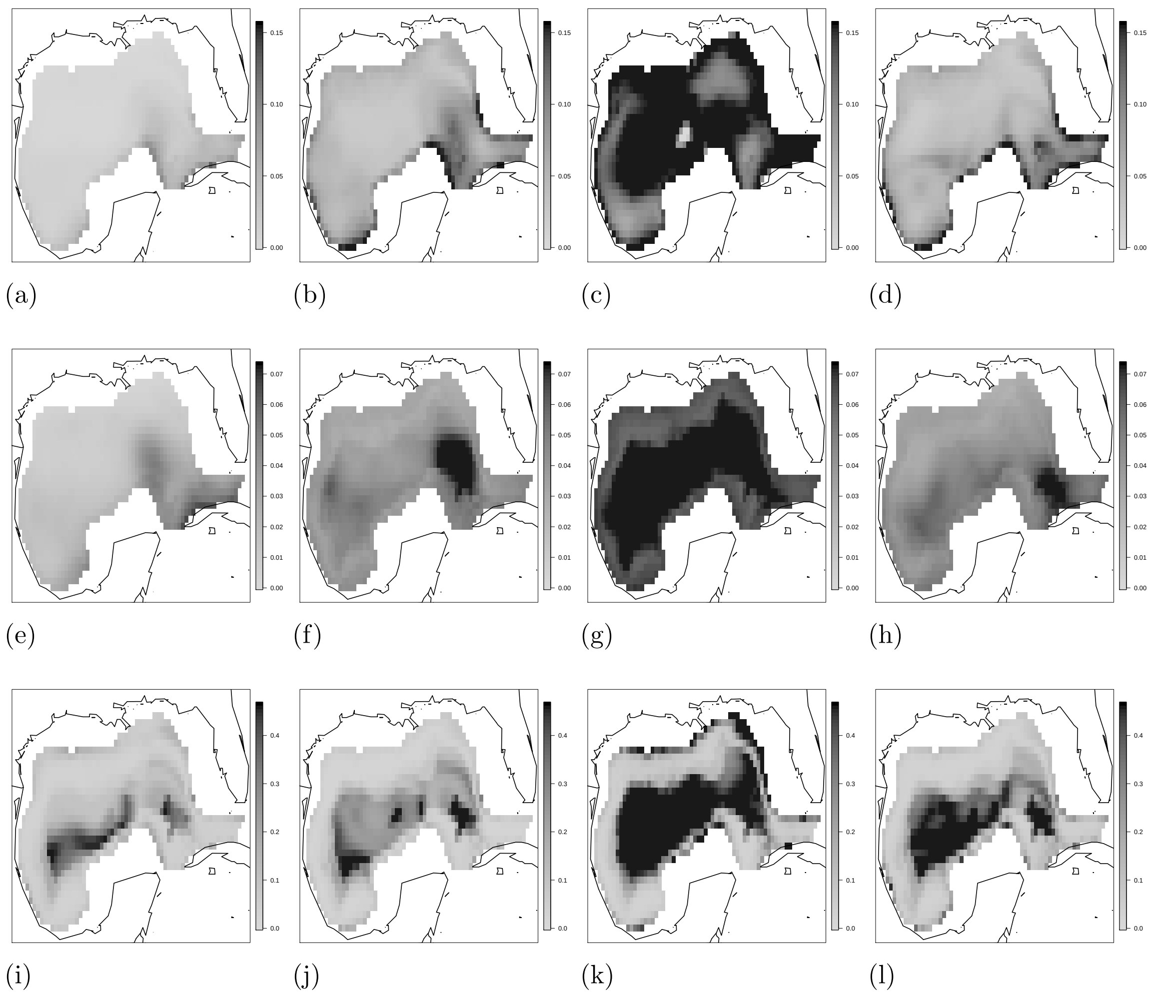


Figure B.20: Catch rates of *other billfish* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

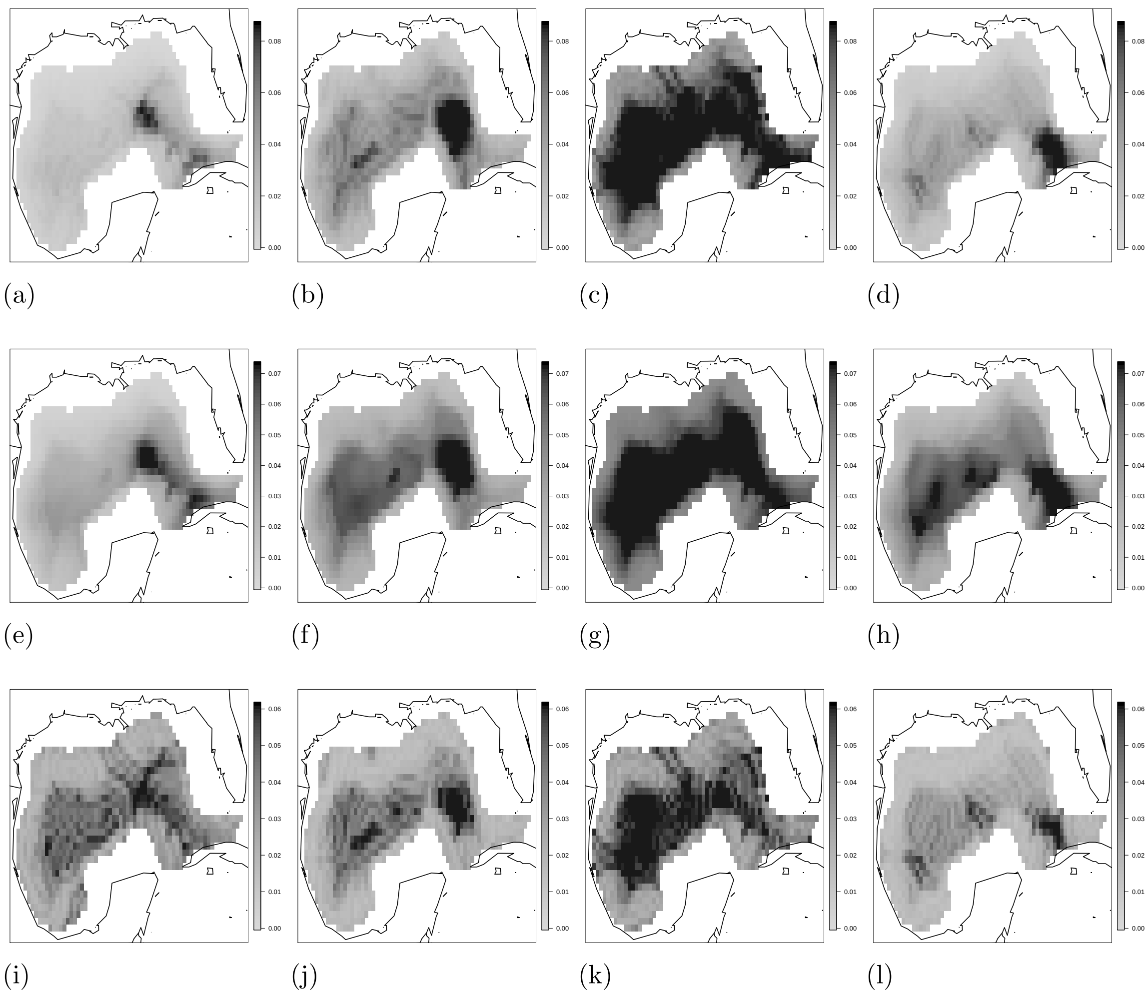
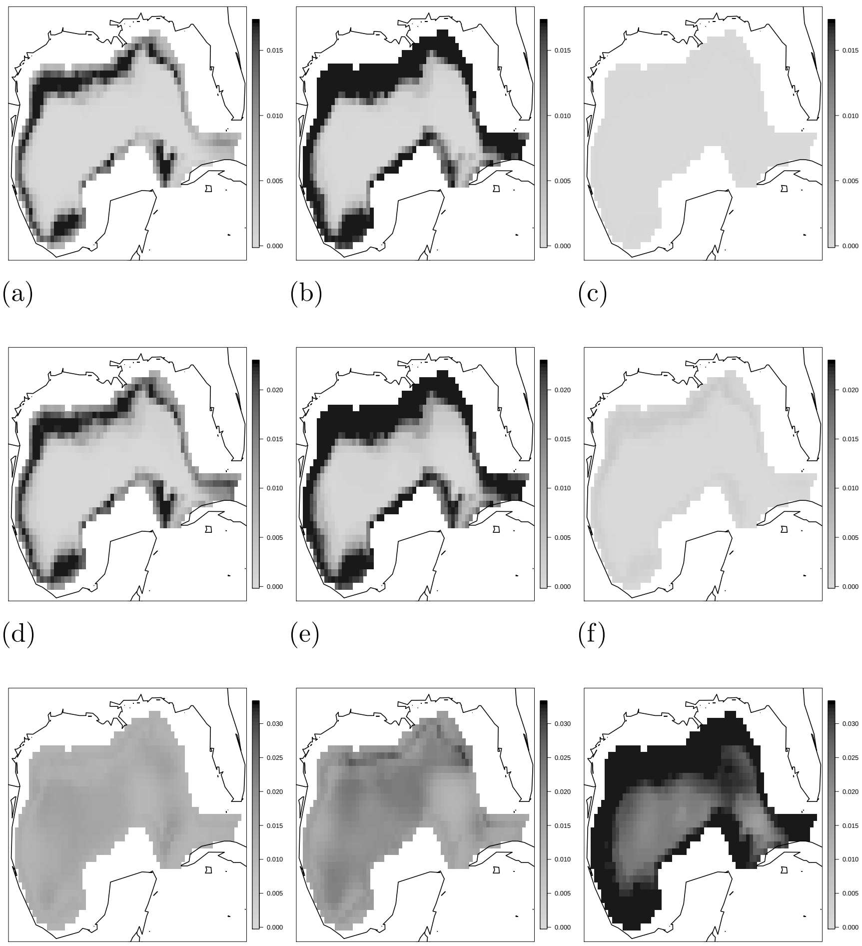


Figure B.21: Catch rates of *blue marlin* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

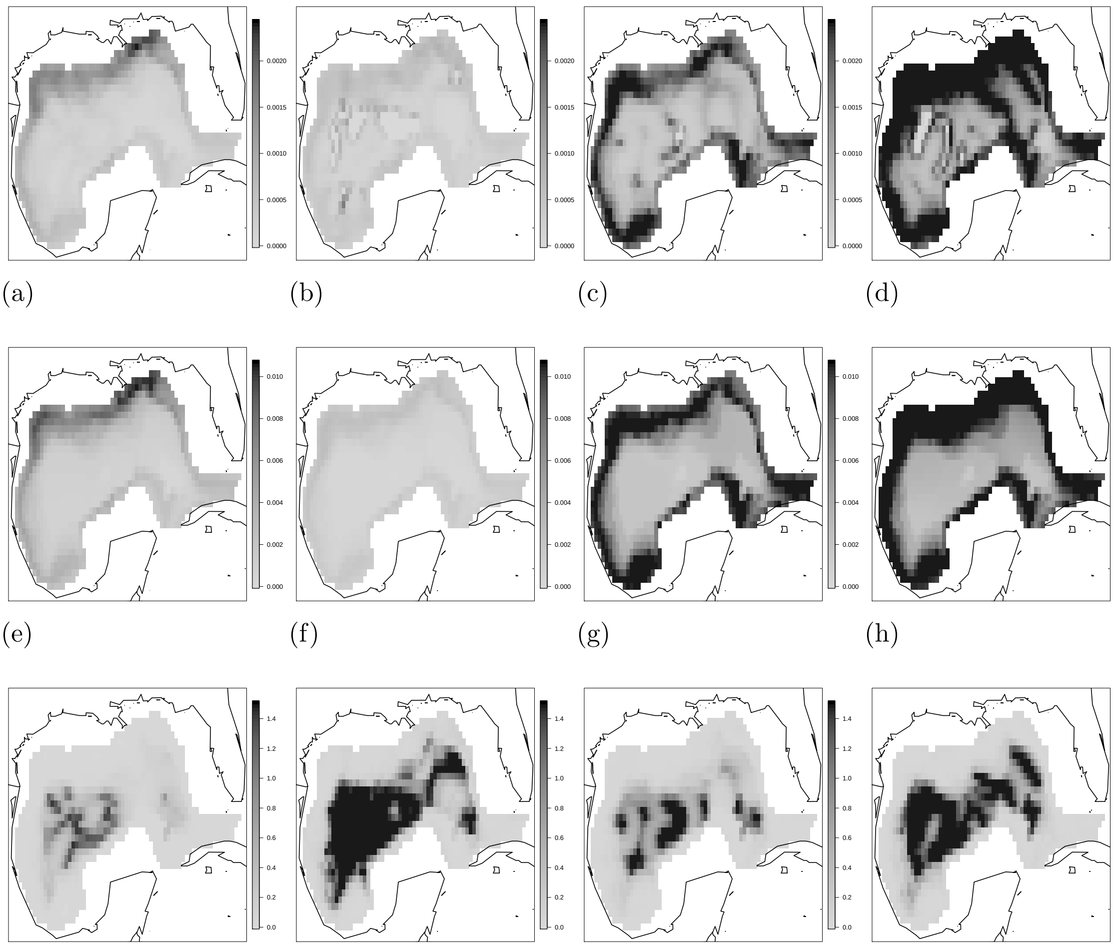


(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure B.22: Catch rates of *bluefin tuna* predicted by GAMs fitted with pelagic longline observer data (a - c), standard error of seasonal predictions from the logistic model (d - f), and standard error of seasonal predictions from the Gamma model (g - i). Columns correspond to season (1, 2, and 4).

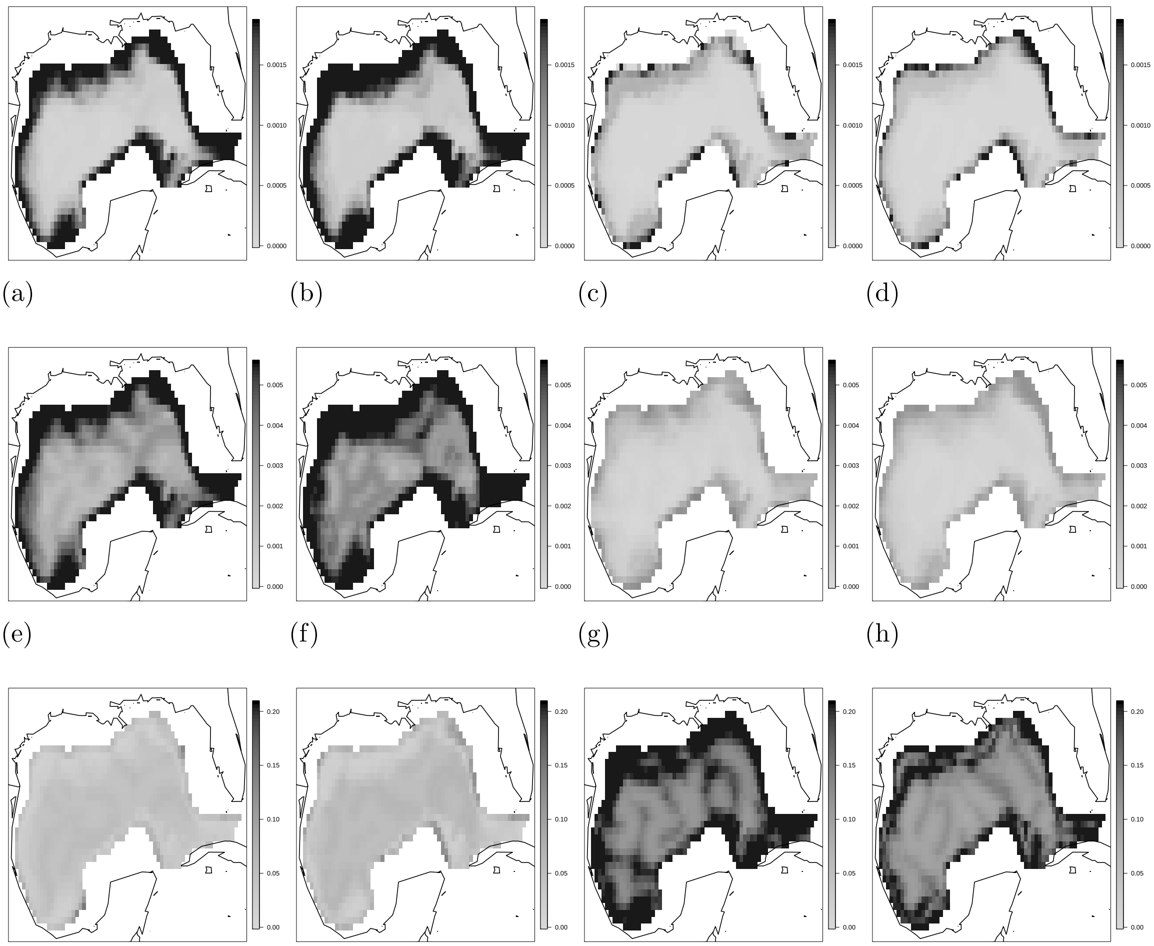


(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

Figure B.23: Catch rates of *deep water fish* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

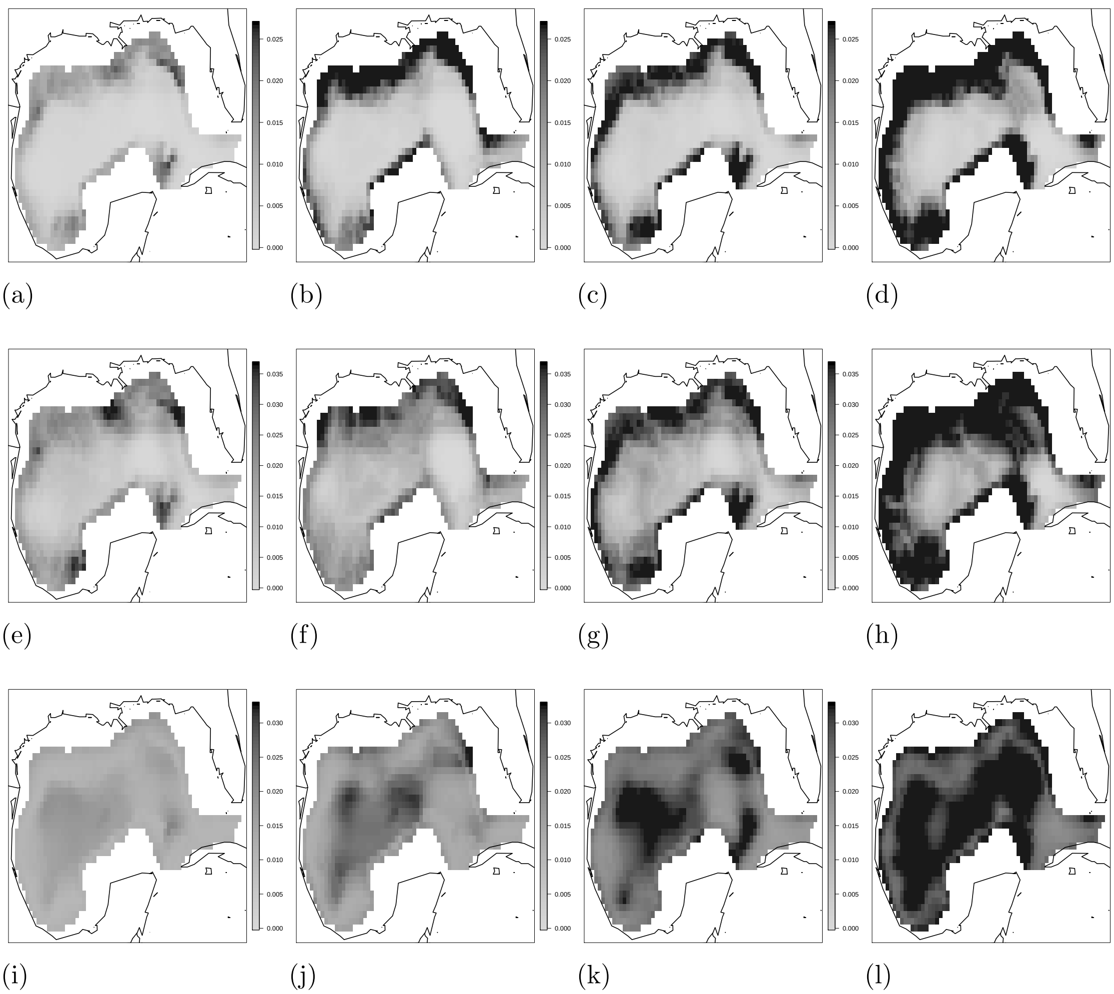


(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

Figure B.24: Catch rates of *filter feeding sharks* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.



(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

Figure B.25: Catch rates of *medium pelagic fish* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

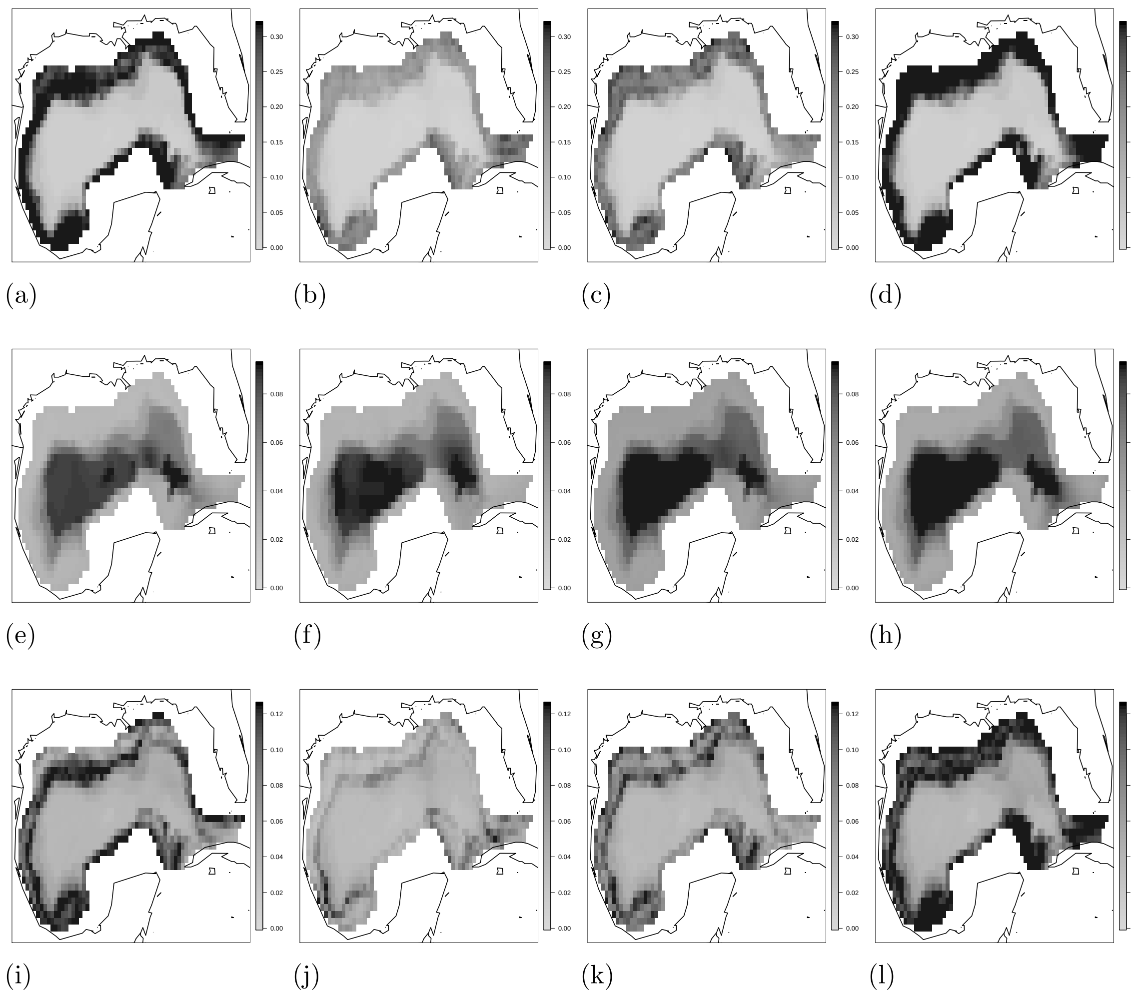


Figure B.26: Catch rates of *spanish mackerel* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

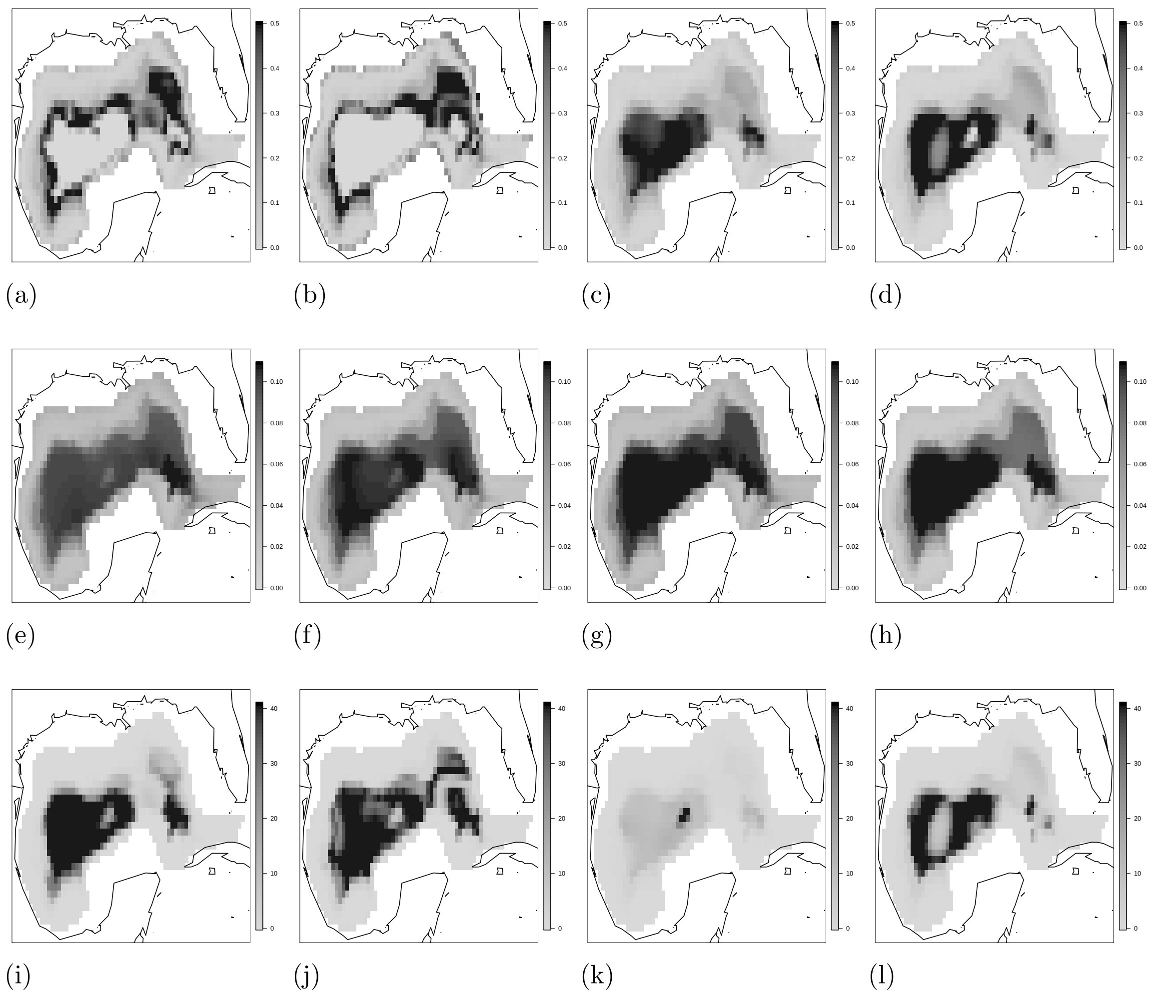


Figure B.27: Catch rates of *small sharks* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

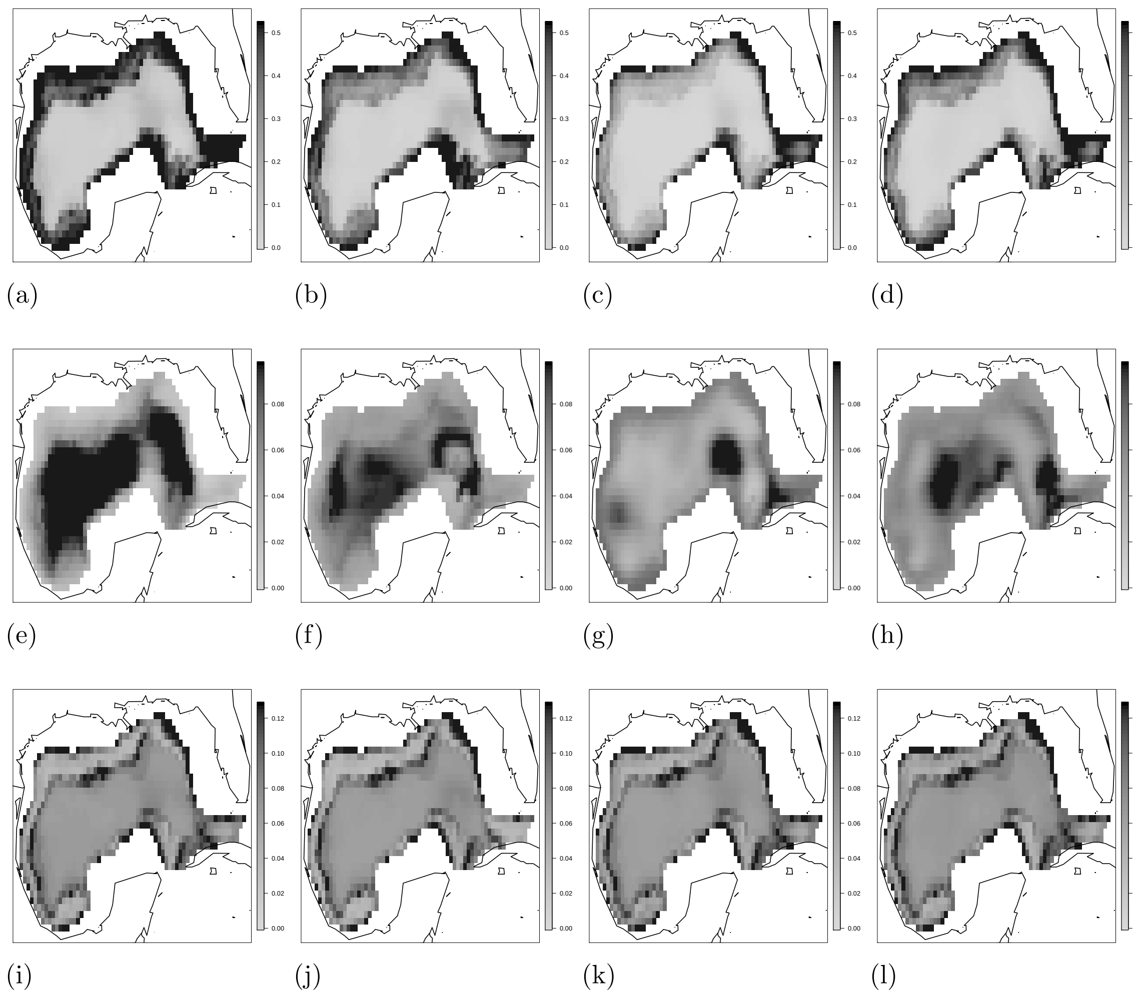
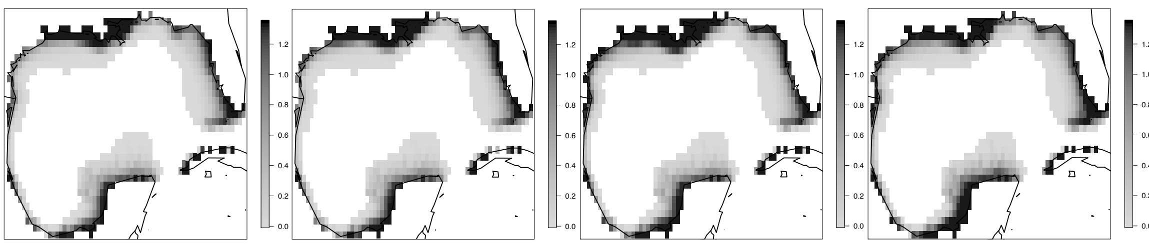
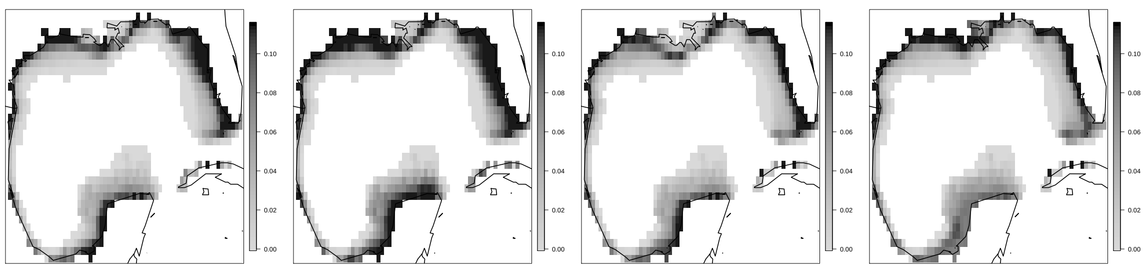


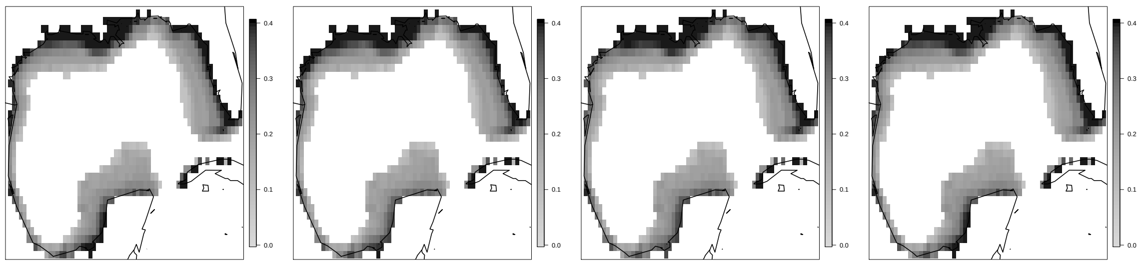
Figure B.28: Catch rates of *swordfish* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.



(a) (b) (c) (d)

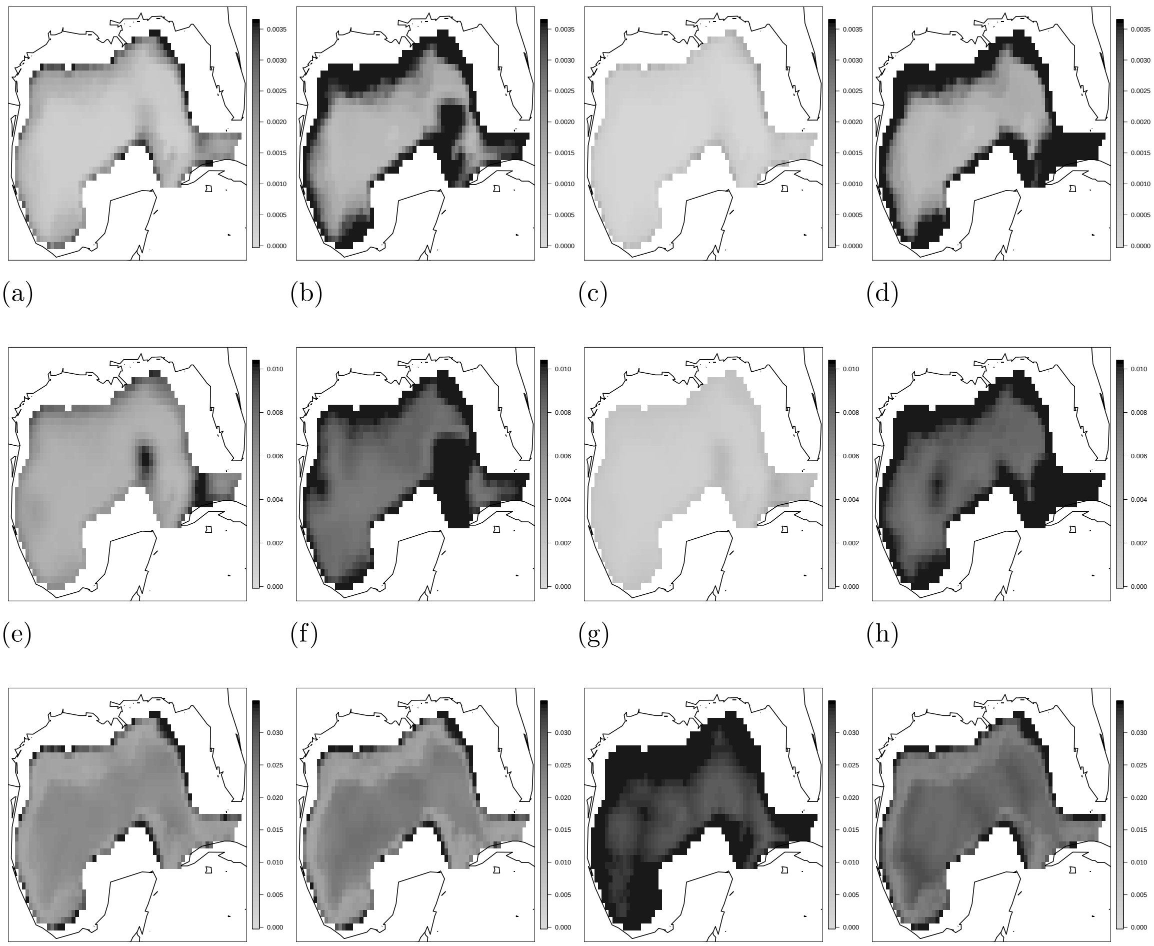


(e) (f) (g) (h)



(i) (j) (k) (l)

Figure B.29: Catch rates of *blacktip sharks* predicted by GAMs fitted with bottom longline survey data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.



(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

Figure B.30: Catch rates of *other turtles* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

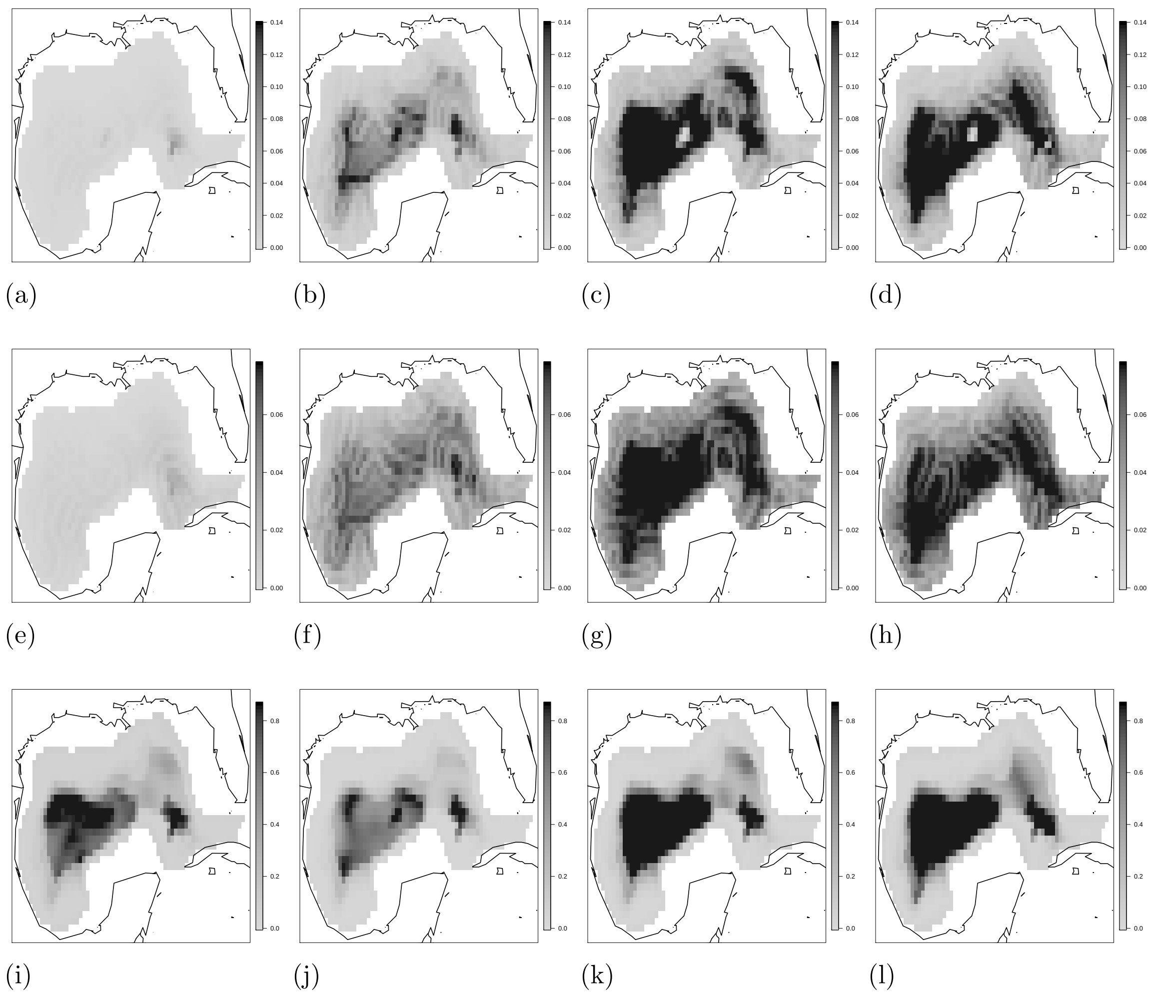


Figure B.31: Catch rates of *white marlin* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

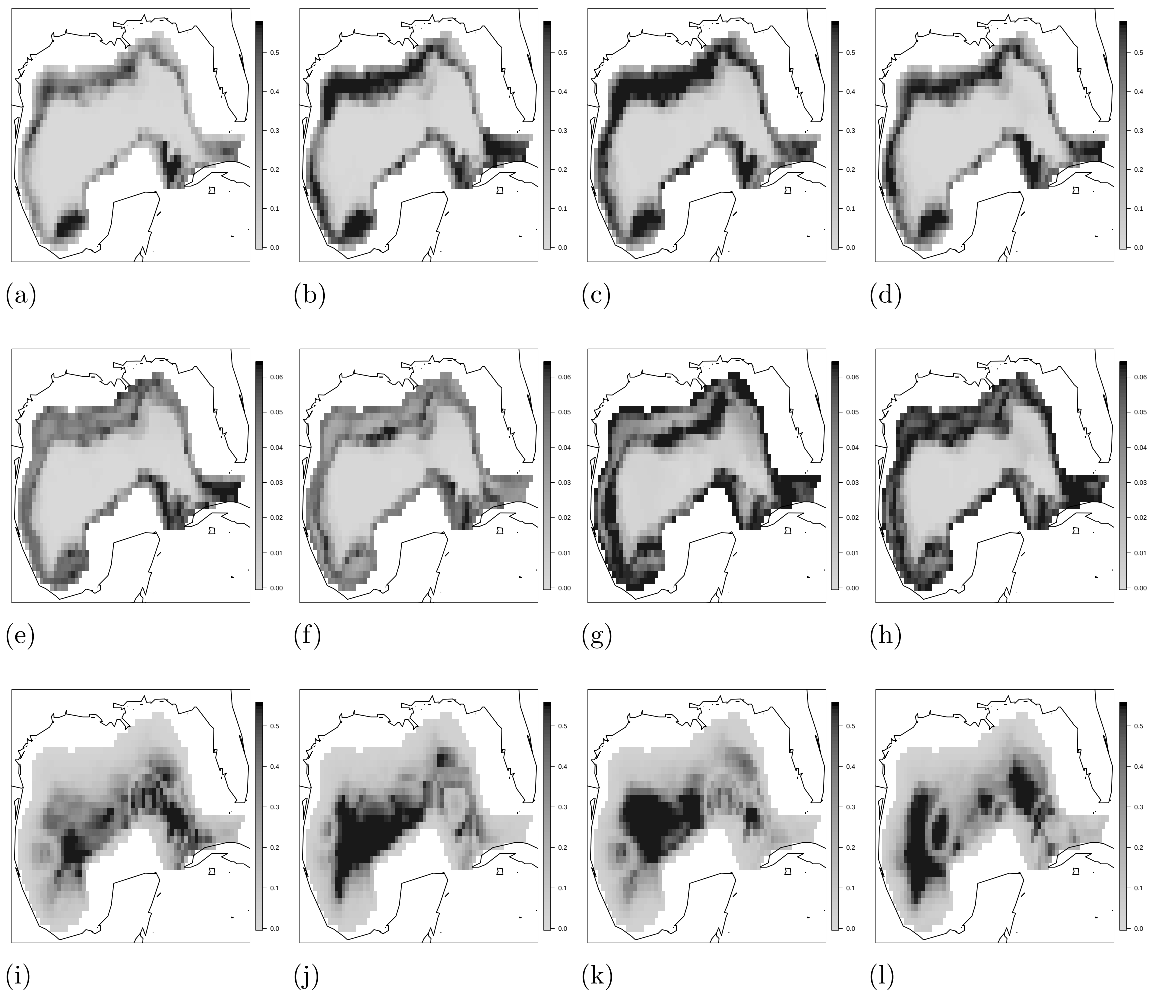


Figure B.32: Catch rates of *yellowfin tuna* predicted by GAMs fitted with pelagic longline observer data (a - d), standard error of seasonal predictions from the logistic model (e - h), and standard error of seasonal predictions from the Gamma model (i - l). Columns correspond to season.

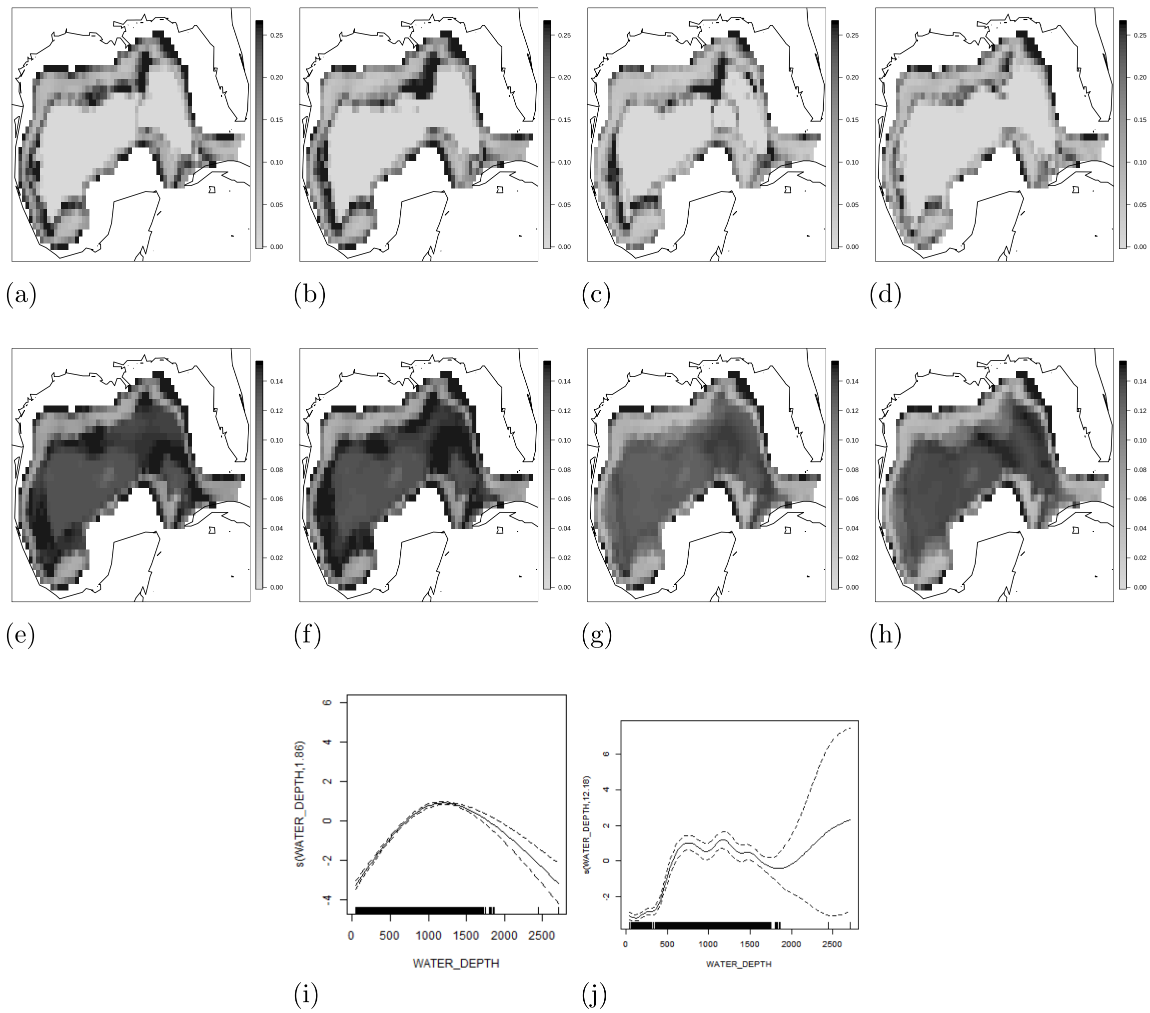


Figure B.33: Panels a - d show the pelagic predictions of *large sharks* as presented in the chapter, from the model selected with training data for cross validation. Panels e - h show the pelagic predictions of *large sharks* from the model selected with data for forecast fitting. Panel i shows the smoothing spline of bottom depth for the *large sharks* Gamma pelagic model presented in the chapter, from the model selected with training data for cross validation. Panel j shows the smoothing spline of bottom depth for the *large sharks* Gamma pelagic model selected with data for forecast fitting.

APPENDIX C

Additional Methodology and Results for Chapter 4

C.1 Exploratory Calibration

C.1.1 Bluefin Tuna

Re-parameterization of the *bluefin tuna* functional group was explored in the attempt to improve diagnostics. Specifically, diet parameters, and migration parameters were adjusted. However, no investigated re-parameterizations meaningfully improved *bluefin tuna* diagnostics. For example, I attempted to adjust the migration parameters to i) reflect time frames described by Block et al. (2005) and Teo et al. (2007), and ii) have a longer transition period into/out of the modeling domain. Adjustments are summarized in Table C.1. These adjustments caused a sudden collapse in the bluefin tuna stock (Figure C.1), which could not be mitigated before the start of this study. Thus, the study was conducted with the original *bluefin tuna* parameterization of diet and migration.

C.2 Additional Methods

C.2.1 Biology Input File

C.2.1.1 Vertical Distribution of Little Tunny

Vectors describing the vertical distribution identify the proportion of functional groups in each depth layer. The first position of the vector identifies the sea floor. The last position of the vector identifies the sea surface. Starting from the last position in the vector and moving forward identifies descending depths. The original nighttime vertical distribution for little tunny (juveniles) put all corresponding biomass in the layer closest to the bottom:

VERTnight_LTN1 6 1 0.0 0.0 0.0 0.0 0.0

I adjusted it to match the nighttime distribution of juveniles of other tuna groups, putting organisms near the sea surface:

VERTnight_LTN1 6 0.0 0.0 0.0 0.0 0.1 0.9

C.2.1.2 Density and Nitrogen Diagnostics

The version of GoMAM I received had poor diagnostics for both the *blue marlin* (BMR) and *white marlin* (WMR) functional groups (Figure C.2). First, both functional groups were quickly collapsing (Figure C.2a,b), Second, adults were losing residual nitrogen (similar to starving), especially WMR (Figure C.2e,f). Lastly, adults were losing structural nitrogen (similar to shrinking), especially WMR (Figure C.2g,h). Since these two functional groups were of focus species for the study it was imperative to improve their diagnostics. Edits were made to the biological input file following suggestions provided by the Atlantis modeling community (http://atlantis.cmar.csiro.au/).

C.2.1.2.1 White Marlin: Diagnostic plots suggested that WMR could be starving and information from the Atlantis wiki suggested, based on the diagnostics, to alter the predator-prey relationship parameter (pprey). This included minor adjustments to slightly expand their prey groups (Llopiz and Cowen, 2008) and allow increased consumption. Table C.2 shows the original matrix and the one used for this study. Updated diagnostic plots are shown in Figure C.3.

C.2.1.2.2 Blue Marlin: Diagnostic plots suggested that BMR could be starving and information from the Atlantis wiki suggested, based on the diagnostics, to alter the predator-prey relationship parameter (pprey). Many attempts were made adjusting pprey parameters with no success in improving diagnostics. Based on information from the Atlantis wiki, the next attempt at improving BMR diagnostics involved adjusting Beverton Holt alpha parameters (BHalpha). The BHalpha for BMR was 3700, but other billfish functional groups had much higher settings: WMR had 150000 and BIL had 78000 (Ainsworth et al., 2015). BHalpha_BMR was iteratively adjusted until density of younger individuals improved. The value used for this study is 18500. Diagnostics for size at age specifically residual nitrogen (RN) were not stabilized. Information from the Atlantis wiki suggested to alter initial conditions for residual nitrogen (KWRR). The original value was 607435.91533 (Ainsworth et al., 2015), which was iteratively adjusted until diagnostics had improved stabilization. The value used is 400000.0. Although BMR are still not stable, I stopped calibrating the model here since BMR were no longer collapsing and size at age improved. The updated diagnostic plots are shown in Figure C.3

C.2.2 Harvest Input File

The version of GoMAM I used simulated harvest using a matrix describing constant, daily fishing mortalities, which was developed using historical landings data described in Chapter 2 of this dissertation (Perryman et al., 2015). However, 2010 landings (Table C.3). This occured because first, simulated fishing mortality rates were computed under the assumption that functional groups are within the modeling domain the entire 365 days (i.e., no migration). Thus, migrating groups are not being fished as hard as they likely are being fished in reality. Second, simulated fishing mortality rates were computed under the assumption that fleets fished the entire modeling domain (i.e., no regional spatial restrictions). Thus, fleets are not harvesting regional areas hard enough since they are fishing all across the spatial domain. Values in the fishing mortality matrix were updated for this study.

First, 2010 bycatch data (National Marine Fisheries Service, 2013) was collected and included into the 2010 landings data reported in Chapter 2 of this dissertation. Then, values for the fishing mortality matrix were iteratively adjusted until 2010 simulated catches were similar to 2010 landings data. The resulting matrix of fishing mortalities is presented in Table C.4.

C.2.3 Additions to Fishery Closure Forcing Files

Forcing files simulating fishery spatial closures were updated to include *Spring Closure*, the seasonal pelagic longline spatial closure off the Louisiana coast, as well as the *Deepwater Horizon* (DWH) emergency fishery closures. The DWH emergency closure drastically changed in spatial coverage in short periods of time. To provide a detailed representation of the DWH closure, alterations were treated as short-lived, individual fishery closures. Shapefiles describing all of the spatial boundaries of the DWH emergency closure were provided by National Centers for Environmental Information (2015). The *Intersect* tool in ArcGIS was used to compute the proportions of the the GoMAM polygons overlapping spatial closures.

Table C.1: Example of alterations made to bluefin tuna migration parameters, with $rep(a, n)$ indicating a vector of n elements of a.

Parameter	jBTN_Migrate_Time
Original	135
Attempted	180
Parameter	BTN_Migrate_Time
Original	364
Attempted	182
Parameter	jBTN_Migrate_Return
Original	340
Attempted	32
Parameter	BTN_Migrate_Return
Original	0
Attempted	32
Parameter	jBTN_Migrate_Period
Original	60
Attempted	90
Parameter	BTN_Migrate_Period
Original	1
Attempted	90
Parameter	MigIOBox_BTNad 66
Original	$rep(0, 66)$
Attempted	$rep(1, 66)$

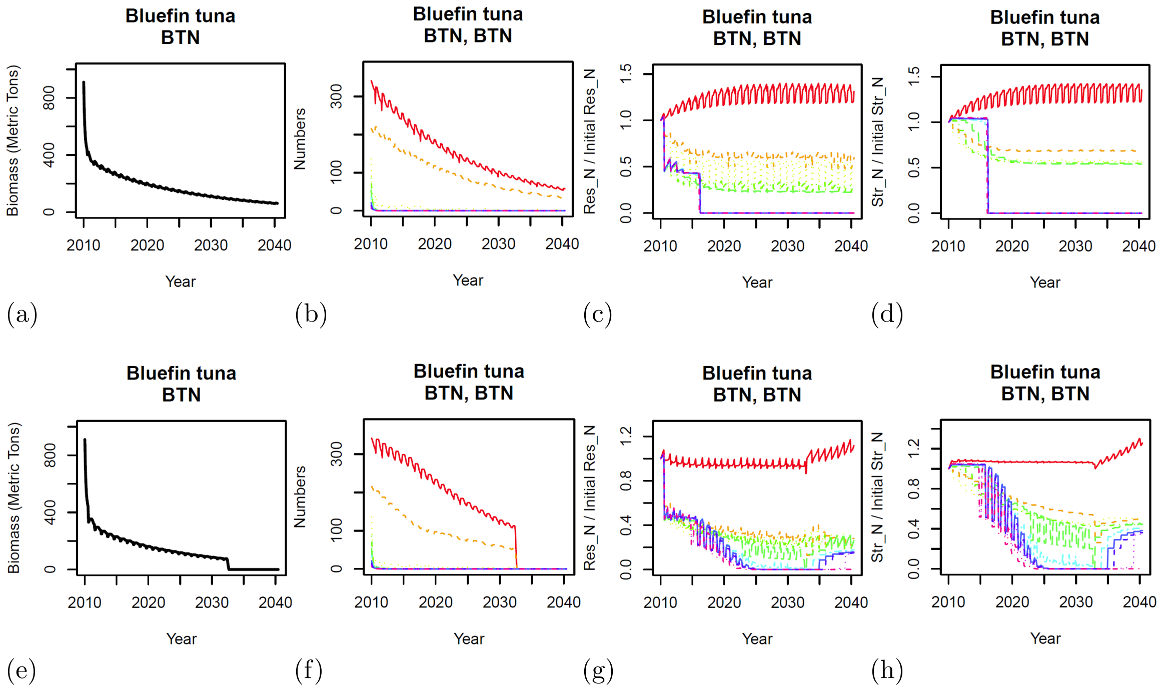


Figure C.1: Diagnostic plots commonly referred to when calibrating an Atlantis model include biomass, density, residual nitrogen (i.e., meat, fat), and structural nitrogen (i.e., bone). This figure *bluefin tuna* diagnostic plots from the original parameterization (a-d), and from the attempted calibration described in Section C.1.1 (e-h). Images with a solid, black line indicate trends for the entire population, while multi-colored lines indicate trends for each of the 10 cohorts (colors are a gradient, with red indicating cohort 1 and blue indicating cohort 10).

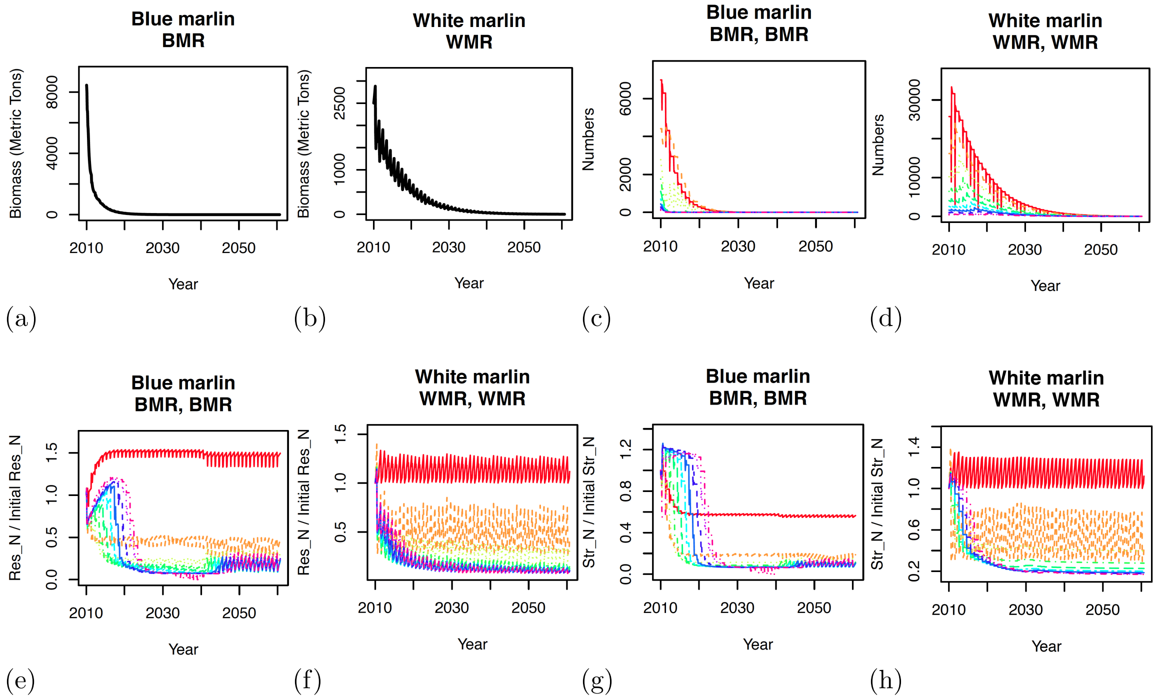


Figure C.2: Diagnostic plots commonly referred to when calibrating an Atlantis model include biomass, density, residual nitrogen (i.e., meat, fat), and structural nitrogen (i.e., bone). This figure displays these diagnostic plots for *white marlin* and *blue marlin* functional groups for the original version of the Gulf of Mexico Atlantis Model provided for this study. Images with a solid, black line indicate trends for the entire population, while multi-colored lines indicate trends for each of the 10 cohorts (colors are a gradient, with red indicating cohort 1 and blue indicating cohort 10).

Table C.2: White Marline Predator-Prey Relationship Parameters.

pPREY1WMR1																
	GAG	RGR	SCM	SSR	DSR	RSN	VSN	LUT	BIO	LRF	SRF	BDR	RDR	SEA	SCI	LDY
Original	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.81E-04	0
Used	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.81E-04	0
	MUL	POM	SHP	SNK	FLT	ODF	SDF	YTN	BTN	LTN	OTN	SWD	WMR	BMR	BIL	AMB
Original	0	0	0.28	0	0	0	0	0	0	0	0	0	0	0	0	0
Used	0	0	0.28	0	0	0	0	0	0	0	0	0	0	0	0	0
	JCK	KMK	SMK	SAR	LPL	DWF	MEN	PIN	MPL	SPL	TIP	BEN	LGS	FIL	SMS	RAY
Original	0	0	0	0	7.50E-03	0.156	5.40E-02	0	0.4	5.14E-03	0	0	0	0	0	0
Used	0	0	0	0	7.50E-03	0.156	5.40E-02	0	0.4	5.14E-03	0	0	0	0	0	0
	BSH	WSH	PSH	OSH	DBR	SBR	MAN	MYS	DOL	DDO	LOG	KMP	TUR	BCR	SCR	LOB
Original	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Used	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	COR	CCA	OCT	SPG	CMB	INF	ECH	OYS	BIV	SES	EPI	GRS	ALG	MPB	LPP	SPP
Original	0	0	0	2.68E-07	0	1.34E-02	0	0	2.96E-03	0	0	0	0	0	0	0
Used	0	0	0	2.68E-07	0	1.34E-02	0	0	2.96E-03	0	0	0	0	0	0	0
	DIN	PRO	JEL	SQU	LZP	SZP	PB	BB	DC	DL	DR	Dcsed	Dlsed	Drsed		
Original	0	0	0	7.23E-02	0	0	0	0	0	0	0	0	0	0		
Used	0	0	0	7.23E-02	0	0.1	0	0	0	0	0	0	0	0		
pPREY2WMR1																
	GAG	RGR	SCM	SSR	DSR	RSN	VSN	LUT	BIO	LRF	SRF	BDR	RDR	SEA	SCI	LDY
Original	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.184	0
Used	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.184	0
	MUL	POM	SHP	SNK	FLT	ODF	SDF	YTN	BTN	LTN	OTN	SWD	WMR	BMR	BIL	AMB
Original	0	0	0	0	0	0	0	3.15E-03	8.18E-05	6.20E-05	1.20E-03	0	0	0	0	0
Used	0	0	0	0	0	0	0	3.15E-03	8.18E-05	6.20E-05	1.20E-03	0	0	0	0	0
	JCK	KMK	SMK	SAR	LPL	DWF	MEN	PIN	MPL	SPL	TIP	BEN	LGS	FIL	SMS	RAY
Original	0	0	0	5.09E-03	0	0	0	0	0	8.78E-04	0	0	0	0	0	0
Used	0	0	0	5.09E-03	0	0	0	0	0	8.78E-04	0	0	0	0	0	0
	BSH	WSH	PSH	OSH	DBR	SBR	MAN	MYS	DOL	DDO	LOG	KMP	TUR	BCR	SCR	LOB
Original	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Used	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	COR	CCA	OCT	SPG	CMB	INF	ECH	OYS	BIV	SES	EPI	GRS	ALG	MPB	LPP	SPP
Original	0	0	0	2.68E-07	0	1.34E-02	0	0	2.96E-03	0	0	0	0	0	0	0
Used	0	0	0	2.68E-07	0	1.34E-02	0	0	2.96E-03	0	0	0	0	0	0	0
	DIN	PRO	JEL	SQU	LZP	SZP	PB	BB	DC	DL	DR	Dcsed	Dlsed	Drsed		
Original	0	0	0	7.23E-02	0	0	0	0	0	0	0	0	0	0		
Used	0	0	0	7.23E-02	0	0.1	0	0	0	0	0	0	0	0		

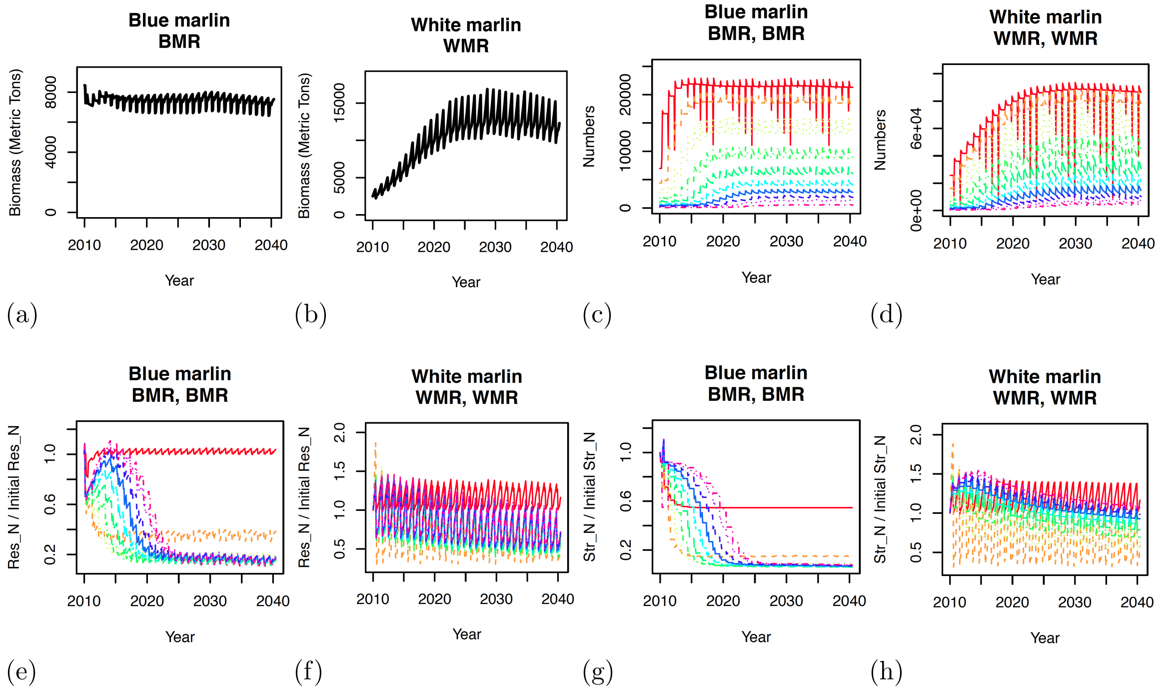


Figure C.3: Diagnostic plots commonly referred to when calibrating an Atlantis model include biomass, density, residual nitrogen (i.e., meat, fat), and structural nitrogen (i.e., bone). This figure displays these diagnostic plots for *white marlin* and *blue marlin* functional groups for the edited version of the Gulf of Mexico Atlantis Model provided for this study. Images with a solid, black line indicate trends for the entire population, while multi-colored lines indicate trends for each of the 10 cohorts (colors are a gradient, with red indicating cohort 1 and blue indicating cohort 10).

Table C.3: Comparing Simulated Catch to Landings Data, 2010 - 2011. This data does not include bycatch data.

	Catch [Data]		Catch [Model]	
Functional Group	2010	2011	2010	2011
GAG	869.2541834	424.2282683	2717.601963	135.328075
RGR	11290.65301	10121.77972	10355.35638	855.230868
SCM	106.6226963	94.49047107	430.10957	60.083291
SSR	1792.514163	1661.260256	11435.88161	7621.159696
DSR	1868.696426	2198.741464	7934.120677	2910.945576
RSN	7834.709603	7485.57075	28111.75431	1718.446258
VSN	2592.430015	2665.645146	11271.09206	960.105507
LUT	13720.23186	9735.783046	82790.55164	34117.61985
BIO	281.4140106	293.7197801	178.205865	233.031601
LRF	2977.391752	3064.836201	9059.557854	3023.253913
SRF	4409.45074	2589.645167	23461.92162	14362.26674
BDR	3389.852953	3716.062303	2410.786693	823.796106
RDR	8248.862435	8994.278344	6978.791807	765.494759
SEA	5541.172513	6454.721288	14497.18305	10304.0511
SCI	1102.736522	1206.850755	23742.39079	31925.21771
LDY	812.1860073	566.0487624	13743.51592	8662.761084
MUL	12768.28809	14392.26876	29209.08988	18324.90213
POM	1104.983016	793.9470391	11626.27994	8623.964201
SHP	2762.648313	4226.622449	43213.71453	14866.45148
SNK	4946.304571	3530.981242	24134.13372	18626.22111
FLT	1008.066502	1158.880923	22315.96577	22307.55464
ODF	77240.27515	145173.1183	56759.784	23882.56042
SDF	3439.940771	2463.022424	11064.00351	29419.49274
YTN	2086.957513	2950.324009	3219.066524	1085.615481
BTN	578.271376	393.0733991	521.231866	27.01504
LTN	1823.500762	1303.117893	11301.83941	4189.151629
OTN	0	0	0	0
SWD	763.6312954	713.6085877	35572.25075	1784.454045
WMR	556.2137959	387.2352518	2613.00091	702.026704
BMR	573.5365847	398.9554236	5902.384574	610.744249
BIL	556.0498356	395.9402602	2110.671917	290.050668
AMB	1672.649993	1191.170086	1315.285888	107.521184
JCK	21037.69288	14666.34909	5635.362462	2791.627347
KMK	4667.319921	4272.613195	16345.66585	906.667556
SMK	6597.037188	5420.938599	8862.800034	2253.458296
SAR	1505.724651	416.941936	42940.34878	84499.3485
LPL	16361.29752	23943.53414	22701.33933	24977.71248
DWF	0	0	0	0
MEN	438694.0209	623487.1235	337037.1668	253451.2215
PIN	1600.016487	1157.607798	25572.70535	17976.11752
MPL	1886.170133	1932.425816	18682.85154	14242.08553
SPL	4295.263388	3764.48995	109872.9597	129306.907
TIP	2352.602061	1677.982504	3747.665649	4264.491933
BEN	571.476492	391.2722242	8287.027566	9297.838878
LGS	7682.870588	3917.657732	55627.02485	40864.83637
FIL	0	0	0	0
SMS	597.7221394	407.9341713	12291.96878	9877.290105
RAY	3945.50903	4292.319974	42096.43535	32712.62274
BSH	54358.80095	71836.5773	208778.7873	38726.54188
WSH	43483.0138	42841.01804	91288.34858	41194.00024
PSH	5969.19728	4981.224216	11606.95687	4051.569203
OSH	1994.476757	2501.451361	98439.45989	16744.92404
DBR	0	0	0	0
SBR	0	0	0	0
MAN	0	0	0	0
MYS	0	0	0	0
DOL	0	0	0	0
DDO	0	0	0	0
LOG	0	0	0	0
KMP	0	0	0	0
TUR	0	0	0	0
BCR	30657.36079	35183.043	230943.2357	318.445866
SCR	3120.00048	3096.57996	150953.5078	12841.43481
LOB	4618.402816	4401.223353	74373.41795	1655.435612
SPG	100.8752321	46.65601953		
CMB	7535.127658	5222.56307	233252.7871	48234.29739
OYS	9610.124849	10343.27108	221967.8541	204935.8659
BIV	1964.155394	1974.751522	129823.2984	130481.7972
SES	0	0	0	0
SQU	22502.49823	26117.92085	2753883.016	264619.8827

Table C.4: Updated Fishing Mortality Matrix for Gulf of Mexico Atlantis Model.

	SprtEst	GillnetEst	TwlShpEst	OytEst	PotCrbEst	SprtShf	TwlShpShf	PotCrbShf
mFC_GAG	0	0	0	0	0	9.58E-04	0	0
mFC_RGR	0	0	0	0	0	1.28E-02	0	1.53E-05
mFC_SCM	0	0	0	0	0	2.69E-04	0	0
mFC_SSR	0	0	0	0	0	1.23E-05	0	1.44E-06
mFC_DSR	0	0	0	0	6.86E-06	6.96E-04	0	1.97E-04
mFC_RSN	0	0	0	0	0	3.92E-04	5.12E-05	0
mFC_VSN	0	0	0	0	0	1.94E-04	2.61E-05	0
mFC_LUT	0	1.01E-09	0	0	0	5.54E-04	1.68E-05	2.55E-07
mFC_BIO	0	0	0	0	0	0	0	0
mFC_LRF	0	3.34E-07	2.30E-06	0	0	1.88E-04	6.00E-07	1.81E-06
mFC_SRF	0	3.87E-07	0	0	0	3.04E-04	3.07E-06	0
mFC_BDR	1.009228641	4.67E-02	3.48E-02	0	2.68E-02	0	0.306036876	0
mFC_RDR	2.125756414	0	0.183536107	0	0	0	0	0
mFC_SEA	3.30E-03	2.21E-05	1.30E-02	0	0	0	2.11E-05	0
mFC_SCI	2.43E-05	1.39E-05	1.57E-03	0	7.63E-08	0	1.59E-03	0
mFC_LDY	6.40E-05	1.21E-04	0	0	0	0	0	0
mFC_MUL	2.03E-04	2.95E-04	0	0	9.55E-08	0	3.19E-07	0
mFC_POM	6.03E-06	4.24E-06	0	0	0	0	0	0
mFC_SHP	2.63E-04	3.51E-06	6.00E-06	0	1.08E-07	0	7.89E-06	0
mFC_SNK	5.27E-09	0	0	0	0	0	0	0
mFC_FLT	0	1.82E-05	8.48E-05	0	1.51E-06	3.26E-05	6.15E-06	1.41E-06
mFC_ODF	0	1.24E-04	6.81E-02	0	1.80E-04	2.688466653	6.81E-02	6.57E-03
mFC_SDF	0	0	1.09E-04	0	0	2.81E-08	0	0
mFC_YTN	0	0	0	0	0	1.42E-03	0	0
mFC_BTN	0	0	0	0	0	0	0	0
mFC_LTN	0	1.79E-06	0	0	0	1.53E-04	0	0
mFC_OTN	0	0	0	0	0	0	0	0
mFC_SWD	0	0	0	0	0	2.96E-06	0	0
mFC_WMR	0	0	0	0	0	0	0	0
mFC_BMR	0	0	0	0	0	9.63E-06	0	0
mFC_BIL	0	0	0	0	0	0	0	0
mFC_AMB	0	0	0	0	0	0.991878998	0	0
mFC_JCK	0	1.93E-02	0	0	9.10E-05	1.757864834	0	4.74E-03
mFC_KMK	0	0	0	0	0	4.70E-04	8.78E-06	0
mFC_SMK	0	1.36E-03	6.29E-04	0	0	4.95E-03	0	0
mFC_SAR	0	0	0	0	0	1.17E-07	0	0
mFC_LPL	0	5.61E-05	1.06E-05	0	0	5.08E-03	0	0
mFC_DWF	0	0	0	0	0	0	0	0
mFC_MEN	0	2.26E-05	0	0	0	1.27E-05	0	0
mFC_PIN	0	0	0	0	0	1.52E-04	0	1.35E-05
mFC_MPL	0	0	0	0	5.51E-08	1.71E-07	0	0
mFC_SPL	0	1.43E-08	0	0	0	5.01E-06	0	0
mFC_TIP	0	0	0	0	0	6.27E-04	0	0
mFC_BEN	0	0	0	0	0	0	0	0
mFC_LGS	0	1.66E-05	2.39E-05	0	0	7.41E-05	2.39E-05	0
mFC_FIL	0	0	0	0	0	0	0	0
mFC_SMS	0	0	0	0	0	0	0	0
mFC_RAY	1.18E-06	3.89E-07	0	0	0	0	0	0
mFC_BSH	0	0	1.18E-04	0	0	0	4.92E-04	0
mFC_WSH	0	0	1.11E-03	0	0	0	2.62E-03	0
mFC_PSH	0	0	4.09E-06	0	0	0	2.44E-03	0
mFC_OSH	0	0	2.85E-05	0	0	0	5.71E-05	1.23E-09
mFC_DBR	0	0	0	0	0	0	0	0
mFC_SBR	0	0	0	0	0	0	0	0
mFC_MAN	0	0	0	0	0	0	0	0
mFC_MYS	0	0	0	0	0	0	0	0
mFC_DOL	0	0	0	0	0	0	0	0
mFC_DDO	0	0	0	0	0	0	0	0
mFC_LOG	0	0	0	0	0	0	4.30E-05	0
mFC_KMP	0	0	0	0	0	0	4.13E-06	0
mFC_TUR	0	0	0	0	0	0	5.98E-07	0
mFC_BCR	0	0	9.91E-07	0	4.79E-04	0	1.00E-07	1.48E-07
mFC_SCR	0	0	0	0	6.01E-05	0	0	0
mFC_LOB	0	0	0	0	6.57E-08	5.67E-05	7.16E-09	0
mFC_COR	0	0	0	0	0	0	0	0
mFC_CCA	0	0	0	0	0	0	0	0
mFC_OCT	0	0	0	0	0	0	0	0
mFC_SPG	0	0	0	0	0	0	0	0
mFC_CMB	0	0	0	0	0	0	0	0
mFC_INF	0	0	0	0	0	0	0	0
mFC_ECH	0	0	0	0	0	0	0	0
mFC_OYS	0	0	0	2.12E-06	0	0	0	0
mFC_BIV	0	2.31E-10	2.00E-10	1.62E-10	5.51E-11	0	7.20E-08	2.84E-09
mFC_SES	0	0	0	0	0	0	0	0
mFC_EPI	0	0	0	0	0	0	0	0
mFC_GRS	0	0	0	0	0	0	0	0
mFC_ALG	0	0	0	0	0	0	0	0
mFC_MPB	0	0	0	0	0	0	0	0
mFC_LPP	0	0	0	0	0	0	0	0
mFC_SPP	0	0	0	0	0	0	0	0
mFC_DIN	0	0	0	0	0	0	0	0
mFC_PRO	0	0	0	0	0	0	0	0
mFC_JEL	0	0	0	0	0	0	0	0
mFC_SQU	0	0	7.80E-09	0	3.36E-09	0	1.26E-08	4.10E-09
mFC_LZP	0	0	0	0	0	0	0	0
mFC_SZP	0	0	0	0	0	0	0	0
mFC_PB	0	0	0	0	0	0	0	0
mFC_BB	0	0	0	0	0	0	0	0
mFC_DC	0	0	0	0	0	0	0	0
mFC_DL	0	0	0	0	0	0	0	0
mFC_DR	0	0	0	0	0	0	0	0

Table C.4: (Continued)

	PotLbtShf	HLReefShf	LLReefShf	SeineMenShf	LLShkShf	LLPelgc	RoyalRed	OtherUS
mFC_GAG	0	3.95E-04	1.44E-04	0	0	0	0	4.93E-05
mFC_RGR	0	0	0.109742601	0	0	0	0	1.00E-03
mFC_SCM	0	3.55E-04	3.74E-04	0	0	0	0	9.94E-06
mFC_SSR	1.56E-07	7.56E-05	4.04E-05	0	0	0	0	2.63E-05
mFC_DSR	0	6.43E-05	2.61E-04	0	0	0	0	5.41E-08
mFC_RSN	0	3.72E-04	1.26E-05	0	0	0	0	2.57E-06
mFC_VSN	0	8.87E-04	1.55E-06	0	0	0	0	6.96E-07
mFC_LUT	1.03E-07	9.22E-05	6.54E-06	0	0	0	0	1.26E-06
mFC_BIO	0	0	0	0	0	0	0	0
mFC_LRF	1.10E-06	4.94E-05	6.37E-06	0	0	0	0	8.93E-05
mFC_SRF	0	9.27E-05	2.28E-04	0	0	1.13E-06	0	6.98E-06
mFC_BDR	0	0.109658285	1.459713061	0	0	3.76E-02	0	8.17E-03
mFC_RDR	0	4.88E-03	0	0	0	0	0	0
mFC_SEA	0	1.81E-04	0	0	0	0	0	6.46E-06
mFC_SCI	0	4.16E-05	0	0	0	0	0	1.69E-05
mFC_LDY	0	7.46E-06	0	0	0	0	0	4.75E-05
mFC_MUL	0	4.98E-07	0	9.37E-06	0	0	0	1.36E-03
mFC_POM	0	1.00E-05	0	0	0	0	0	3.84E-06
mFC_SHP	0	1.82E-05	1.67E-06	1.10E-08	0	0	0	7.52E-06
mFC_SNK	0	0	0	0	0	0	0	0
mFC_FLT	0	3.67E-06	3.54E-06	0	0	1.58E-06	0	3.08E-05
mFC_ODF	1.79E-05	0.01939481	8.53E-04	0	0	0	0	1.30E-04
mFC_SDF	0	0	0	0	0	0	0	0
mFC_YTN	0	2.75E-05	0	0	0	2.27E-03	0	0
mFC_BTN	0	0	0	0	0	9.36E-03	0	0
mFC_LTN	0	1.88E-05	0	0	0	0	0	0
mFC_OTN	0	0	0	0	0	8.50E-05	0	0
mFC_SWD	0	4.68E-06	0	0	0	1.83E-04	0	0
mFC_WMR	0	0	0	0	0	3.53E-05	0	0
mFC_BMR	0	0	0	0	0	4.74E-05	0	0
mFC_BIL	0	0	0	0	0	1.82E-05	0	0
mFC_AMB	0	0.85650951	1.26E-02	0	0	0	0	2.19E-02
mFC_JCK	0	0.261193261	6.24E-03	0	0	0	0	0.11331893
mFC_KMK	0	5.26E-04	0	0	0	1.38E-04	0	0
mFC_SMK	0	1.69E-04	0	3.16E-06	0	1.02E-04	0	4.50E-05
mFC_SAR	0	1.42E-07	0	0	0	0	0	1.47E-06
mFC_LPL	0	1.18E-04	4.50E-06	4.61E-06	0	9.99E-05	0	2.24E-06
mFC_DWF	0	0	0	0	0	0	0	0
mFC_MEN	0	1.22E-08	0	0.10065426	0	0	0	1.93E-05
mFC_PIN	0	6.20E-06	0	0	0	0	0	3.25E-06
mFC_MPL	0	1.97E-05	0	0	0	1.75E-07	0	4.33E-05
mFC_SPL	0	0	0	0	0	0	0	4.72E-05
mFC_TIP	0	1.76E-03	0	0	1.55E-04	0	0	0
mFC_BEN	0	0	0	0	0	0	0	0
mFC_LGS	0	1.26E-05	1.81E-06	1.50E-08	1.42E-05	1.31E-05	0	7.73E-08
mFC_FIL	0	0	0	0	0	0	0	0
mFC_SMS	0	0	0	0	0	0	0	0
mFC_RAY	0	0	0	0	0	0	0	0
mFC_BSH	0	0	0	0	0	0	0	2.06E-07
mFC_WSH	0	0	0	0	0	0	0	1.12E-06
mFC_PSH	0	0	0	0	0	0	0	0
mFC_OSH	0	0	0	0	0	0	6.17E-06	3.85E-09
mFC_DBR	0	0	0	0	0	0	0	0
mFC_SBR	0	0	0	0	0	0	0	0
mFC_MAN	0	0	0	0	0	0	0	0
mFC_MYS	0	0	0	0	0	0	0	0
mFC_DOL	0	0	0	0	0	0	0	0
mFC_DDO	0	0	0	0	0	0	0	0
mFC_LOG	0	0	0	0	0	7.93E-06	0	0
mFC_KMP	0	0	0	0	0	0	0	0
mFC_TUR	0	0	0	0	0	9.89E-06	0	0
mFC_BCR	0	2.25E-09	1.21E-07	0	0	0	0	0
mFC_SCR	9.71E-07	0	0	0	0	0	0	0
mFC_LOB	2.33E-04	0	0	0	0	0	0	8.07E-06
mFC_COR	0	0	0	0	0	0	0	0
mFC_CCA	0	0	0	0	0	0	0	0
mFC_OCT	0	0	0	0	0	0	0	0
mFC_SPG	0	0	0	0	0	0	0	0
mFC_CMB	0	0	0	0	0	0	0	0
mFC_INF	0	0	0	0	0	0	0	0
mFC_ECH	0	0	0	0	0	0	0	0
mFC_OYS	0	0	0	0	0	0	0	7.16E-08
mFC_BIV	3.25E-10	1.89E-11	3.09E-11	0	0	2.26E-11	0	9.91E-10
mFC_SES	0	0	0	0	0	0	0	0
mFC_EPI	0	0	0	0	0	0	0	0
mFC_GRS	0	0	0	0	0	0	0	0
mFC_ALG	0	0	0	0	0	0	0	0
mFC_MPB	0	0	0	0	0	0	0	0
mFC_LPP	0	0	0	0	0	0	0	0
mFC_SPP	0	0	0	0	0	0	0	0
mFC_DIN	0	0	0	0	0	0	0	0
mFC_PRO	0	0	0	0	0	0	0	0
mFC_JEL	0	0	0	0	0	0	0	0
mFC_SQU	0	1.43E-09	0	0	0	0	0	3.66E-11
mFC_LZP	0	0	0	0	0	0	0	0
mFC_SZP	0	0	0	0	0	0	0	0
mFC_PB	0	0	0	0	0	0	0	0
mFC_BB	0	0	0	0	0	0	0	0
mFC_DC	0	0	0	0	0	0	0	0
mFC_DL	0	0	0	0	0	0	0	0
mFC_DR	0	0	0	0	0	0	0	0

Table C.4: (Continued)

	TwlShpMX	LLReefMX	LLShkMX	GillnetMackMX	OctpsMX	MixedMX	MixedCB
mFC_GAG	0	0	0	0	0	0	0
mFC_RGR	0	0.161361716	0	0	0	0.161361716	0
mFC_SCM	0	0	0	0	0	0	0
mFC_SSR	0	2.35E-04	0	0	0	2.35E-04	3.49E-04
mFC_DSR	0	6.48E-04	0	0	0	0	0
mFC_RSN	0	4.81E-04	0	0	0	4.81E-04	6.35E-05
mFC_VSN	0	3.11E-04	0	0	0	3.11E-04	0
mFC_LUT	0	1.25E-04	0	0	0	1.25E-04	3.23E-05
mFC_BIO	0	0	0	0	0	0	1.32E-02
mFC_LRF	0	0	0	0	0	2.58E-03	3.09E-04
mFC_SRF	0	0	0	0	0	5.44E-04	1.51E-04
mFC_BDR	0	0	0	0	0	0	0
mFC_RDR	0	0	0	0	0	0.275696236	0
mFC_SEA	0	0	0	0	0	3.09E-03	0
mFC_SCI	0	0	0	0	0	9.02E-05	0
mFC_LDY	0	0	0	0	0	0	0
mFC_MUL	0	0	0	9.08E-04	0	9.08E-04	2.20E-05
mFC_POM	0	0	0	0	0	4.09E-04	0
mFC_SHP	9.97E-06	0	0	9.97E-06	0	9.97E-06	0
mFC_SNK	0	0	0	0	0	2.04E-03	0
mFC_FLT	2.74E-05	0	0	2.74E-05	0	2.74E-05	0
mFC_ODF	0	0	0	0	0	7.50E-02	3.56E-03
mFC_SDF	0	0	0	0	0	2.84E-03	0
mFC_YTN	0	0	3.19E-03	0	0	3.19E-03	2.39E-06
mFC_BTN	0	0	1.74E-02	0	0	1.74E-02	0
mFC_LTN	0	0	4.11E-04	0	0	4.11E-04	6.19E-06
mFC_OTN	0	0	0	0	0	0	0
mFC_SWD	0	0	8.07E-05	0	0	8.07E-05	1.25E-07
mFC_WMR	0	0	6.64E-04	0	0	6.64E-04	0
mFC_BMR	0	0	4.45E-04	0	0	4.45E-04	4.06E-06
mFC_BIL	0	0	1.16E-03	0	0	1.16E-03	1.28E-04
mFC_AMB	0	0	0.431905909	0	0	0.431905909	0
mFC_JCK	0	0	3.276053863	0	0	3.276053863	3.76E-03
mFC_KMK	0	0	6.07E-04	6.07E-04	0	0	2.10E-07
mFC_SMK	0	0	3.58E-03	3.58E-03	0	0	9.73E-07
mFC_SAR	0	0	0	0	0	1.24E-04	0
mFC_LPL	0	0	0	1.58E-03	0	0	7.78E-05
mFC_DWF	0	0	0	0	0	0	0
mFC_MEN	0	0	0	0	0	0	0
mFC_PIN	0	0	0	0	0	8.35E-05	0
mFC_MPL	0	0	0	0	0	6.72E-04	1.91E-06
mFC_SPL	0	0	0	0	0	3.47E-05	2.66E-05
mFC_TIP	0	0	1.15E-02	0	0	0	0
mFC_BEN	2.73E-06	0	2.73E-06	0	0	2.73E-06	0
mFC_LGS	0	0	1.39E-04	0	0	1.39E-04	5.58E-06
mFC_FIL	0	0	0	0	0	0	0
mFC_SMS	1.28E-05	0	1.28E-05	1.28E-05	0	1.28E-05	0
mFC_RAY	1.51E-04	0	1.51E-04	0	0	1.51E-04	7.60E-05
mFC_BSH	1.96E-04	0	0	0	0	0	0
mFC_WSH	5.08E-05	0	0	0	0	5.08E-05	0
mFC_PSH	7.22E-04	0	0	0	0	0	0
mFC_OSH	1.98E-05	0	0	0	0	1.98E-05	0
mFC_DBR	0	0	0	0	0	0	0
mFC_SBR	0	0	0	0	0	0	0
mFC_MAN	0	0	0	0	0	0	0
mFC_MYS	0	0	0	0	0	0	0
mFC_DOL	0	0	0	0	0	0	0
mFC_DDO	0	0	0	0	0	0	0
mFC_LOG	0	0	0	0	0	0	0
mFC_KMP	0	0	0	0	0	0	0
mFC_TUR	0	0	0	0	0	0	0
mFC_BCR	0	0	0	0	0	1.82E-04	1.10E-06
mFC_SCR	0	0	0	0	0	1.42E-05	0
mFC_LOB	0	0	0	0	0	6.16E-05	7.62E-05
mFC_COR	0	0	0	0	0	0	0
mFC_CCA	0	0	0	0	0	0	0
mFC_OCT	0	0	0	0	0	0	0
mFC_SPG	0	0	0	0	0	0	0
mFC_CMB	3.00E-05	0	0	0	0	3.00E-05	2.16E-06
mFC_INF	0	0	0	0	0	0	0
mFC_ECH	0	0	0	0	0	0	0
mFC_OYS	0	0	0	0	0	4.94E-07	0
mFC_BIV	0	0	0	0	0	1.84E-06	6.95E-08
mFC_SES	0	0	0	0	0	0	0
mFC_EPI	0	0	0	0	0	0	0
mFC_GRS	0	0	0	0	0	0	0
mFC_ALG	0	0	0	0	0	0	0
mFC_MPB	0	0	0	0	0	0	0
mFC_LPP	0	0	0	0	0	0	0
mFC_SPP	0	0	0	0	0	0	0
mFC_DIN	0	0	0	0	0	0	0
mFC_PRO	0	0	0	0	0	0	0
mFC_JEL	0	0	0	0	0	0	0
mFC_SQU	1.26E-07	0	0	0	1.24E-05	1.26E-07	0
mFC_LZP	0	0	0	0	0	0	0
mFC_SZP	0	0	0	0	0	0	0
mFC_PB	0	0	0	0	0	0	0
mFC_BB	0	0	0	0	0	0	0
mFC_DC	0	0	0	0	0	0	0
mFC_DL	0	0	0	0	0	0	0
mFC_DR	0	0	0	0	0	0	0

C.3 Additional Results

Functional group-specific performance measures were also computed for functional groups not identified in the main text, as well as functional group assemblages not identified in the main text. This allowed some investigation into indirect impacts from pelagic longline fisheries. There was a lot of information, and all of it could not be discussed in the main text. Some examples of additional biomass and catch metrics are presented in Table C.5, and addition results for average weight and proportion mature metrics are presented in Table C.6.

Table C.5: Additional biomass and catch performance metrics. Metrics are relative to the status quo. Metrics for functional group assemblages (i.e., elasmobranchs and reef fish) are the sum across all associated functional groups. Functional group-specific metrics are shown for the functional groups: large sharks (LGS), blacktip sharks (TIP), king mackerel (KMK), and amberjack (AMB).

	Biomass						Catch					
Scenarios	Elasmobranchs	LGS	TIP	KMK	AMB	Reef fish	Elasmobranchs	LGS	TIP	KMK	AMB	Reef fish
Status Quo	1	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.001	1.010	1.003	1.044	0.996	1.041	0.927	0.858	0.953	0.965	0.994	0.945
All longlining F * 0.5	1.001	1.005	1.002	1.021	0.998	1.019	0.964	0.930	0.977	0.984	0.997	0.977
All longlining F * 2	0.999	0.990	0.997	0.963	1.004	0.966	1.071	1.137	1.045	1.027	1.005	1.033
Pelagic longlining F * 0	1.001	1.004	1.000	1.043	1.000	1.000	0.982	0.939	1.000	0.964	1.000	1.000
Pelagic longlining F * 0.5	1.000	1.002	1.000	1.020	1.000	1.000	0.991	0.970	1.000	0.983	1.000	1.000
Pelagic longlining F * 2	0.999	0.996	1.000	0.963	1.000	1.000	1.018	1.060	1.000	1.028	1.000	1.000
No DeSoto Canyon	1.000	1.000	1.000	0.999	1.000	1.000	1.002	1.005	1.000	1.001	1.000	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No PLL Spatial Closures	1.000	1.000	1.000	0.999	1.000	1.000	1.002	1.005	1.000	1.001	1.000	1.000
Seasonal PLL Closure	1.000	1.000	1.000	1.006	1.000	1.000	0.999	0.998	1.000	0.991	1.000	1.000
Status Quo	1	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.001	1.010	1.003	1.027	0.996	1.051	0.924	0.877	0.952	0.995	0.994	0.939
All longlining F * 0.5	1.001	1.005	1.001	1.013	0.998	1.024	0.962	0.939	0.976	0.998	0.997	0.973
All longlining F * 2	0.999	0.990	0.997	0.977	1.004	0.958	1.073	1.119	1.046	1.003	1.005	1.038
Pelagic longlining F * 0	1.001	1.004	1.000	1.026	1.000	1.000	0.985	0.960	1.000	0.993	1.000	1.000
Pelagic longlining F * 0.5	1.000	1.002	1.000	1.013	1.000	1.000	0.992	0.980	1.000	0.997	1.000	1.000
Pelagic longlining F * 2	0.999	0.996	1.000	0.978	1.000	1.000	1.015	1.040	1.000	1.004	1.000	1.000
No DeSoto Canyon	1.000	1.000	1.000	0.999	1.000	1.000	1.011	1.028	1.000	1.032	1.000	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No PLL Spatial Closures	1.000	1.000	1.000	0.999	1.000	1.000	1.011	1.028	1.000	1.032	1.000	1.000
Seasonal PLL Closure	1.000	1.000	1.000	1.004	1.000	1.000	0.999	0.998	1.000	0.997	1.000	1.000
Status Quo	1	1	1	1	1	1	1	1	NA	1	1	1
All longlining F * 0	1.001	1.010	1.000	1.038	0.996	1.143	0.892	0.868	NA	0.980	0.992	0.959
All longlining F * 0.5	1.000	1.005	1.000	1.018	0.998	1.068	0.947	0.935	NA	0.991	0.996	0.986
All longlining F * 2	0.999	0.991	1.000	0.967	1.004	0.885	1.104	1.128	NA	1.015	1.008	1.000
Pelagic longlining F * 0	1.000	1.004	1.000	1.037	1.000	0.999	0.959	0.950	NA	0.979	1.000	0.999
Pelagic longlining F * 0.5	1.000	1.002	1.000	1.018	1.000	1.000	0.980	0.975	NA	0.990	1.000	0.999
Pelagic longlining F * 2	1.000	0.996	1.000	0.968	1.000	1.001	1.040	1.049	NA	1.016	1.000	1.001
No DeSoto Canyon	1.000	1.000	1.000	0.999	1.000	1.000	1.013	1.016	NA	1.007	1.000	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.000	1.001	1.001	NA	1.006	1.000	1.000
No PLL Spatial Closures	1.000	1.000	1.000	0.999	1.000	1.000	1.014	1.017	NA	1.014	1.000	1.000
Seasonal PLL Closure	1.000	1.000	1.000	1.005	1.000	1.000	0.999	0.998	NA	1.000	1.000	1.000

Table C.6: Additional average individual weight, and proportion mature performance metrics. Metrics are relative to the status quo. Metrics for functional group assemblages (i.e., elasmobranchs and reef fish) are the sum across all associated functional groups. Functional group-specific metrics are shown for the functional groups: large sharks (LGS), blacktip sharks (TIP), king mackerel (KMK), and amberjack (AMB).

	Average Individual Weight [Biomass]						Proportion Mature [Biomass]					
Scenarios	Elasmobranchs	LGS	TIP	KMK	AMB	Reef fish	Elasmobranchs	LGS	TIP	KMK	AMB	Reef fish
Status Quo	1	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.001	1.000	1.002	1.027	0.999	1.027	0.999	1.002	1.002	1.017	1.000	1.007
All longlining F * 0.5	1.000	1.000	1.001	1.013	1.000	1.013	1.000	1.001	1.001	1.009	1.000	1.003
All longlining F * 2	0.999	1.000	0.998	0.977	1.001	0.978	1.001	0.998	0.998	0.984	1.000	0.994
Pelagic longlining F * 0	1.000	1.000	1.000	1.026	1.000	1.000	1.000	1.001	1.000	1.017	1.000	1.000
Pelagic longlining F * 0.5	1.000	1.000	1.000	1.012	1.000	1.000	1.000	1.000	1.000	1.008	1.000	1.000
Pelagic longlining F * 2	1.000	1.000	1.000	0.978	1.000	1.000	1.000	0.999	1.000	0.984	1.000	1.000
No DeSoto Canyon	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No PLL Spatial Closures	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
Seasonal PLL Closure	1.000	1.000	1.000	1.004	1.000	1.000	1.000	1.000	1.000	1.003	1.000	1.000
Status Quo	1	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.001	1.000	1.002	1.018	0.999	1.029	0.999	1.002	1.002	1.017	1.000	1.005
All longlining F * 0.5	1.000	1.000	1.001	1.009	1.000	1.014	1.000	1.001	1.001	1.008	1.000	1.003
All longlining F * 2	0.999	1.000	0.998	0.985	1.001	0.976	1.001	0.998	0.998	0.985	1.000	0.995
Pelagic longlining F * 0	1.000	1.000	1.000	1.017	1.000	1.000	1.000	1.001	1.000	1.016	1.000	1.000
Pelagic longlining F * 0.5	1.000	1.000	1.000	1.008	1.000	1.000	1.000	1.000	1.000	1.008	1.000	1.000
Pelagic longlining F * 2	1.000	1.000	1.000	0.985	1.000	1.000	1.000	0.999	1.000	0.985	1.000	1.000
No DeSoto Canyon	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No PLL Spatial Closures	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
Seasonal PLL Closure	1.000	1.000	1.000	1.002	1.000	1.000	1.000	1.000	1.000	1.002	1.000	1.000
Status Quo	1	1	1	1	1	1	1	1	1	1	1	1
All longlining F * 0	1.000	1.000	1.000	1.024	0.999	1.115	1.000	1.000	1.000	1.017	1.000	1.023
All longlining F * 0.5	1.000	1.000	1.000	1.011	1.000	1.055	1.000	1.000	1.000	1.008	1.000	1.011
All longlining F * 2	1.000	1.000	1.000	0.980	1.001	0.904	1.000	1.000	1.000	0.984	1.000	0.977
Pelagic longlining F * 0	1.000	1.000	1.000	1.023	1.000	0.999	1.000	1.000	1.000	1.017	1.000	1.000
Pelagic longlining F * 0.5	1.000	1.000	1.000	1.011	1.000	1.000	1.000	1.000	1.000	1.008	1.000	1.000
Pelagic longlining F * 2	1.000	1.000	1.000	0.980	1.000	1.001	1.000	1.000	1.000	0.984	1.000	1.000
No DeSoto Canyon	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
No Spring Closure	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
No PLL Spatial Closures	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
Seasonal PLL Closure	1.000	1.000	1.000	1.003	1.000	1.000	1.000	1.000	1.000	1.003	1.000	1.000

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