PATTERNS IN LONGLINE REEF FISH CATCH AND FISHING GEAR ANALYSIS IN THE GULF OF MEXICO USING NOAA FISHERY OBSERVER DATA

A Dissertation

by

ALEXANDRIA ELIZABETH RIVARD

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Chair of Committee,	Wyndylyn von Zharen
Co-Chair of Committee,	Wesley Highfield
Committee Members,	Jhenny Galan
	Frances Gelwick
Interdisciplinary Faculty Chair,	Anna Armitage

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ABSTRACT

The objectives of this study were to assess existing fishing practices (both spatial and gear use) employed by longline reef fish fishers in the Gulf of Mexico; to evaluate the gear and set parameters that contribute to catching larger individual fish of a target species; and to assess the gear and set parameters that contribute to successfully catching a fish of a target species. Data were collected by the Southeast Fisheries Science Center (SEFSC) Galveston Reef Fish Observer Program from 2006-2014. Explanatory variables included in the study were only those that could be manipulated directly by fishers: soak time, fishing depth, main line length, hooks deployed, gangion length, hook distance, and the temporal variables month and year.

Gear change assessments were conducted using analyses of variance for soak time, fishing depth, gangion length, hook distance, mainline length, and hook count across years. Significant differences were detected between years for all variables, however, there was no discernable trend over time. This suggests that fishing practices remained relatively stable from 2006-2014. Spatial analysis of catches was conducted for five species targeted during the study period (gag grouper, red grouper, scamp grouper, mutton snapper, and red snapper) using ArcGIS. However, no spatial trends were apparent given the uneven effort and coverage of the survey area.

To assess which fishing gear and set parameters contributed to catching the largest fish of a target species, ordinary least squares (OLS) linear models were used to predict

fish length as a function of the explanatory variables. Significant models were generated for blacknose shark, gag grouper, mutton snapper, red porgy, Atlantic sharpnose shark, and speckled hind.

Binomial regression models were constructed using backwards regression to predict target species catch success using the explanatory variables. Significant models were generated for speckled hind, red grouper, scamp, gag grouper, red snapper, mutton snapper, jolthead porgy, and red porgy. These models ultimately serve as guidelines for fishers to adjust fishing practices to improve the likelihood of successfully obtaining the targeted species, which may reduce bycatch mortality of non-target species and its resulting environmental impacts.

DEDICATION

For Patrick, Batman Bear.

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All other work conducted for the dissertation was completed by the student independently. Graduate study was supported by a graduate teaching assistantship from the Department of Marine Sciences at Texas A&M University at Galveston.

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1. INTRODUCTION AND GENERAL FISHING PRACTICES

1.1 General Introduction

1.1.1 Principles in Fishery Management

Fishery resources are a fundamental part of the global and domestic economy, providing critical nutrients and supporting a multibillion dollar industry in the United States. (Rodger and von Zharen 2011; Golden et al. 2016). Responsible exploitation of fishery resources is necessary to ensure the long-term sustainability of fishing practices. Using ecosystem based management strategies and abiding by the precautionary principle can provide useful guidance when determining how best to utilize these resources.

Ecosystem based management, while more complex than managing a population in isolation, is a more effective strategy for conservation. Managing fish stocks in isolation fails to consider that the health of the population is dependent not only on the stock's interactions with humans, but on its interactions with the environment (Link 2002). Robust ecosystems (those which can absorb, resist, and recover from disturbances and adapt to change while maintaining their essential functions) support healthy populations (Rodger and von Zharen 2011). An ecosystem based strategy must endeavor to avoid degradation of marine ecosystems, account for the requirements of other components of the ecosystem, consider human social and economic factors, and attempt to understand the consequences of human actions on the broader system (Pikitch et al. 2004). To best support productive fisheries, managers must tackle the increased complexity of an ecosystem based management strategy.

Avoiding degradation and accounting for other components of the ecosystem requires an understanding of interactions within the system. Disruptions to the ecosystem may be natural (e.g. increased rain lowering salinity) or anthropogenic (e.g. pollution resulting in nutrient enrichment). When disruption or degradation of the ecosystem occurs, critical ecosystem functions such as maintenance of water quality or resistance to pests and pathogens are reduced (Levin and Lubchenco 2008). Loss of these functions may threaten survival of the target species if, for example, water quality parameters are no longer sufficient to sustain life or invasion of parasites exerts pressure on stock survival. Thus, managers will need to understand potential sources of disruption and integrate management of these sources into the management plan.

Ecosystem based strategies must also consider the interactions of the target species with other parts of the environment: for instance, if the species forages on benthic invertebrates and dredging ship channels destroys this environment, the target species will not thrive. Managers must consider how species interact with their environment and maintain environmental health at all levels, rather than by focusing only on the management of the target species.

Ecosystem based management also considers humans as part of the marine ecosystem. Indeed, humans should be considered the direct top predator for many marine food webs (Darimont et al. 2015). An ecosystem based strategy should consider the direct impacts of human use of marine resources, e.g. fish as a source of food (Golden et al. 2016), as well as indirect effects, e.g. noise pollution from shipping. Human uses that induce stress on marine systems also include recreation, oil and gas exploration and extraction, and transportation (Crowder and Norse 2008). An ecosystem based strategy should aim to protect the environment while maintaining access for human social and economic usage needs.

The precautionary approach is rooted in the idea that steps to minimize risk of harm should be taken even if the relationships have not been fully established scientifically (Kriebel et al. 2001). There are four major tenants of the precautionary approach per Kriebel et al. (2001): "…taking preventative action in the face of uncertainty; shifting the burden of proof to the proponents of an activity; exploring a wide range of alternatives to possibly harmful actions; and increasing public participation in decision making." The first principle requires that managers assume that the full extent of the risk to the environment posed by fishing is not known. Managers should assume that known levels of mortality in fishing represent a minimum rather than an absolute, and that the full extent of environmental damage and mortality to target and non-target species cannot be known. Thus, in setting allowable catch levels, managers should be conservative in their estimates to prevent potentially serious environmental damage. The second principle dictates that proponents of an activity should be responsible for proving its benefits. In the case of fishery management, proponents of increasing allowable catch, permitting the use of new gear, etc. should be responsible for demonstrating that their intended activity will not result in further environmental harm. This encourages the generation of scientific information on which managers can base their decisions. Third, the precautionary approach states that a range of alternatives to harmful actions should be explored. In practice in fisheries, this means that fishing methodologies deemed harmful should be restricted or banned. For example, the United Nations enacted pelagic driftnet fishing bans in response to the damage they caused to their environments (Rodger and von Zharen 2011). Extensive scientific studies to quantify the detrimental effects of a practice are not required to restrict or prohibit a given harmful practice. Finally, the precautionary approach encourages public involvement with decision making. This tenant is already enforced in United States fishery management: a public comment period is mandated in the rulemaking process. This comment period encourages public involvement and provides an opportunity for dissention, reducing the possibility of poor unilateral decisions and allowing all stakeholders a voice.

Application of a precautionary approach in fishery management has many benefits. Managing a fishery inherently involves uncertainty in that the risks can be difficult to quantify and anticipate. Use of the principles described here will help managers to make conservative decisions. In environmental management, this is beneficial; harmful effects to the ecosystem are generally difficult, time-consuming, and expensive to correct. While avoiding environmental damage has its own costs associated with economic losses, reversing damage to the environment can prove impossible. Therefore, a precautionary approach that avoids inflicting harm is a useful tool in fishery management.

Commercial fishing is important to human social and economic needs. Fish are a critical source of micronutrients such as iron, zinc, other vitamins, and omega-3 fatty acids (Golden et al. 2016). Particularly in poorer countries, access to alternative micronutrient sources can be challenging and expensive (Golden et al. 2016). Economically, commercial fishing represents a multibillion dollar industry and employs thousands in the United States alone, particularly when considering employees in supporting industries such as fish processing or ship construction (Rodger and von Zharen 2011). Many communities in the US and beyond are reliant on the economic success of fisheries; in fact, the US mandates that managers consider these communities when developing fishery management plans (National Standard 9, 50 CFR Ch. VI § 600.345). In addition to commercial fishing, recreational fishing supports several fishing-related tourism industries.

When managed appropriately, the negative impacts associated with commercial fishing can be mitigated. Control methods such as setting fishing seasons, limiting participation in the fishery, restricting gear, and setting total allowable catch can be combined to effectively limit the amount of fish removed and reduce collateral environmental damage (Rodger and von Zharen 2011). Several national and international laws enforce such restrictions (Rodger and von Zharen 2011). To effectively manage fish populations, managers should use an ecosystem based management strategy to determine how the fishing proposed (both scale and type) might impact the broader environment. Second, managers should use the precautionary principle as a guide. Management decisions regarding the use of natural resources should take preventative action when the impacts are uncertain, in an effort to minimize the negative impacts on the environment (Kriebel et al. 2001). With smart management on an appropriate scale, commercial fishing is sustainable and environmental damage can be minimized, so that fishery resources can continue to be used for their valuable economic and social purposes.

1.1.2 Federal Fishery Management

The Gulf of Mexico Reef Fish Fishery Management Plan was implemented in November 1984 as a response to declining reef fish stocks (Gulf of Mexico Fishery Management Council 2010c). Fishery management plans (FMP) are held to ten national standards (NS) under NOAA Fisheries to ensure that fishery resources are used appropriately. These standards govern the design of the Gulf of Mexico Reef Fish FMP and all other FMPs across all regions in the United States.

The first three standards concern the determination of regulations put forth by the FMP. NS1 dictates that FMPs must endeavor to prevent overfishing while achieving the optimum yield (OY) on a continuing basis, where OY is defined as the amount of fish harvested which produces the greatest overall benefit to the nation with consideration of biological, ecological, social, and economic factors. FMPs must be based on the best scientific information available, again including biological, ecological, economic, and social factors, per NS2. Stock Assessment and Fishery Evaluation (SAFE) reports provide periodic summaries of the most current information. The scientific information used should be relevant, inclusive, objective, transparent, timely, validated and verified, and peer reviewed. NS3 dictates that, to the extent practicable, stocks should be managed as a unit, and interrelated stocks should be managed as a unit or in coordination with other fishery management councils. The management unit is defined as the fishery or portion thereof relevant to the FMP's objectives.

Standards four through seven concern the utilization of fishery resources. Discrimination among residents of different states through management and conservation measures is prohibited by NS4. Allocation must be deemed fair and equitable and calculated to promote conservation. Measures also exist to prevent any one entity from acquiring an excessive share of fishing privileges. NS5 states that conservation and management measures shall consider efficiency in the use of fishery resources, where ideal efficiency is a fishery that can harvest the OY with minimal use of labor, capital, fuel, and interest. This standard also prohibits the application of economic allocation as the sole purpose for any measure. Per NS6, FMPs must account for variations and contingencies in fisheries, fishery resources, and catches. FMPs can protect against uncertainty by: reducing OY; establishing a reserve that can be released or withheld later; adjusting management techniques; and highlighting habitat conditions. Contingencies are flexible management regimes that allow for a quick response to sudden changes without amending the FMP. Conservation and management measures should minimize costs and avoid unnecessary duplication per NS7; no regulation should be enacted without some benefit. To determine if an FMP is needed, managers should consider the importance of the fishery, condition of the stock, existing state-level management, competing interests, economic conditions, the needs of a developing fishery, and costs.

The remaining standards focus on human factors and bycatch concerns. NS8 states that conservation and management measures should consider the importance of a fishery to a community, and provide for sustained participation and minimize economic impacts to fishery dependent communities. This does not, however, permit preferential treatment or allocation (which would violate NS4), and allows for sustained participation only as the resource permits. Under NS9, FMPs should include measures to minimize bycatch to the extent possible, and when unavoidable, minimize mortality of bycatch. Bycatch is defined as fish harvested but not kept for personal use or sold. FMPs should consider the population, ecosystem, marine mammals and birds, costs, practices, research, social costs, benefit distribution, and social effects of bycatch. Finally, NS10 dictates that FMPs shall address the safety of human life at sea. This includes avoiding the creation of derby fishing conditions, where fishers compete for catch within a limited window of time. Managers should consider avoiding hazardous weather, allowing for flexible seasons, permitting pre- or post-season fixed gear soak time, using smaller and lighter gear for smaller vessels, avoiding at-sea inspection when an alternative is equally sufficient, limiting participation in a fishery, spreading effort over time to reduce conflicts, and reducing the "race for fish" when designing FMPs.

1.1.3 Gulf of Mexico Fisheries

The Gulf of Mexico Large Marine Ecosystem (LME) covers an area of over 1.6 million square kilometers. The United States Exclusive Economic Zone (EEZ) extends 200 nautical miles from the area beyond and adjacent to its territorial sea, thus giving the U.S. sovereign rights to manage the northern Gulf of Mexico (National Ocean Service 2014). In the past four decades, the Gulf of Mexico has experienced significant increases in sea surface temperatures, which may influence the health and distribution of resident fish stocks (Karnauskas et al. 2013). The Gulf of Mexico is also vulnerable to effects of hypoxia resulting from the outflow of the Mississippi River; the potential for hurricane activity that may disrupt the marine environment; and damaging oil spills from drilling and transport (Karnauskas et al. 2013).

Coastal communities in the Gulf of Mexico are particularly reliant on fishery resources. Commercial fishing in the Gulf of Mexico accounts for approximately 25 percent of national seafood landings, with Louisiana accounting for the majority of landings (Adams et al. 2004). Fishing vessels and the processing industry also play key roles in the economy of Gulf of Mexico states (Adams et al. 2004). Communities reliant on fishery resources are economically vulnerable to perturbations in marine ecosystems, and natural or anthropogenic disasters contribute special strain to these areas (Jacob et al. 2013). Managers must consider the impact of additional regulation to the social and economic stability of fishing communities in the Gulf of Mexico and their resiliency.

The National Oceanic and Atmospheric Administration (2015) has achieved great success in fishery management through ecosystem-based strategies that address the marine environment as a complete system including biota, physical spaces, nutrients, and anthropogenic impacts. In 2014, United States' fisheries limited overfishing to the lowest extent since the initiation of monitoring, with just 26 stocks on the overfishing list (actively being over exploited) and 37 stocks on the overfished list (stocks depleted), representing an improvement from 28 and 40 stocks, respectively, listed in the previous assessment in 2013 (National Oceanic and Atmospheric Administration 2015). However, problems persist. In 2015, these figures declined to 28 species on the overfishing list and 38 on the overfished list (National Oceanic and Atmospheric Administration 2016). In the Gulf of Mexico, three species remain on the overfished list as of 2015: greater amberjack (*Seriola dumerili*), gray triggerfish (*Balistes capriscus*), and red snapper (*Lutjanus campechanus*). Greater amberjack (*Seriola dumerili*), gray triggerfish (*Balistes capriscus*), and hogfish (*Lachnolaimus maximus*) were on the overfishing list for 2014, but were removed in 2015 (National Oceanic and Atmospheric Administration 2015, 2016). No species in the Gulf of Mexico were actively undergoing overfishing as of 2015 (National Oceanic and Atmospheric Administration 2016).

It should be noted that fishery landings are not necessarily indicative of the health of fish populations collectively. While a low mean trophic level for landings has been interpreted to indicate a decline in higher trophic level species, this is not the case in the Gulf of Mexico; lower trophic level species are often targeted in this region (de Mutsert et al. 2008). Catch data may be misleading, particularly in fisheries where aggregations form. Landing data should always be interpreted in the context of the relevant regulations and fishery effort (de Mutsert et al. 2008). Ideally, fishery-independent data are preferable for drawing conclusions regarding the overall welfare of a population; however, these data are expensive to collect. Fishery-dependent data are useful when considering the success of a fishery, but caution is required that these results are not interpreted to represent the general population strength of a stock or stock complex. Consequently, no attempt will be made herein to extrapolate the results of catch models to the general welfare of Gulf of Mexico fisheries.

1.1.4 Longline Fishing

Longline fishing is permitted for a number of species in the Gulf of Mexico, including snapper, grouper, and other reef fish (Gulf of Mexico Fishery Management Council 2010a). Modern longline fishing methods originated in Japan in the 19th century (Watson and Kerstetter 2006). This fishing gear consists of a long mainline attached to a series of floats to suspend the line at depth, and a gangion line (a moderate weight line bearing hooks) suspended from the main line, and a hook (typically J-style, ringed, or circle hooks) (Watson and Kerstetter 2006). Fishers may adjust the length and depth of the gear set and hook shape and size based on the desired species (Watson and Kerstetter 2006).

Pelagic longline fisheries necessitate a relatively moderate level of regulation as compared with methods such as bottom trawls and gillnets, which pose serious environmental threats and require more stringent regulation (Chuenpagdee et al. 2003). Possible ecological impacts of pelagic longlines include risk of entanglement and bycatch of non-target species including protected species (Chuenpagdee et al. 2003). Management of reef fish fisheries in the Gulf of Mexico has been overseen by the Gulf of Mexico Fishery Management Council (GMFMC) since the implementation of the Fishery Management Plan for the Reef Fish Resources of the Gulf of Mexico in November 1984 (Waters 2001). The original plan, initiated in response to declining fish stocks, included gear prohibitions, minimum fish-size limits, and data reporting requirements (Gulf of Mexico Fishery Management Council 2010c).

1.2 Fishing Gear Usage

1.2.1 Data Source

The Southeast Fisheries Science Center (SEFSC) Galveston Reef Fish Observer Program provided data pertaining to the commercial bottom longline reef fishery in the Gulf of Mexico for fishing depths less than 328 feet. This program was initiated in July 2006 per Amendment 22 of the GMFMC Reef Fish FMP, and data collection is conducted by trained observers onboard commercial fishing vessels (Scott-Denton et al. 2011; National Marine Fisheries Service 2013).

The goals of the reef fish observer program include: characterization of finfish bycatch; estimation of finfish discard and mortality; and estimation of bycatch of protected species (Scott-Denton and Williams 2013). To that end, observers report: trip, vessel, environmental, and gear characteristics; fish and protected species composition and disposition; size of target species caught; and catch-per-unit effort (CPUE) trends (Scott-Denton and Williams 2013). The data collected by observers on bottom longline reef fish fishing vessels in the Gulf of Mexico (NMFS Southeast Region statistical zones 1-21) are the basis for this study (Figure 1, reprinted from NMFS 2013). Per NOAA Administrative Order 216-100 and a non-disclosure agreement with NMFS SEFSC, raw data are confidential.

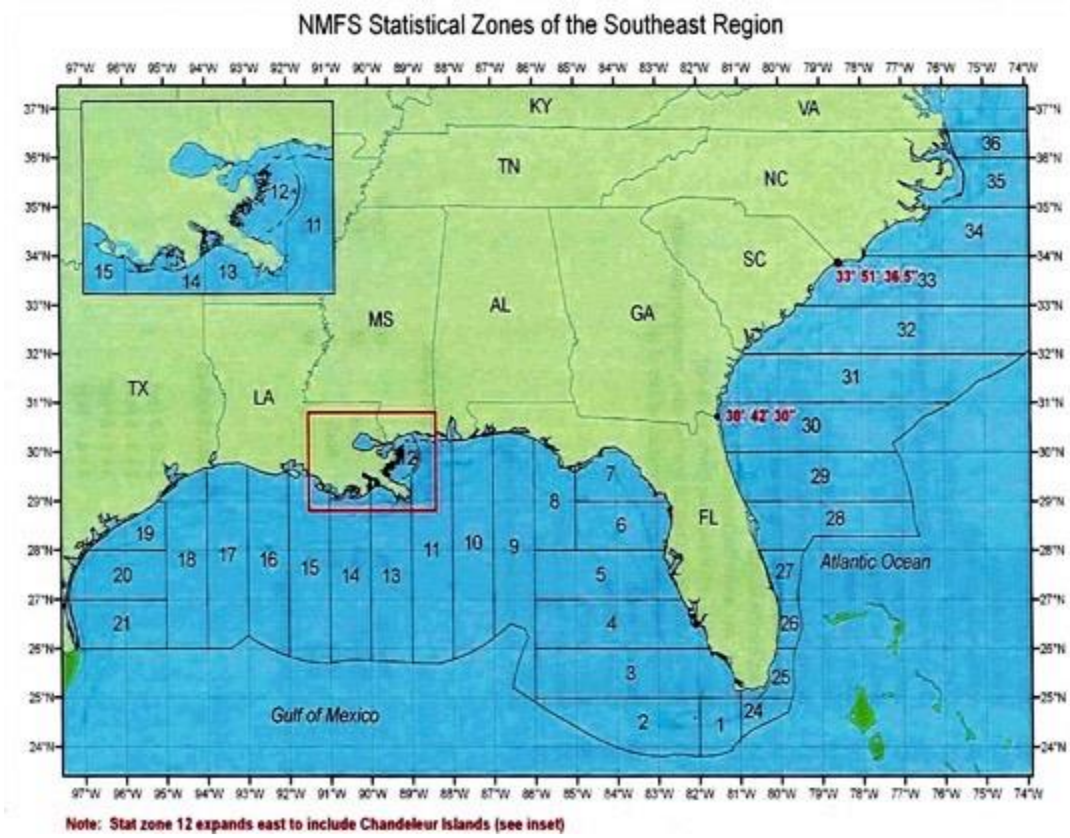

Figure 1. NMFS Southeast Region statistical zones. At least three companies must be active inside a statistical zone to release statistics for the zone. Zones 1-21 constitute the Gulf of Mexico. (Reprinted from National Marine Fisheries Service 2013.)

1.2.2 Gear Analysis Methods

Between 2006 and 2014, fishery observers documented 5,983 fishing gear sets with complete gear information, with between 50 and 1,860 sets documented per year (Table 1). Separate analyses of variance (ANOVAs) were used to assess changes over time in soak time, fishing depth, gangion length, hook distance, mainline length, and hook count. Boxplots of gear usage and residuals were generated, and QQ-norm plots were generated for each year to assess normality across all years. The Tukey HSD post-hoc test ($p < 0.1$) was used to detect significant differences across years, and results were plotted into a table to visualize differences. It should be noted, however, that results herein are representative only of fishing sets documented by NOAA observers and not necessarily of fishing practices collectively. While these results are informative and useful, they should not be construed to represent broad-scale usage of longline reef fish fishing practices at large, or even within the Gulf of Mexico.

Table 1. Total number of gear sets documented by observers, 2006-2014.

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014
Sets	196	163	50	322	1006	1860	400	1589	397

1.2.3 Gear Change Results

Total gear soak time differed significantly across years ($F_{8,5983} = 88.515$, $p < 0.01$). Significant differences in soak time were detected amongst several years. No broad-scale patterns are detectable over time (Table 2).

Significant differences were detected in fishing depth between years ($F_{8,5983} = 11.397$, $p < 0.01$). Later years and earlier years appear to differ more than years closer together, but again, there was no discernable pattern over time (Table 3).

Gangion length differed significantly between years ($F_{8,5983} = 29.008$, $p < 0.01$). Years closer together are generally more similar, but no detectible pattern emerged during the years tested (Table 4).

Hook distance varied significantly over time ($F_{8,5983} = 17.809$, $p < 0.01$). While the differences appear more marked in later years, there is no discernable pattern to the differences observed (Table 5).

Mainline length differed significantly across years surveyed ($F_{8,5983} = 139.34$, $p < 0.01$). Again, no pattern emerged over time (Table 6).

Hook count also differed significantly during the study period ($F_{8,5983} = 32.419$, $p < 0.01$), but no trend in the differences was observed (Table 7).

Table 2. Results of Tukey HSD post-hoc test for soak time. Years marked with a * are significantly different from each other ($p < 0.1$).

	Year								
Year	2006	2007	2008	2009	2010	2011	2012	2013	2014
2006			*		*	*	*	*	*
2007			*		*	*	*	*	*
2008				*					
2009					*	*	*	*	*
2010						*	*	*	
2011							*		
2012								*	*
2013									
2014									

* = Significantly Different

Table 3. Results of Tukey HSD post-hoc test for fishing depth. Years marked with a * are significantly different from each other ($p < 0.1$).

		Year								
		2006	2007	2008	2009	2010	2011	2012	2013	2014
Year	2006					*	*		*	
	2007					*			*	
	2008					*	*		*	
	2009					*	*		*	
	2010							*		*
	2011							*		*
	2012								*	
	2013									*
	2014									

* = Significantly Different

Table 4. Results of Tukey HSD post-hoc test for gangion length. Years marked with a * are significantly different from each other ($p < 0.1$).

		Year								
		2006	2007	2008	2009	2010	2011	2012	2013	2014
Year	2006			*		*		*		
	2007			*				*		*
	2008				*	*	*		*	*
	2009					*		*		*
	2010						*	*	*	*
	2011							*		*
	2012								*	
	2013									*
	2014									

* = Significantly Different

Table 5. Results of Tukey HSD post-hoc test for hook distance. Years marked with a * are significantly different from each other ($p < 0.1$).

	Year								
Year	2006	2007	2008	2009	2010	2011	2012	2013	2014
2006		*						*	*
2007			*	*	*	*	*	*	*
2008					*	*	*	*	*
2009					*	*		*	*
2010								*	*
2011								*	*
2012								*	*
2013									
2014									

* = Significantly Different

Table 6. Results of Tukey HSD post-hoc test for mainline length. Years marked with a * are significantly different from each other ($p < 0.1$).

	Year								
Year	2006	2007	2008	2009	2010	2011	2012	2013	2014
2006		*	*	*	*	*		*	
2007			*		*	*	*	*	*
2008				*			*		
2009					*	*	*	*	*
2010						*	*	*	*
2011							*		
2012								*	*
2013									
2014									

* = Significantly Different

Table 7. Results of Tukey HSD post-hoc test for hook count. Years marked with a * are significantly different from each other (*p* < 0.1).

		Year								
		2006	2007	2008	2009	2010	2011	2012	2013	2014
Year	2006		*	*	*	*	*		*	
	2007			*		*	*	*	*	*
	2008				*			*		
	2009					*	*	*	*	*
	2010						*	*	*	*
	2011							*		
	2012								*	*
	2013									
	2014									

* = Significantly Different

1.3 Spatial Visualization

1.3.1 Description of Dataset

From 2006-2014, a total of 352,089 individual fish (349,465 with complete gear and set information) were caught aboard commercial longline vessels and documented by fishery observers during 260 separate fishing trips. A total of 187 different species were recorded during fishery observation. Fishing gear and set configurations were defined by soak time, fishing depth, mainline length, hook count, gangion length, hook distance, month, and year.

1.3.2 Spatial Distribution of Catches

Per federal regulations, visual representation of catch data is permitted only when three or more separate fishing vessels have operated within a statistical zone during the period of interest. Catches were documented in 13 statistical zones during the study period. Total catches in each statistical zone for 2006-2014 are given in Table 8.

Spatial plotting of data was conducted for all species targeted by commercial reef fish fishers with sufficient data during the study period (2006-2014). These species included gag grouper (*Mycteroperca microlepis*, Figure 2), red grouper (*Epinephelus morio*, Figure 3), scamp grouper (*Mycteroperca phenax*, Figure 4), mutton snapper (*Lutjanus analis*, Figure 5), and red snapper (*Lutjanus capechanus*, Figure 6). In all cases, data were sufficient for visual presentation only in statistical zones 2-6 and 8 off the western coast and panhandle of Florida. While catches occurred outside these areas for targeted species and other species, the coverage was insufficient for inclusion in the spatial analysis. It should be noted that in May 2009 on, an emergency rule prohibited bottom longline gear east of Cape San Blas, Florida shoreward of the 50-fathom contour (Scott-Denton et al. 2011). Subsequent modification prohibited gear June through August east of the 35-fathom contour and limited the total hooks aboard to 1,000 of which only 750 could be set, as well as reducing vessel pressure through an endorsement system (Scott-Denton et al. 2011).

To determine the density of catches, data were analyzed in R version 3.2.3 "Wooden Christmas-Tree"[1] using the mapplots package[1] (Gerritsen 2014). Catches were plotted within a 0.145° latitude by 0.145° longitude (approximately 15x15 km) grid.

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[1] Mention of trade names or commercial companies is for identification purposes only and does not imply endorsement by the National Marine Fisheries Service, NOAA.

These grids were visualized using ArcGIS for desktop version 10.2[1] (Environmental Systems Research Institute (ESRI) 2014).

Table 8. Total catches documented in each statistical zone, 2006-2014.

Statistical Zone	Catches
2	7907
3	40493
4	95970
5	151605
6	43523
7	161
8	10452
11	283
13	70
14	434
15	250
18	30
21	911

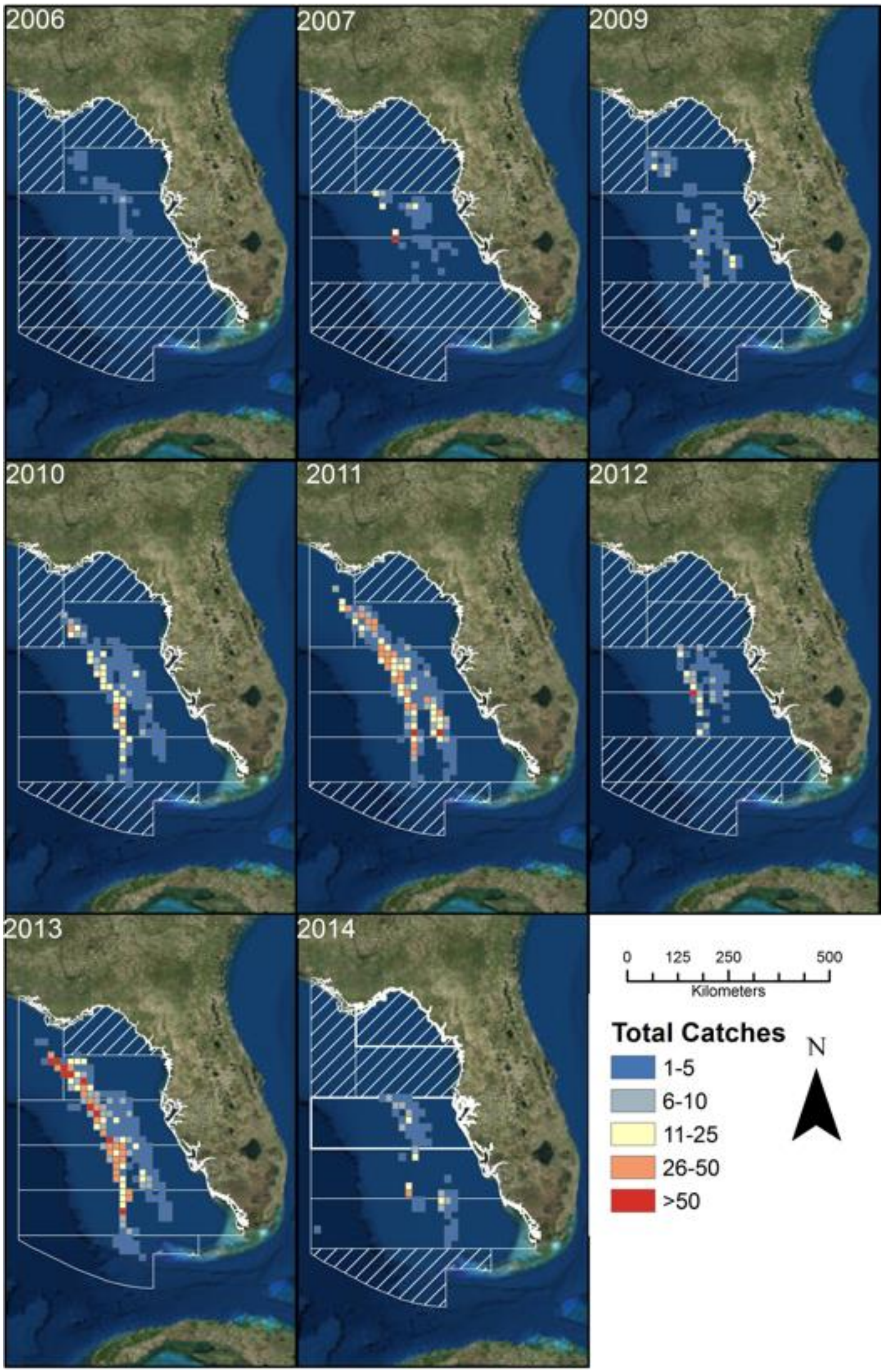

Figure 2. Gag grouper catches, 2006-2014 (exclusive of 2008). Statistical zones not included are indicated with white hatched lines.

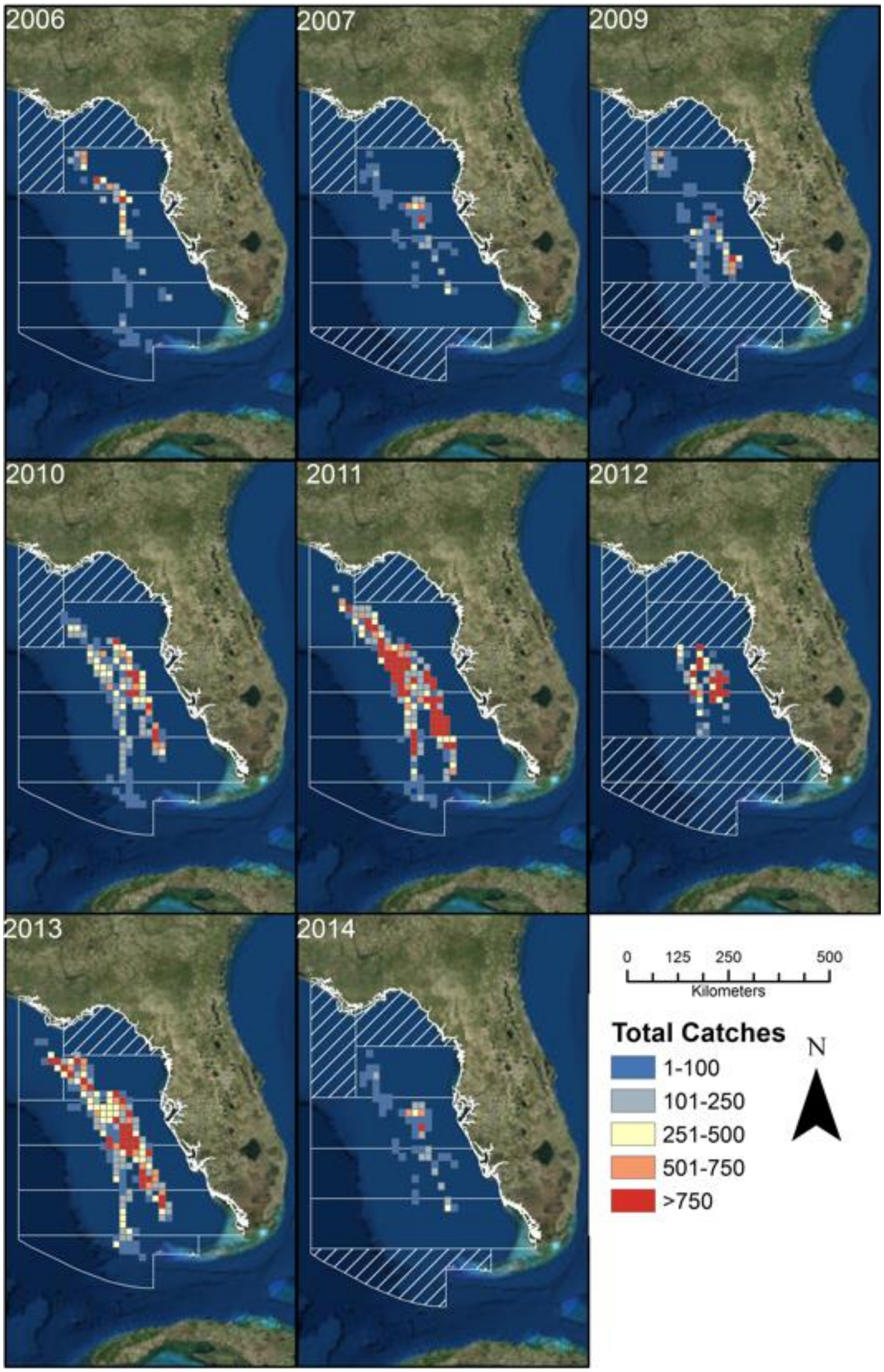

Figure 3. Red grouper catches, 2006-2014 (exclusive of 2008). Statistical zones not included are indicated with white hatched lines.

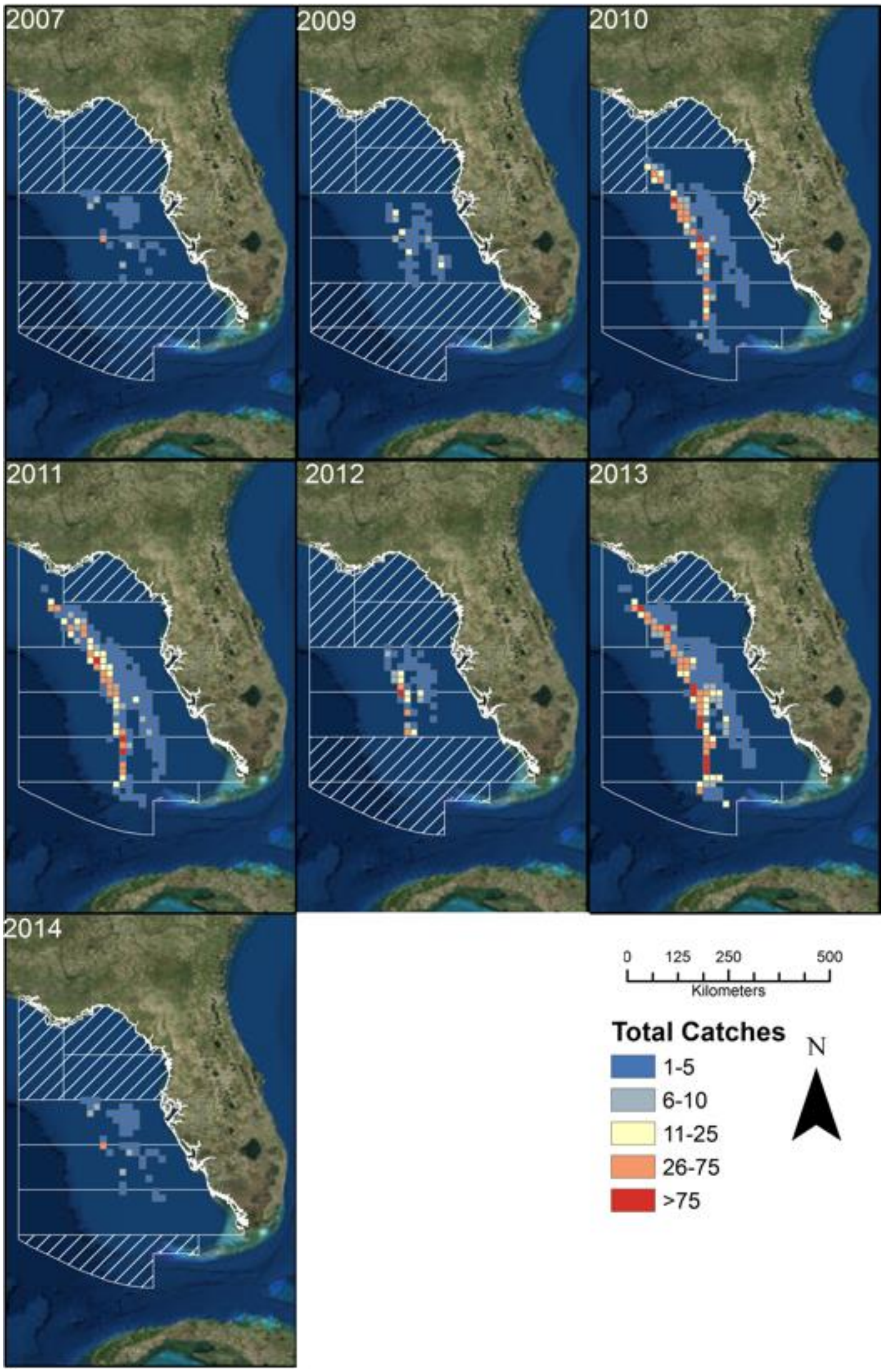

Figure 4. Scamp catches, 2007-2014 (exclusive of 2008). Statistical zones not included are indicated with white hatched lines.

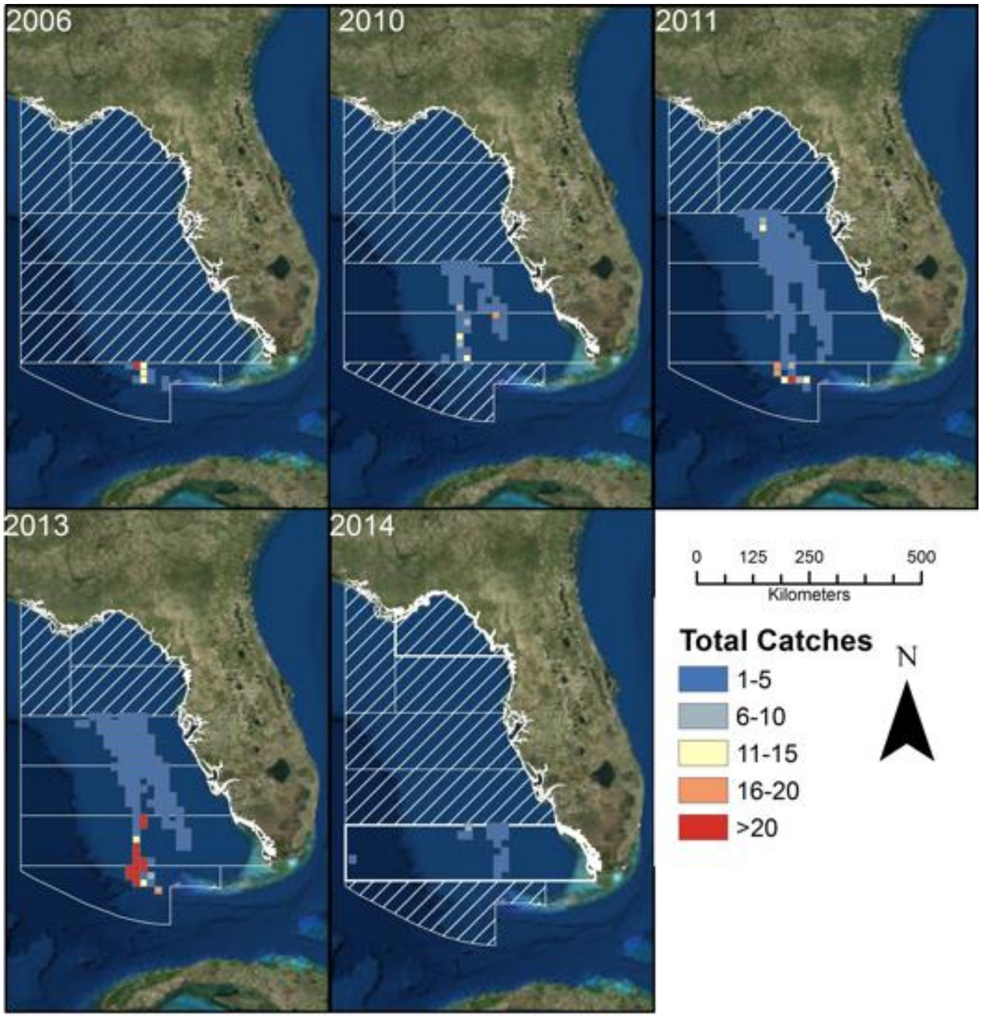

Figure 5. Mutton snapper catches, 2006 and 2010-2014. Statistical zones not included are indicated with white hatched lines.

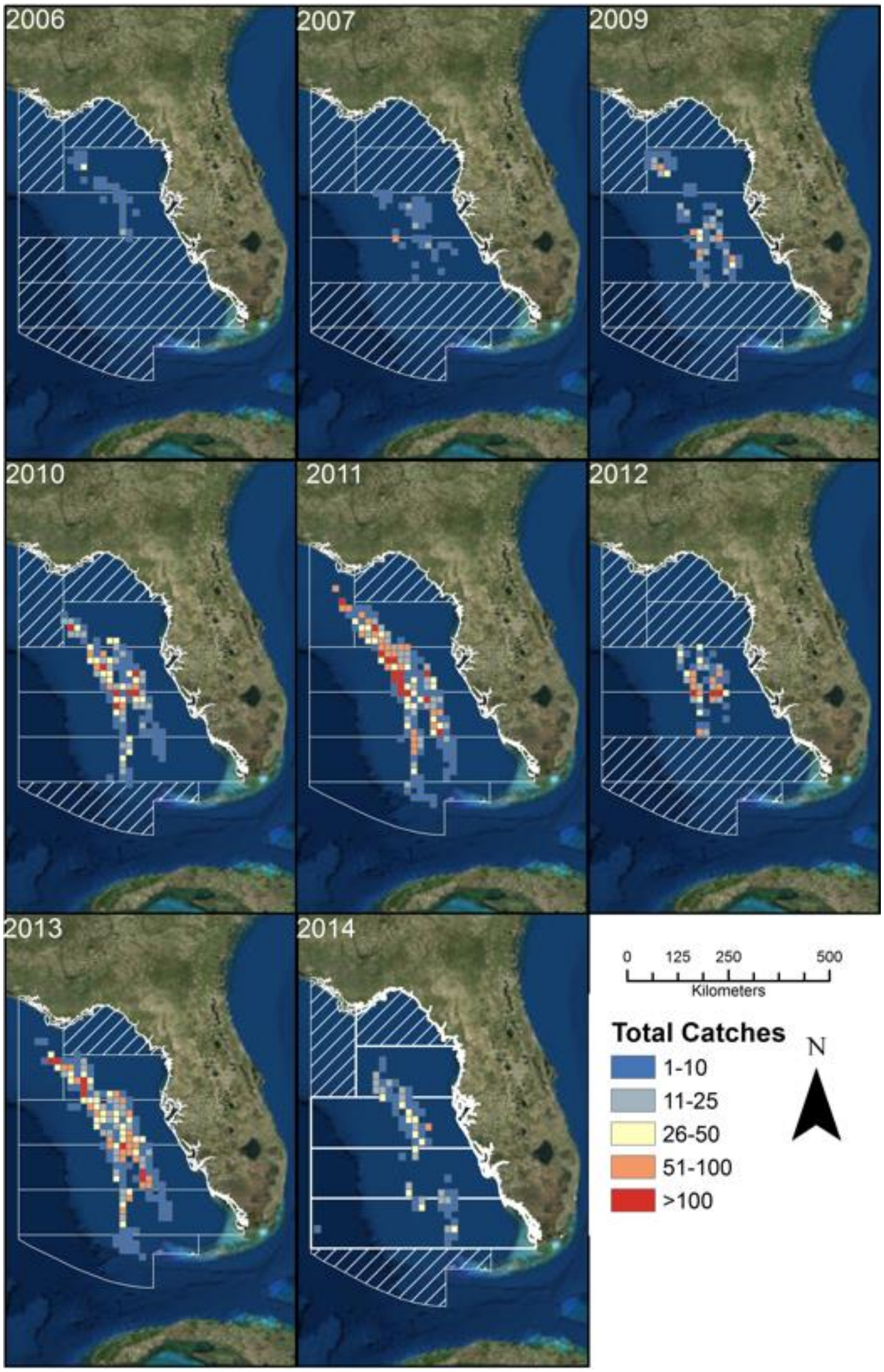

Figure 6. Red snapper catches, 2006-2014 (exclusive of 2008). Statistical zones not included are indicated with white hatched lines.

1.4 Gear Use and Spatial Distribution Conclusions

Inconsistencies in observer coverage (ranging from as few as 50 trips to as many as 1,860 trips in a year) and fishing effort render broad scale conclusions regarding changes in gear usage and fishing success difficult to draw. However, these findings are ultimately useful in the pursuit of broad-scale research questions regarding the efficacy of fishing methods. Because no general trend is apparent in changes in gear use over time, changes in catch success over time are more readily attributable to changes in fishing gear (though changes in fishery success should not be assumed to be indicative of a thriving or declining population). Additionally, because differences in gear usage between years do not follow a general trend, it is unlikely that confounding between gear and set methodology and time has occurred in models presented later in this dissertation. It should be noted, however, that the differences observed herein are not necessarily indicative of fishing methodology of all reef fish fishers collectively or even those based in the Gulf of Mexico. It is plausible that observation by NOAA observers may change the gear usage behaviors of fishers.

NOAA fishery observer coverage shows some inconsistency across species. Because only statistical zones with at least three or more separate trips may be used in spatial analyses, usable data is limited to the western coast of Florida. Per Scott-Denton and Williams (2013), observer coverage was determined by randomized selection and stratified by season, gear, and region and therefore focused more heavily on areas of fishing effort. While trips were observed outside of the statistical zones represented in chapter 1.3, these data were insufficient for inclusion in the spatial analysis. For the longline fishery, this represents coverage of about five percent of the fishery for years 2010-2011 (Scott-Denton and Williams 2013). When funding and personnel allow, an effort should be made to expand observer coverage outside of the western Florida region as a considerable portion of fishing effort occurs on the coasts of the other Gulf states. Given the inconsistencies in observer effort over time, meaningful spatial statistical analysis is not possible with the existing dataset.

The observer program represents a crucial step towards obtaining a functional understanding of the longline reef fish fishery in the Gulf of Mexico. Significant shipping and oil drilling activity occurs in the Gulf of Mexico, making the region's fisheries vulnerable to anthropogenic disasters. Natural disturbances (e.g. hurricanes) are common in the region as well. Coastal communities in the Gulf of Mexico are particularly reliant on fishery resources. A thorough understanding of fishery dynamics is important to ensure the continued economic success of these communities, as well as to ensure adequate aid in the face of disasters. Collecting meaningful information regarding the distribution of catches in the Gulf of Mexico and the methods employed to catch fish represents an important precautionary step to safeguard a vital and dynamic ecosystem.

2. FISH LENGTH AS A FUNCTION OF GEAR AND SET METHODOLOGY

2.1 Introduction

2.1.1 Bycatch in Longline Fisheries

Bycatch in longline fisheries is a priority for managers. Bycatch herein is defined per Alverson (1999) as, "…the capture of any species, size of species, or sex of species that is not the primary target(s) of a fishing activity." Species outside the fishery include marine mammals, turtles, and seabirds; other species of fish not targeted by fishers; and fish of the target species that fall outside of size and sex restrictions. Total mortality in a fishery can be quantified as the sum of intentional legal landing mortality, illegal landing mortality, unintentional discard mortality, catch stress and avoidance mortality, mortality in lost gear, mortality resulting from gear impacts on habitat, and mortality of individual stressed fish unable to avoid predation (Alverson 1999). Even in instances where fish do not sustain a physical injury, behavior impairment has been observed in some species (Davis 2005). While reported landing mortality is known, other sources of fishing mortality can be difficult or impossible to quantify and therefore are challenging to regulators. Bycatch of non-target fish and other organisms can contribute to discard mortality, mortality resulting from the stress of capture, and mortality to those unable to avoid predation as a result of this stress.

While completely eliminating bycatch is unrealistic, measures to reduce or minimize it have proven effective. For instance, a significant reduction in stingray catch in the Mediterranean Sea was noted for pelagic longliners using larger J-hooks or circle hooks (Piovano et al. 2010). Seabird entanglement may be reduced in the Mediterranean by setting longlines at night (Belda and Sánchez 2001). Use of visible light deterrents may be effective at avoiding sea turtle bycatch, as turtles and pelagic fishes have dramatically different visual capabilities (Southwood et al. 2008). Such measures demonstrate that bycatch reduction is possible using simple changes to current fishing practices with only minimal cost and practice implications for fishers.

2.1.2 Focal Species

Grouper and snapper are the primary target species for bottom longliners in the Gulf of Mexico (Scott-Denton and Williams 2013). However, the frequency with which a species was targeted over the course of observation varied widely. From 2006 to 2014, observers documented 14 species targeted by fishers: general sharks (12 trips), yellowedge grouper (*Epinephelus flavolimbatus*, 2 trips), red grouper (*Epinephelus morio*, 5802 trips), Warsaw grouper (*Epinephelus nigritus*, 3 trips), snowy grouper (*Ephinephelus niveatus*, 3 trips), tilefish (*Lopholatius chamaeleonticeps*, 2 trips), mutton snapper (*Lutjanus analis*, 146 trips), blackfin snapper (*Lutjanus buccanella*, 9 trips), red snapper (*Lutjanus campechanus*, 203 trips), black grouper (*Mycteroperca bonaci*, 41 trips), gag grouper (*Mycteroperca microlepis*, 968 trips), scamp (*Mycteroperca phenax*, 891 trips), and vermilion snapper (*Rhomboplites aurorubens*, 1 trip).

Southeast Data, Assessment, and Review (SEDAR) is a joint management council composed of the Caribbean, Gulf of Mexico, and South Atlantic Regional Fishery Management Councils; National Marine Fisheries Services (NOAA Fisheries); and Gulf and Atlantic state management councils, with the intent of improving stock management in these regions (SEDAR 2013, 2014). Current assessments include, but are not limited to, gag grouper, SEDAR 33 (SEDAR 2014); and red snapper, SEDAR 31 (SEDAR 2013). The historical landings of gag grouper in the Gulf of Mexico are difficult to quantify as they were categorized as “unclassified grouper” through 1962, and data are not available for all states for most years (SEDAR 2014). Gag grouper were removed from the overfishing and overfished lists and added to the rebuilt stock list in 2014 (National Oceanic and Atmospheric Administration 2015). The Southeast Area Monitoring and Assessment Program (SEAMAP) provides a fishery-independent evaluation of the gag grouper population. From 1980 to 2005, the total biomass of the gag grouper population increased, then declined sharply in 2006 following a 2005 red tide event, but recovered to an all-time high by 2012 (SEDAR 2014). While female biomass and mean age increased (except immediately following the red tide event), male overall length and mean age declined up to 2012 (SEDAR 2014).

No formal assessments of the red snapper population in the Gulf of Mexico were conducted prior to the institution of the GMFMC Reef Fish FMP in 1984 (SEDAR 2013). In 1999, a red snapper stock assessment using an age-structured model was conducted for the first time, and indicated that the stock was overfished; the stock remained on the overfished list for the next two and a half decades (SEDAR 2013). While red snapper in the Gulf of Mexico are no longer actively undergoing overfishing, they presently remain on the overfished list (National Oceanic and Atmospheric Administration 2015).

2.1.3 Regulation of Target Species

Fishery management in federal waters is overseen by eight fishery management councils established under the Fishery Conservation and Management Act of 1976 (Gulf of Mexico Fishery Management Council 2016). Proposed rules and rule changes are submitted by the Council to National Marine Fisheries Service, which reviews and approves the new rules before implementation by the Secretary of Commerce (Gulf of Mexico Fishery Management Council 2016). Fisheries may be regulated using minimum size limits, trip limits, quotas and closed seasons, or any combination of two or three control measures.

Reef Fish FMP Amendment 26, implemented in January 2007, introduced an individual fishing quota (IFQ) system for red snapper in an effort to reduce derby fishing conditions, wherein fishers attempt to catch as many fish as possible within an open season (Gulf of Mexico Fishery Management Council 2006). Amendment 29 to the Reef Fish FMP established an IFQ system for grouper and tilefish, effective 2010 (Gulf of Mexico Fishery Management Council 2010b; SEDAR 2014). IFQ programs seem to have changed the compliance rates in the fishery, by increasing violation reporting and minimizing other types of violations (Porter et al. 2013). However, noncompliance remains a problem, as enforcement officials are faced with regulating a large fishing fleet spread throughout the Gulf of Mexico, presenting a challenge for long-term regulation (Porter et al. 2013).

The IFQ program's success indicates that, at least in the short term, allocation management can improve productivity of the fishery and successfully protected the stock from further overfishing (National Oceanic and Atmospheric Administration 2015; Solís et al. 2015). However, despite the initiation of the IFQ system, gag grouper remained overexploited and Amendment 30B was implemented in 2009 to define gag grouper stock size and optimum yield; and further restrictions in the shallow water grouper quota allowed the gag grouper stock to rebuild (Gulf of Mexico Fishery Management Council 2010b; SEDAR 2014). Moreover, Amendment 32 established 2012 and 2015 annual catch limits and annual catch targets for gag grouper (SEDAR 2014).

Amendment 40 separated the red snapper fishery into federal for-hire and private for-hire or recreational fishers with separate quotas (Gulf of Mexico Fishery Management Council 2010b). A new action is currently awaiting approval by the Secretary of Commerce that would set the 2015 red snapper quota at 14.30 million pounds (7.293 mp commercial, 7.007 mp recreational, 5.605 mp annual recreational catch target (ACT); 2016 at 13.96 mp (7.120 mp commercial, 6.840 mp recreational, 5.473 recreational ACT); and 2017 onward at 13.74 mp (7.007 mp commercial, 6.733 mp recreational, 5.386 recreational ACT) (Gulf of Mexico Fishery Management Council 2010c).

Both mutton and red snappers are managed under the Gulf of Mexico Fishery Management Council. Mutton snappers must be greater than 16 inches in total length, and no trip limits are imposed; the fishery is under the control of the Gulf Council as of 2008 (Gulf of Mexico Fishery Management Council 2016). Red snappers have a 13-inch total-length minimum, but are managed under an individual fishing quota (IFQ) up to a total of 6,768,000 pounds gutted weight, including a 4.9% withholding allocation, which is reserved by managers to release to fishers at a later time in the season pending landings (Gulf of Mexico Fishery Management Council 2016).

Gag grouper, red grouper, speckled hind, and scamp are managed under an IFQ program and angling requires prior possession of an IFQ allocation (Gulf of Mexico Fishery Management Council 2016). Gag grouper must be a minimum of 22 inches in total length, and total catch per year is allocated as 0.939 million pounds gutted weight (GMFMC 2016). Red grouper must be at least 18 inches in total length, and 5.72 million pounds gutted weight is allocated per year (GMFMC 2016). Scamp must be 16 inches in total length and included in the 0.525-million-pound annual quota for all shallow water grouper (including black, yellowfin, and yellowmouth) (GMFMC 2016). Scamp may be caught under a deep water grouper IFQ allocation once an account holder's shallow water grouper allocation has been fulfilled or transferred (GMFMC 2016). Speckled hind do not a have a minimum size limit, but are included in the shallow water grouper allocation (GMFMC 2016). The IFQ program has increased productivity for the fleet, indicating that, at least in the short term, allocation management can improve productivity of the fishery, and has successfully protected the stock from further overfishing (National Oceanic and Atmospheric Administration 2015; Solís et al. 2015). Amendment 32 established 2012 and 2015 annual catch limits and annual catch targets for gag grouper (SEDAR 2014).

Porgys, toadfishes, and shark suckers are not currently regulated under the GMFMC. Sharks, including Atlantic sharpnose and blacknose, are managed as Atlantic Highly Migratory Species (50 C. F. R. § 635.24). Non-blacknose sharks in the Gulf of Mexico are managed under an annual commercial quota in the Gulf of Mexico (50 C. F. R. § 635.24).

2.1.4 Prior Modeling of Catch Data

Multiple studies have previously attempted to quantify the selectivity of fishing gear with both respect to both fish size and species. For cod, larger-size bait caught fewer small fish, but no relationship with bait size was documented for emperor fish; bait size has proven statistically inconclusive in other studies (Løkkeborg and Bjordal 1992; Huse and Soldal 2000). Hook size selectivity has proven difficult to accurately quantify, as studies that demonstrated some relationship between hook size and fish size were confounded by bait size (Løkkeborg and Bjordal 1992; Erzini et al. 1996; Huse and Soldal 2000). A strong relationship between fishing depth and fish "catchability" has been documented for pelagic longline species, wherein catchability generally increases with depth (Ward and Myers 2005a). An increase in line sinking speed, which should move the line through shallow waters inhabited by smaller fish more quickly, contributed to reducing catch of undersized haddock in one instance, but this trend was inconsistent (Huse and Soldal 2000). Use of hooks with inedible plastic bodies reduced undersized catch, but also reduced overall catch (Huse and Soldal 2000).

The objective of this study is to quantify the size selectivity of bottom longline fishing gear for several species of reef fish. Prior research has not addressed seasonality to the month level, nor included hook placement parameters (e.g. gangion length, hook distance), which may be influential for some species based on their group behavior or avoidance of groups. Discard mortality (immediately after being caught or resulting from stress or injury from catch and handling) represents a portion of total fishery mortality that is often difficult to quantify (Alverson and Hughes 1996). Results from this study should aid managers in setting fishing seasons, and fishers in determining the optimum gear and set configuration to obtain the largest individuals of the desired species. Such changes should minimize the number of undersized individuals caught and discarded that may not survive. Ultimately, changing fishing methods per the results of the models generated should aid in reducing bycatch mortality of undersized fish and allow catch of larger fish of greater commercial value with greater frequency.

2.2 Methods

2.2.1 Data Collection

Data were collected by the Southeast Fisheries Science Center (SEFSC) Galveston Reef Fish Observer Program as described in chapter 1. Per NOAA Administrative Order 216-100 and a non-disclosure agreement with NMFS SEFSC, raw data are confidential.

2.2.2 Data Analysis

The purpose of the models derived herein is to determine the effect of gear and set parameters on the length of individual fish in the catch. The Southeast Fisheries Science Center (SEFSC) Galveston Reef Fish Observer Program provided bottom longline reef fish fishery catch data from 2006-2014. All statistical analysis was conducted using R version 3.2.3 “Wooden Christmas-Tree” or later.[2] The objective of this analysis is to assess the variance in fish length for each species explainable by

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[2] Mention of trade names or commercial companies is for identification purposes only and does not imply endorsement by the National Marine Fisheries Service, NOAA.

fishing gear and set parameters, with the intent of providing recommendations for fishing that will maximize the length of fish caught, thereby minimizing catch of undersized individuals. Fish length in millimeters was selected as the primary means of fish measurement, as fish weights are unavailable for a large portion of the dataset. Lengths were recorded by observers per the NOAA observer training manual prescribed measurement code and are consistent within the species. Lengths given are fork length, except for scamp, leopard toadfish, sharpnose sharks, and blacknose sharks which are given in total length.

Only variables that can be directly manipulated by fishers were included in the analysis, as these variables can be controlled and are therefore the useful for management purposes. Therefore, abiotic factors (e.g. salinity, water temperature) and biotic and population factors (e.g. prey availability, population size) were excluded. Year has been included to allow for the determination of how changes over time contribute to the variance. Excluded biotic and abiotic factors presumably contribute to the unexplained variance in the models. Years have been numbered from dummy year 1 (2006) to 9 (2014). The following explanatory variables were included in the analysis: soak time in hours; fishing depth in feet; main line length in miles; hooks deployed (actual when available, and approximate otherwise); gangion length in feet; hook distance in feet; and month of the year. The dependent variable was total fish length in millimeters. Coefficient significance for categorical variables was evaluated against a baseline level; year 1 for year and April for month. To account for the large number of explanatory variables in the analysis, only species with $n > 500$ individuals after removal of entries with missing data were analyzed (Table 9). Requiring a higher sample size and using $p < 0.01$ as the standard for significance produced a more robust analysis.

Table 9. The names and sample sizes for species ($n > 500$) for length analysis.

Common Name	Scientific Name	Total Sample Size (n)
Jolthead Porgy	*Calamus bajonado*	1183
Blacknose Shark	*Carcharhinus acronotus*	1265
Speckled Hind	*Epinephelus drummondhayi*	800
Red Grouper	*Epinephelus morio*	268764
Red Snapper	*Lutjanus campechanus*	15870
Mutton Snapper	*Lutjanus analis*	2126
Scamp	*Mycteroperca phenax*	6529
Gag Grouper	*Mycteroperca microlepis*	5404
Red Porgy	*Pagrus pagrus*	897
Leopard Toadfish	*Opsanus pardus*	562
Atlantic Sharpnose Shark	*Rhizoprionodon terraenovae*	5976

Prior to analysis, data entries with missing values were removed from the dataset as necessitated by the software package. Linear regression with interaction and ordinary least squares (OLS) models were used to predict fish length as a function of fishing variables. Linear regression models with interaction were determined using an exhaustive search of all combinations and comparing the best models determined by the search as determined by the corrected Bayesian Information Criterion (BIC). The best model by BIC was the model which best explains the data while penalizing complexity. This process was repeated for the OLS model. The best resulting OLS models and interaction models for each species were assessed for normality, presence of influential points, homoscedasticity, and multicollinearity using diagnostic tests. First, variance inflation factors (VIF) were calculated to assess whether problematic multicollinearity existed in the model, where a VIF greater than five was considered problematic. If VIFs presented issues, backwards regression was used to assure that multicollinearity did not influence results. A residuals vs. fitted plot was used to assess the model fit across predicted values and check for homoscedasticity. Then, a Cook's distance plot was used to check for influential points where a resulting Cook's distance greater than one was considered influential. Finally, a normal Q-Q plot and density distribution were used to assess normality. The model's overall significance, significance of each coefficient, and variance explained (R^2_{adj}) were determined. The best model for the species was determined by BIC.

2.3 Results

2.3.1 Jolthead Porgy

An exhaustive search of all linear models with interaction was performed and models were compared by BIC. The highest ranked resulting model included fishing depth, year, and their interaction. While the model was significant overall ($p < 0.01$) and the diagnostic plots do not indicate problems with the assumptions the model, the R^2_{adj} (0.08) indicates that the model explains only a small portion of the variance in jolthead porgy length (Table 10, Figure 7). Within the model, neither of the individual variables nor their interaction was significant (Table 10).

Table 10. The results of the top linear model with interaction for jolthead porgy detected by the exhaustive search. $R^2_{adj} = 0.081$, $p < 0.01$

	Estimate	Std. Error	*p*-value
(Intercept)	541.316	234.450	0.021
Fishing Depth	0.106	1.216	0.930
DummyYear2	-63.308	316.081	0.841
DummyYear3	-139.624	681.485	0.838
DummyYear4	4.962	238.112	0.983
DummyYear5	127.544	241.226	0.597
DummyYear6	94.070	235.826	0.690
DummyYear7	40.226	239.217	0.867
DummyYear8	-33.298	235.370	0.888
DummyYear9	-40.009	235.771	0.865
Fishing Depth:DummyYear2	-0.071	1.585	0.964
Fishing Depth:DummyYear3	1.214	4.220	0.774
Fishing Depth:DummyYear4	-0.366	1.244	0.769
Fishing Depth:DummyYear5	-0.907	1.239	0.465
Fishing Depth:DummyYear6	-0.845	1.221	0.489
Fishing Depth:DummyYear7	-0.560	1.241	0.652
Fishing Depth:DummyYear8	-0.187	1.219	0.878
Fishing Depth:DummyYear9	-0.198	1.222	0.871

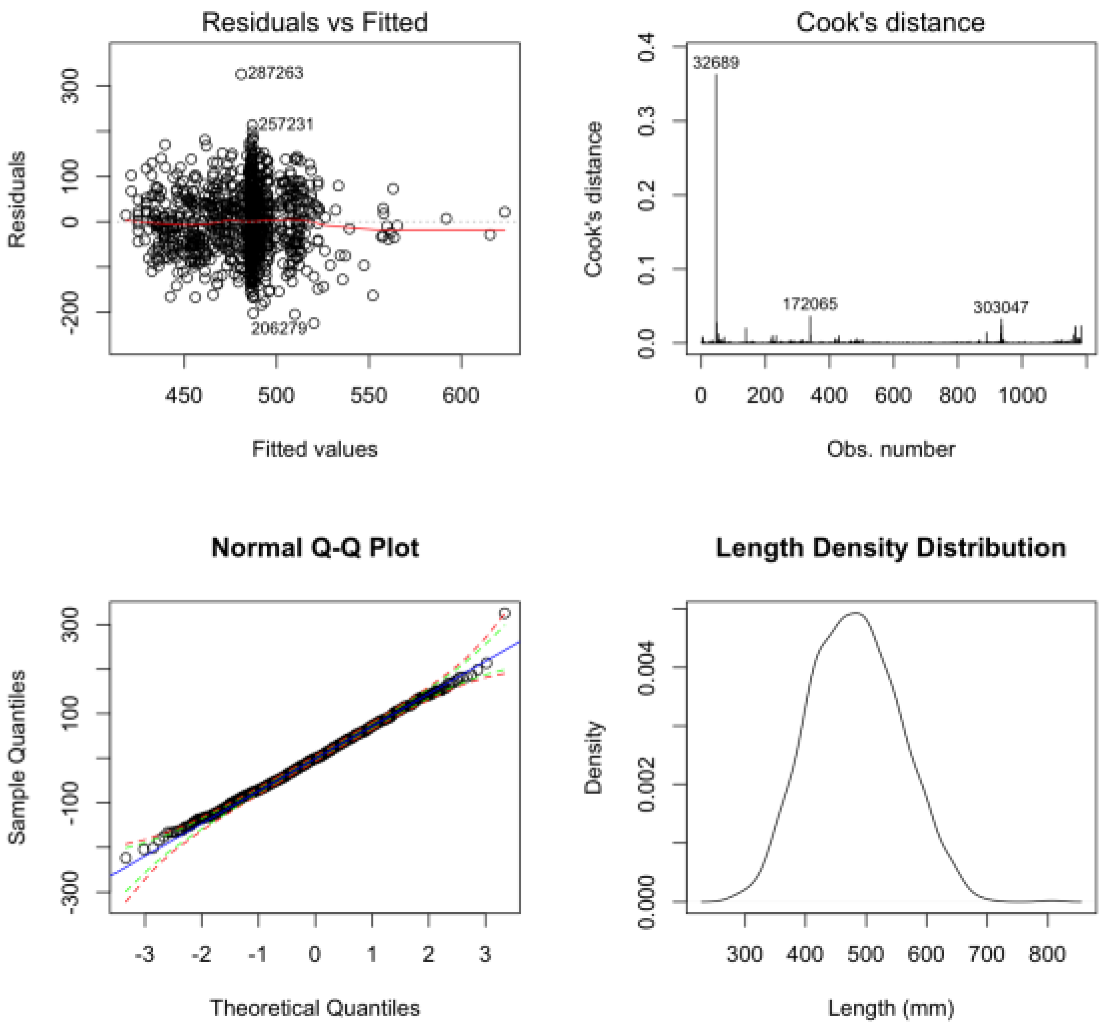

Figure 7. Diagnostic plots for the jolthead porgy linear model predicting length as a function of year, fishing depth, and their interactions. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes. The Cook's distance plot indicates all points < 1, confirming no influential points in the model. Finally, the normal Q-Q plot and density distribution show an approximately normal distribution.

Next, a model average dredge of ordinary least squares linear models was conducted, and the top models were ranked by BIC. The strongest model from this process predicted length as a function of fishing depth, hooks, and mainline length (Table 11). Each of these variables are significant predictors of jolthead porgy length; the model is significant overall with no clear diagnostic issues (Figure 8). This model explains 4.6% of the variation in jolthead porgy length, and ranks above the linear model when compared directly by BIC.

Table 11. The results of the top ordinary least squares linear model for jolthead porgy. $R^2_{adj} = 0.046$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	543.648	15.334	0.000
Fishing Depth	-0.271	0.046	0.000
Hooks	-0.033	0.012	0.007
Mainline Length	6.522	1.562	0.000

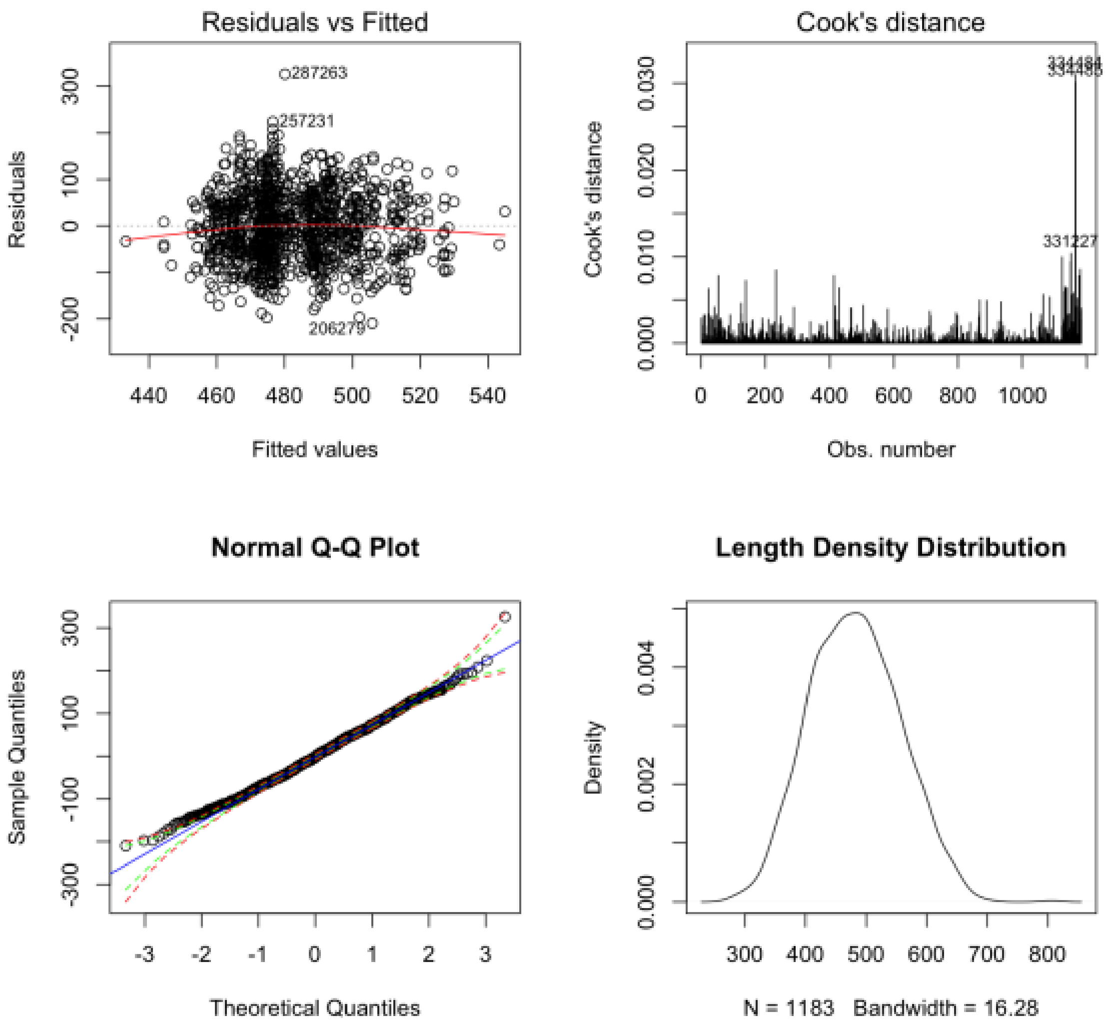

Figure 8. Diagnostic plots for the jolthead porgy OLS model. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes. The Cook's distance plot indicates all points < 1, confirming no influential points in the model. The normal Q-Q plot and density distribution show an approximately normal distribution.

2.3.2 Blacknose Shark

The highest ranked linear model by BIC included month, year, and their interaction. The model was significant overall ($p < 0.01$), and the R^2_{adj} value (0.307) suggests a strong fit (Table 12). While the diagnostic plots indicate a skewed distribution, the large sample size is sufficient for analysis (Figure 9). Month:DummyYear interactions where no catches were recorded have been removed from the results table.

Table 12. The results of the top linear model for blacknose sharks detected by the exhaustive search. $R^2_{adj} = 0.307$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	624.494	64.827	0.000
MonthAug	628.840	103.064	0.000
MonthDec	36.818	48.617	0.449
MonthFeb	127.282	121.914	0.297
MonthJan	49.205	115.857	0.671
MonthJul	-85.682	140.344	0.542
MonthJun	341.318	140.344	0.015
MonthMar	33.609	28.069	0.231
MonthMay	-76.849	60.395	0.204
MonthNov	-48.432	45.195	0.284
MonthOct	141.340	76.207	0.064
MonthSep	117.792	38.096	0.002
DummyYear2	80.938	90.117	0.369
DummyYear3	13.854	56.561	0.807
DummyYear4	117.199	70.309	0.096
DummyYear5	406.506	86.095	0.000
DummyYear6	311.605	67.218	0.000
DummyYear7	240.302	84.384	0.005
DummyYear8	261.188	61.359	0.000
DummyYear9	202.725	130.845	0.122
MonthDec:DummyYear2	102.417	88.808	0.249

Table 12 continued.

	Estimate	Std. Error	*p*-value
MonthJul:DummyYear2	260.813	157.539	0.098
MonthJan:DummyYear4	183.960	119.689	0.125
MonthMar:DummyYear4	-87.125	51.589	0.092
MonthMay:DummyYear4	220.510	69.206	0.002
MonthNov:DummyYear4	149.522	60.172	0.013
MonthDec:DummyYear5	-221.238	78.706	0.005
MonthFeb:DummyYear5	-176.802	137.271	0.198
MonthJan:DummyYear5	-423.705	135.046	0.002
MonthJul:DummyYear5	156.932	166.496	0.346
MonthMar:DummyYear5	-23.846	64.844	0.713
MonthMay:DummyYear5	185.849	103.485	0.073
MonthNov:DummyYear5	-163.011	73.360	0.027
MonthOct:DummyYear5	-151.689	96.556	0.116
MonthSep:DummyYear5	-81.417	76.582	0.288
MonthAug:DummyYear6	-739.938	143.413	0.000
MonthFeb:DummyYear6	-150.496	125.007	0.229
MonthJan:DummyYear6	-121.250	121.458	0.318
MonthJun:DummyYear6	-268.917	172.167	0.119
MonthMar:DummyYear6	-57.958	45.459	0.203
MonthMay:DummyYear6	107.950	76.740	0.160
MonthOct:DummyYear6	-249.317	80.345	0.002
MonthSep:DummyYear6	-270.668	62.505	0.000
MonthDec:DummyYear7	-49.114	122.110	0.688
MonthFeb:DummyYear7	-25.713	113.228	0.820
MonthJul:DummyYear7	330.886	204.630	0.106
MonthMar:DummyYear7	-85.329	63.791	0.181
MonthOct:DummyYear8	-107.688	92.626	0.245

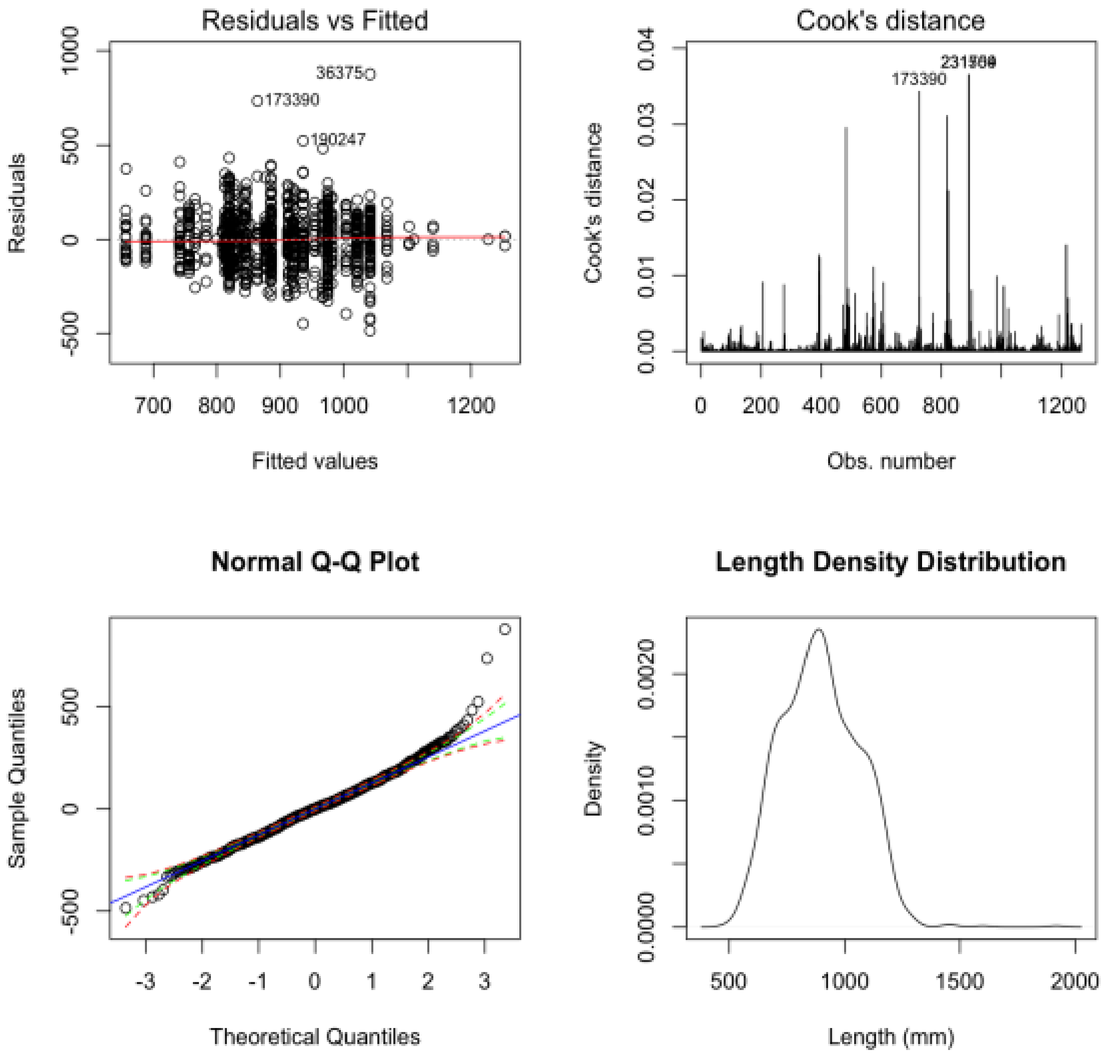

Figure 9. Diagnostic plots for the blacknose shark linear model with interaction. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes. The Cook's distance plot indicates all points < 1, confirming no influential points in the dataset. Some skew in the distribution is apparent in the Q-Q plot and density distribution, however, the sample size is sufficient for analysis despite the skew.

A model average dredge of ordinary least squares linear models was conducted, and the top models were ranked by BIC. The strongest model predicted length as a function of year, fishing depth, gangion length, hooks, mainline length, and month

(Table 13). This model explains 20.9% of the variation in blacknose shark length, but is inferior to the interaction model when compared directly by BIC. Diagnostics again indicate some minor problems with normality, but no influential points and a good fit across all lengths (Figure 10).

Table 13. The results of the top ordinary least squares linear model for blacknose shark. $R^2_{adj} = 0.209$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	872.431	54.954	0.000
DummyYear2	-46.003	51.838	0.375
DummyYear3	-187.099	48.072	0.000
DummyYear4	-34.050	42.268	0.421
DummyYear5	92.254	41.043	0.025
DummyYear6	14.289	39.079	0.715
DummyYear7	1.364	42.674	0.975
DummyYear8	56.326	39.970	0.159
DummyYear9	37.005	44.179	0.402
Fishing Depth	0.530	0.136	0.000
Ganglion Length	-9.707	2.278	0.000
Hooks	-0.165	0.025	0.000
Mainline Length	28.425	3.431	0.000
MonthAug	100.758	74.046	0.174
MonthDec	-80.460	26.602	0.003
MonthFeb	40.740	21.235	0.055
MonthJan	-42.663	22.237	0.055
MonthJul	56.752	43.317	0.190
MonthJun	135.508	87.306	0.121
MonthMar	-15.858	17.895	0.376
MonthMay	47.962	23.861	0.045
MonthNov	-140.252	19.182	0.000
MonthOct	-23.380	19.400	0.228
MonthSep	22.405	25.739	0.384

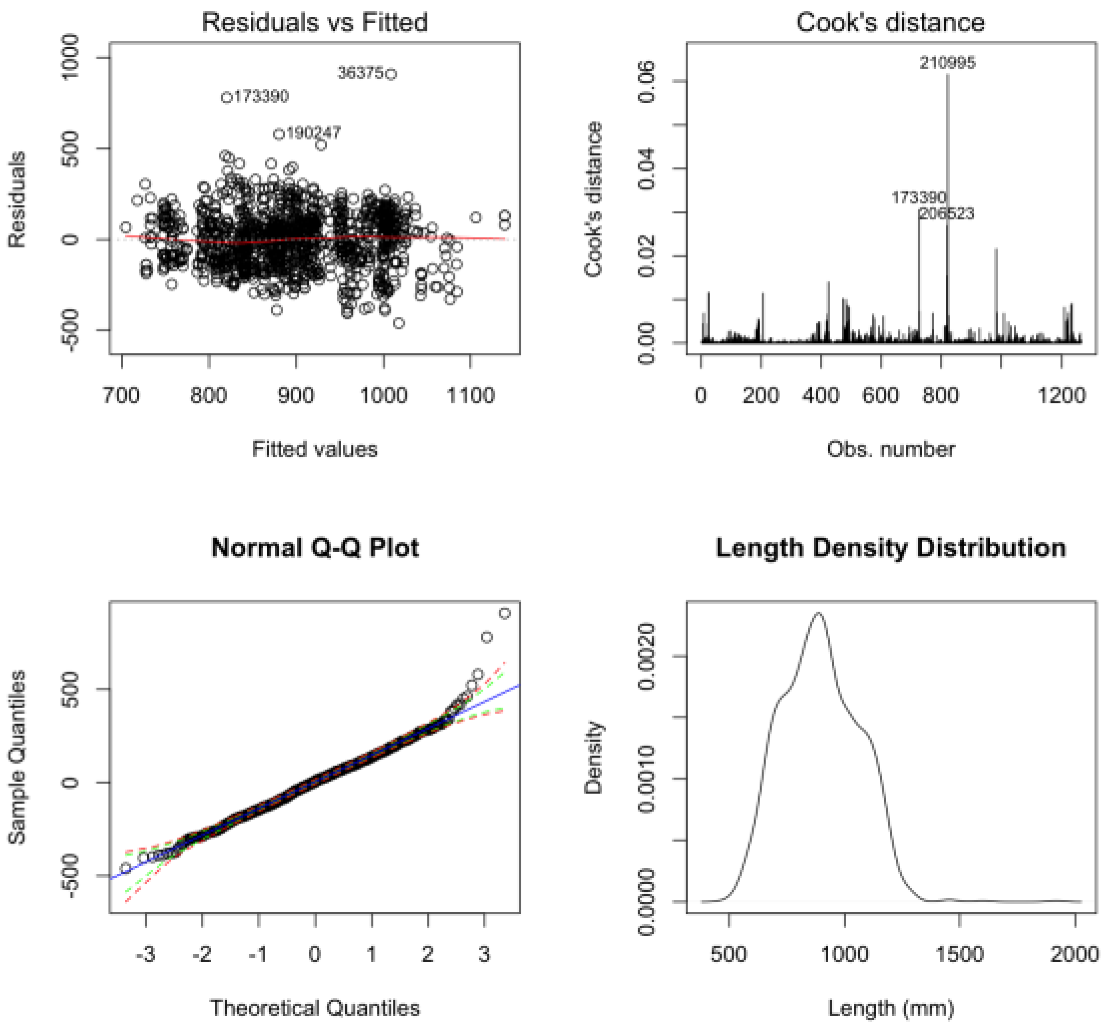

Figure 10. Diagnostic plots for the blacknose shark OLS model. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes. The Cook's distance plot indicates all points < 1, confirming no influential points in the dataset. Some skew in the distribution is apparent in the Q-Q plot and density distribution, however, the sample size is sufficient to compensate for the skewed distribution.

2.3.3 Speckled Hind

The highest ranked linear model by BIC included fishing depth, year, and their interaction. The model was significant overall ($p < 0.01$) and a moderate fit was achieved ($R^2_{adj} = 0.143$), though only fishing depth and one year are significant within the model (Table 14). Diagnostics indicate a strong model fit, though the distribution possesses a long right-hand tail (Figure 11).

Table 14. The results of the top linear model with interaction for speckled hind by BIC. $R^2_{adj} = 0.143$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-90.603	180.407	0.616
Fishing Depth	2.105	0.773	0.007
DummyYear2	272.659	293.410	0.353
DummyYear4	584.568	213.643	0.006
DummyYear5	231.807	190.037	0.223
DummyYear6	236.273	189.720	0.213
DummyYear7	212.207	211.931	0.317
DummyYear8	256.979	188.166	0.172
DummyYear9	237.902	201.675	0.239
Fishing Depth:DummyYear2	-1.176	1.080	0.277
Fishing Depth:DummyYear4	-2.080	0.883	0.019
Fishing Depth:DummyYear5	-0.811	0.808	0.316
Fishing Depth:DummyYear6	-0.837	0.808	0.300
Fishing Depth:DummyYear7	-0.485	0.911	0.595
Fishing Depth:DummyYear8	-0.830	0.801	0.300
Fishing Depth:DummyYear9	-0.592	0.875	0.499

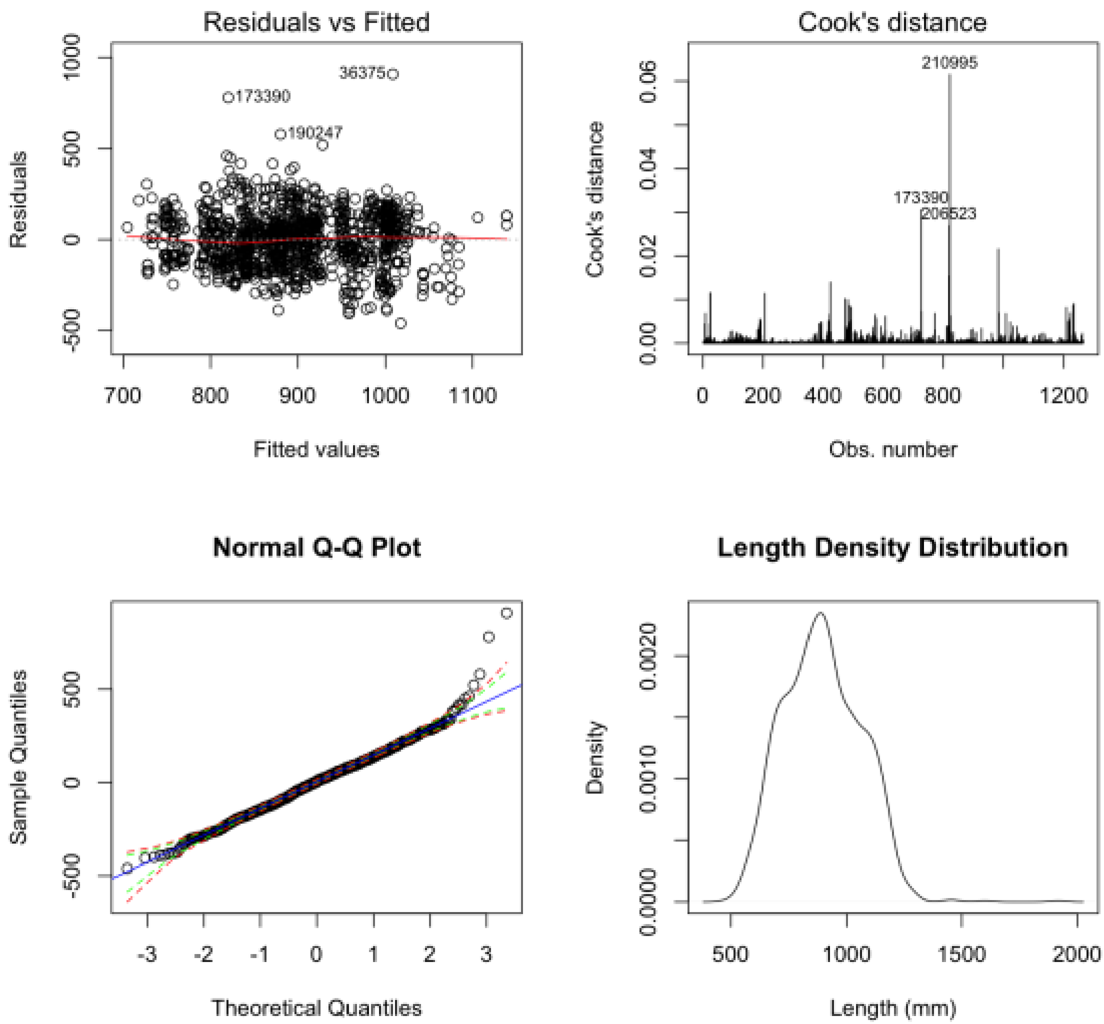

Figure 11. Diagnostic plots for the speckled hind linear model predicting length as a function of hook count, fishing depth, and their interaction. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes, and no influential points are present in the Cook's distance plot. The normal Q-Q plot and density distribution suggest sufficient normality though there is a long right-hand tail.

The strongest ordinary least squares linear model by BIC for speckled hind length included only fishing depth, which was significant within the model (Table 15). This model accounts for 11.4 % of the variance in speckled hind length, and ranks above the linear model when compared directly by BIC. Diagnostics do not indicate any major issues and the model provides a fairly good fit across all lengths (Figure 12).

Table 15. The results of the top ordinary least squares linear model for speckled hind. $R^2_{adj} = 0.114$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	198.172	27.044	0.000
Fishing Depth	1.091	0.107	0.000

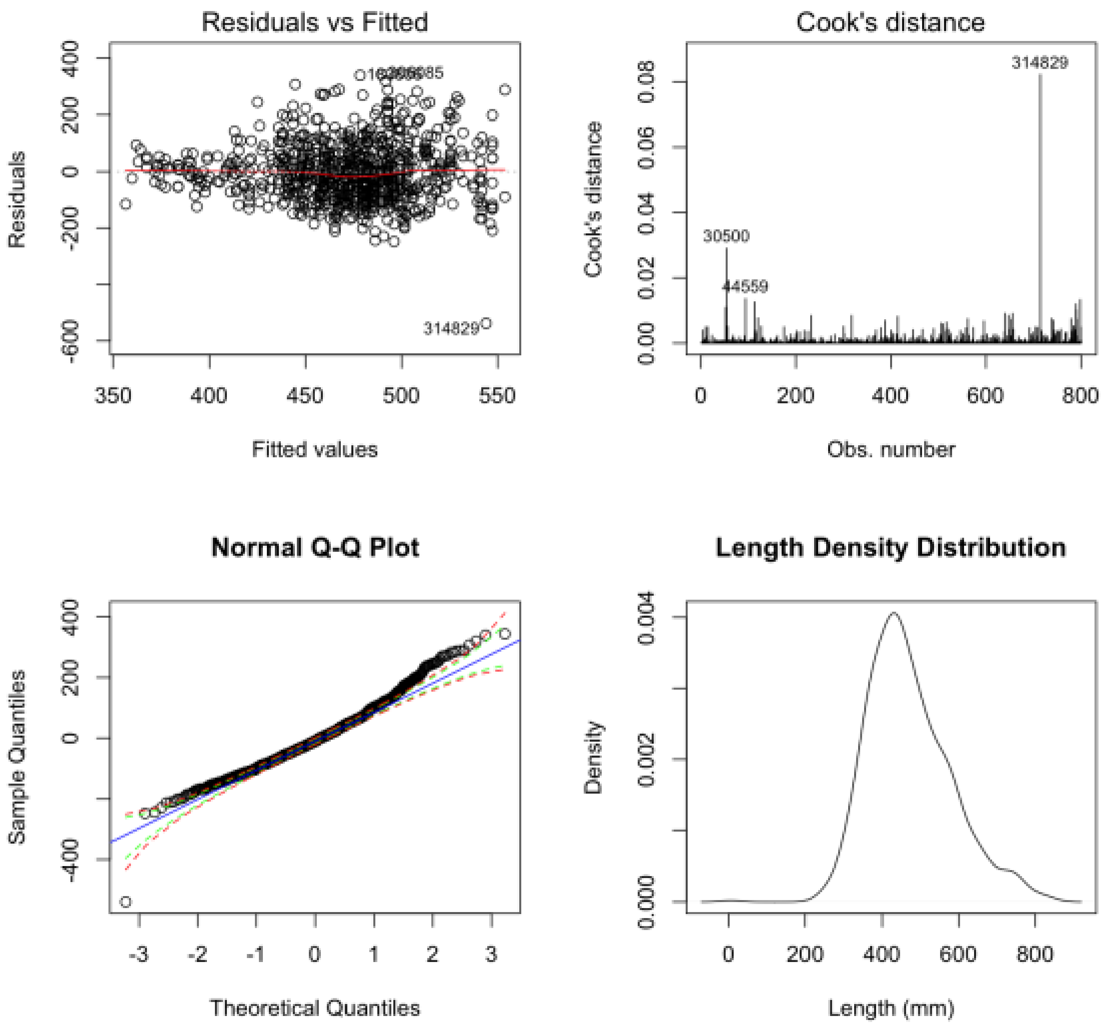

Figure 12. Diagnostic plots for the results of the speckled hind OLS model. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes, and no influential points are present in the Cook's distance plot. The normal Q-Q plot and density distribution suggest sufficient normality though there is a long left-hand tail.

2.3.4 Red Grouper

The highest ranked linear model with interaction by BIC for red grouper included fishing depth, year, and their interaction. The model was significant overall ($p < 0.01$) but the fit achieved was poor ($R^2_{adj} = 0.048$) (Table 16). Within the model, fishing depth, some years, and some interactions were significant predictors of red grouper length (Table 16). Diagnostics indicate a distribution slightly skewed towards smaller fish, but overall a good model fit (Figure 13).

Table 16. The results of the top linear model with interaction for red grouper by BIC. $R^2_{adj} = 0.048$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	397.290	5.315	0.000
Fishing Depth	0.574	0.035	0.000
DummyYear2	-20.230	8.057	0.012
DummyYear3	9.843	22.914	0.668
DummyYear4	-34.012	6.896	0.000
DummyYear5	4.096	5.673	0.470
DummyYear6	37.621	5.513	0.000
DummyYear7	-2.835	5.967	0.635
DummyYear8	26.219	5.568	0.000
DummyYear9	2.728	6.382	0.669
Fishing Depth:DummyYear2	0.148	0.051	0.004
Fishing Depth:DummyYear3	-0.096	0.156	0.538
Fishing Depth:DummyYear4	0.218	0.044	0.000
Fishing Depth:DummyYear5	-0.100	0.037	0.006
Fishing Depth:DummyYear6	-0.230	0.036	0.000
Fishing Depth:DummyYear7	0.011	0.038	0.765
Fishing Depth:DummyYear8	-0.062	0.036	0.083
Fishing Depth:DummyYear9	0.073	0.041	0.074

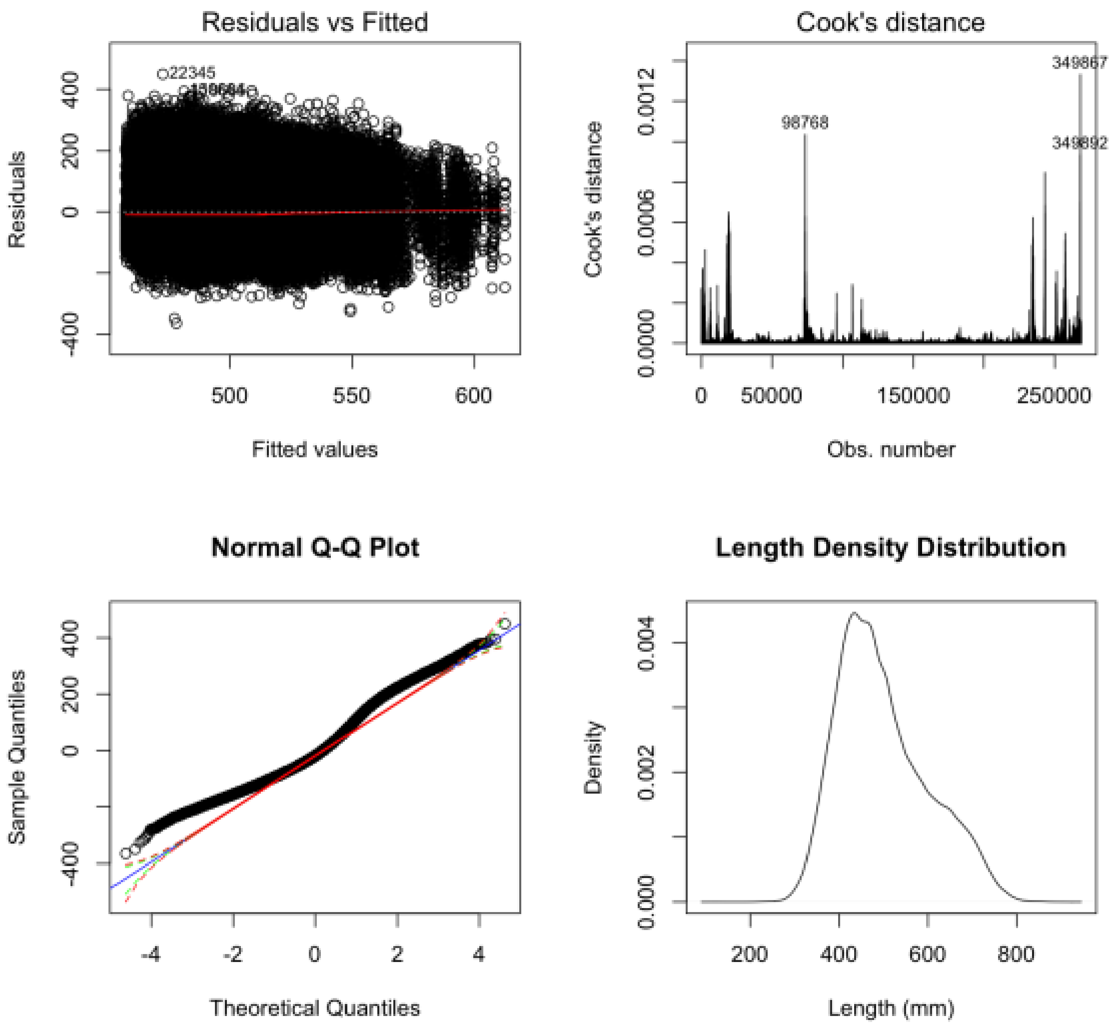

Figure 13. Diagnostic plots for the red grouper linear model predicting length as a function of fishing depth, year, and their interaction. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes, and no influential points are present in the Cook's distance plot. The normal Q-Q plot and density distribution suggest sufficient normality though there is a long left-hand tail.

The strongest ordinary least squares linear model by BIC for red grouper explains length as a function of year, fishing depth, hook distance, mainline length, and month (Table 17). All variables with the exception of some levels of year and month were significant predictors of red grouper length (Table 17). While no diagnostic issues are readily apparent, the model explains only 5.3% of the variance in length, but is significant overall ($p < 0.01$) (Figure 14). The OLS model is superior to the interaction model.

Table 17. The results of the top ordinary least squares generalized linear model for red grouper. $R^2_{adj} = 0.053$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	383.832	1.774	0.000
Fishing Depth	0.405	0.006	0.000
Hook Distance	0.160	0.019	0.000
Mainline Length	6.181	0.178	0.000
MonthAug	0.124	1.335	0.926
MonthDec	8.156	1.026	0.000
MonthFeb	5.805	0.806	0.000
MonthJan	0.960	1.012	0.343
MonthJul	12.461	1.309	0.000
MonthJun	-1.776	1.216	0.144
MonthMar	6.855	0.740	0.000
MonthMay	-3.872	0.894	0.000
MonthNov	-0.177	0.962	0.854
MonthOct	-4.623	0.852	0.000
MonthSep	-4.138	0.766	0.000
DummyYear2	2.623	1.781	0.141
DummyYear3	4.753	2.677	0.076
DummyYear4	-1.727	1.555	0.267
DummyYear5	-4.157	1.313	0.002
DummyYear6	7.031	1.303	0.000
DummyYear7	8.111	1.414	0.000
DummyYear8	25.658	1.284	0.000
DummyYear9	21.594	1.547	0.000

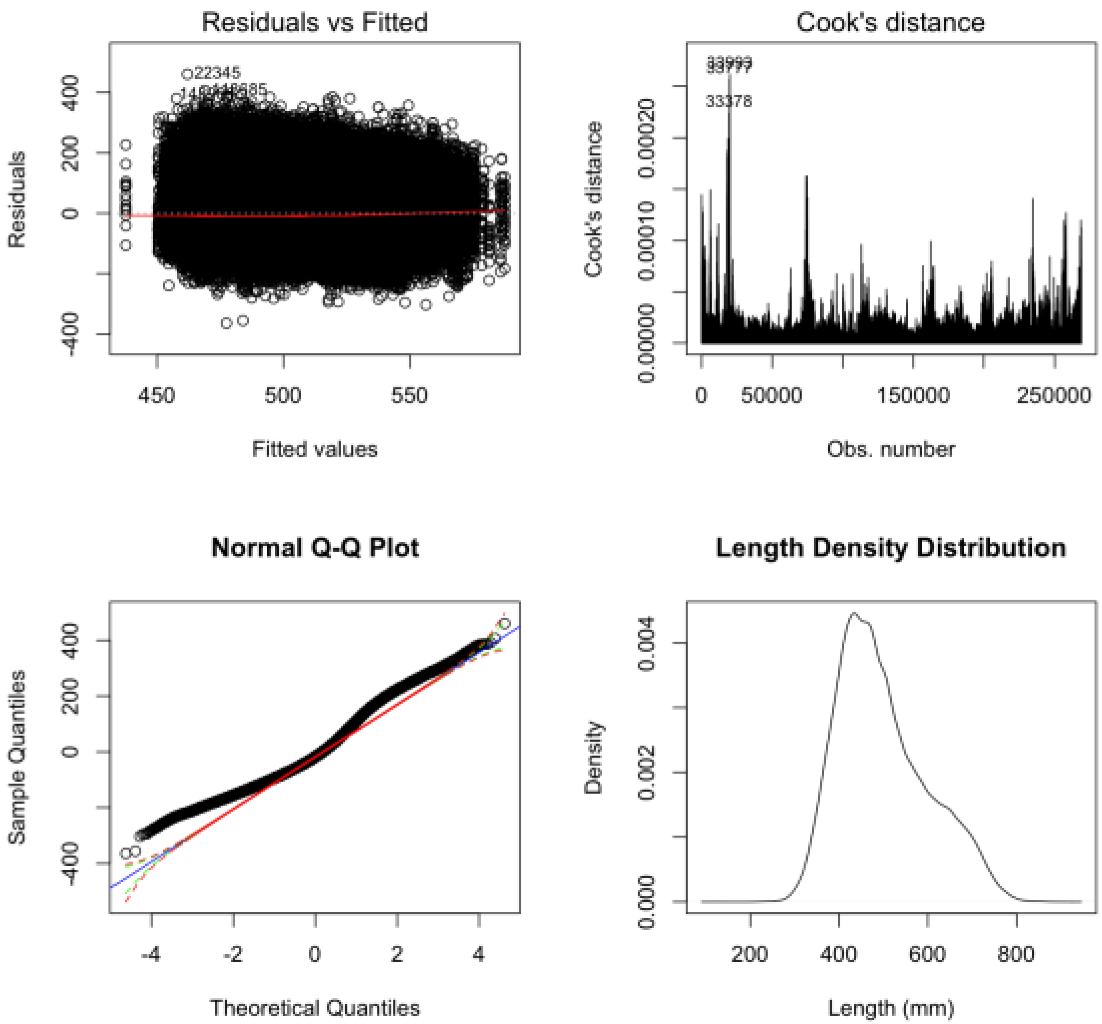

Figure 14. Diagnostic plots for the results of the red grouper OLS model. The residuals vs. fitted plot indicates the model is predicting length sufficiently across all sizes, and no influential points are present in the Cook's distance plot. The normal Q-Q plot and density distribution suggest sufficient normality though there is a long left-hand tail.

2.3.5 Red Snapper

The highest ranked linear model with interaction by BIC for red snapper explained length as a function of month, year, and their interaction. The model was significant overall (p < 0.01) and explained a moderate amount of the variance in length (R^2_{adj} = 0.119) (Table 18). Diagnostics do not indicate any issues with normality (Figure 15).

Table 18. The results of the top linear model with interaction for red snapper by BIC. R^2_{adj} = 0.119, p < 0.01. Month:year interactions with no catches documented have been excluded from the table.

	Estimate	Std. Error	*p*-value
(Intercept)	506.216	13.585	0.000
MonthAug	-14.645	34.755	0.674
MonthDec	184.784	61.370	0.003
MonthFeb	124.273	12.952	0.000
MonthJan	93.003	12.815	0.000
MonthJul	84.946	7.286	0.000
MonthJun	40.922	5.260	0.000
MonthMar	39.864	5.780	0.000
MonthMay	30.579	6.564	0.000
MonthNov	0.917	25.731	0.972
MonthOct	-57.550	17.810	0.001
MonthSep	22.414	5.368	0.000
DummyYear2	76.935	17.880	0.000
DummyYear3	7.794	19.308	0.687
DummyYear4	28.422	14.260	0.046
DummyYear5	117.102	22.587	0.000
DummyYear6	55.177	13.775	0.000
DummyYear7	80.311	15.009	0.000
DummyYear8	62.279	12.969	0.000
DummyYear9	-6.403	17.343	0.712
MonthAug:DummyYear2	-46.309	37.912	0.222
MonthDec:DummyYear2	-217.516	63.781	0.001
MonthJul:DummyYear2	-164.551	28.974	0.000

Table 18 continued.

	Estimate	Std. Error	*p*-value
MonthJun:DummyYear2	-137.406	50.504	0.007
MonthNov:DummyYear2	-72.735	37.339	0.051
MonthSep:DummyYear2	-66.027	20.964	0.002
MonthFeb:DummyYear3	-62.480	21.241	0.003
MonthFeb:DummyYear4	-79.340	34.784	0.023
MonthJan:DummyYear4	-49.895	15.378	0.001
MonthJun:DummyYear4	-58.115	29.024	0.045
MonthMar:DummyYear4	-53.518	12.952	0.000
MonthMay:DummyYear4	-23.145	8.894	0.009
MonthNov:DummyYear4	14.230	26.655	0.593
MonthAug:DummyYear5	-79.451	48.264	0.100
MonthDec:DummyYear5	-236.708	64.205	0.000
MonthFeb:DummyYear5	-181.005	22.902	0.000
MonthJan:DummyYear5	-246.564	22.693	0.000
MonthJul:DummyYear5	-142.833	20.579	0.000
MonthJun:DummyYear5	-87.240	86.699	0.314
MonthMar:DummyYear5	-106.029	19.954	0.000
MonthMay:DummyYear5	-103.807	19.989	0.000
MonthNov:DummyYear5	-72.825	31.602	0.021
MonthOct:DummyYear5	-12.380	25.646	0.629
MonthSep:DummyYear5	-93.055	19.544	0.000
MonthAug:DummyYear6	18.539	35.691	0.604
MonthFeb:DummyYear6	-103.357	13.481	0.000
MonthJan:DummyYear6	-102.086	13.477	0.000
MonthJul:DummyYear6	-65.321	10.099	0.000
MonthJun:DummyYear6	-55.540	7.389	0.000
MonthMar:DummyYear6	-26.464	7.446	0.000
MonthMay:DummyYear6	-32.765	8.102	0.000
MonthOct:DummyYear6	71.138	18.825	0.000
MonthSep:DummyYear6	-42.517	6.986	0.000
MonthDec:DummyYear7	-148.614	61.959	0.017
MonthFeb:DummyYear7	-138.804	15.981	0.000
MonthJan:DummyYear7	-76.781	33.546	0.022
MonthJul:DummyYear7	-63.863	12.574	0.000
MonthMar:DummyYear7	-12.051	10.567	0.254
MonthNov:DummyYear7	10.081	27.281	0.712

Table 18 continued.

	Estimate	Std. Error	*p*-value
MonthOct:DummyYear7	92.522	62.767	0.141
MonthAug:DummyYear8	88.538	35.031	0.012
MonthDec:DummyYear8	-157.456	61.343	0.010
MonthJan:DummyYear8	19.501	85.506	0.820
MonthNov:DummyYear8	15.202	25.753	0.555
MonthOct:DummyYear8	93.287	18.140	0.000

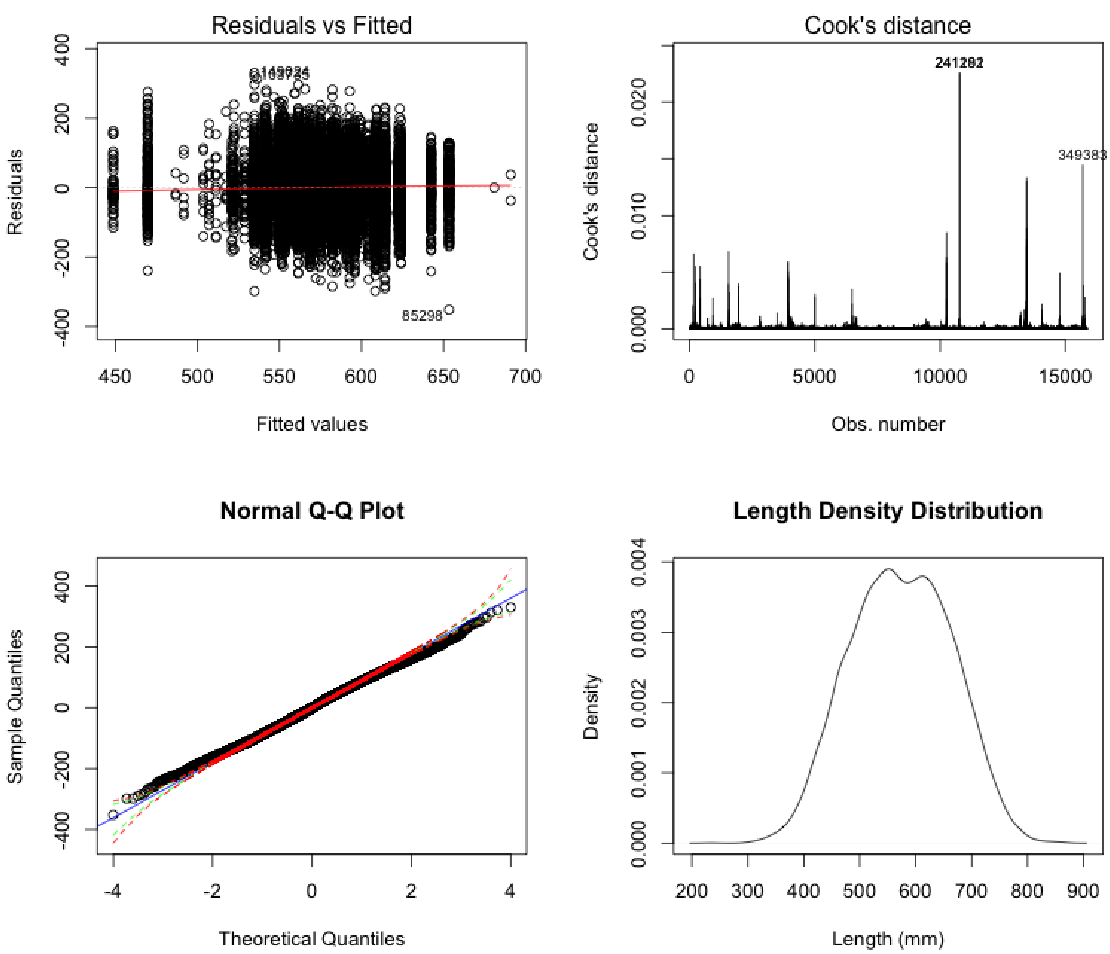

Figure 15. Diagnostic plots for the results of the red snapper interaction model. The residuals vs. fitted plot indicates the model is predicting length well across all sizes, and no influential points are present in the Cook's distance plot. The normal Q-Q plot and density distribution suggest sufficient normality.

The strongest ordinary least squares linear model by BIC for red snapper explains length as a function of soak time, year, fishing depth, gangion length, and month (Table 19). With the exception of some months, all variables were significant predictors of red snapper length (Table 19). No diagnostic issues are apparent and the model explains 11.1% of the variance in length, and is significant overall ($p < 0.01$) (Figure 16). The OLS model ranks higher than the interaction model by BIC.

Table 19. The results of the top ordinary least squares linear model for red snapper. $R^2_{adj} = 0.111$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	430.050	8.942	0.000
Soak Time	2.573	0.587	0.000
Fishing Depth	0.286	0.017	0.000
Ganglion Length	-3.362	0.261	0.000
MonthAug	21.349	4.770	0.000
MonthDec	17.877	3.424	0.000
MonthFeb	14.019	2.893	0.000
MonthJan	-16.145	3.088	0.000
MonthJul	22.585	3.850	0.000
MonthJun	2.452	3.453	0.478
MonthMar	17.614	2.935	0.000
MonthMay	3.515	3.012	0.243
MonthNov	11.381	3.085	0.000
MonthOct	19.190	3.480	0.000
MonthSep	5.435	2.966	0.067
DummyYear2	46.876	9.726	0.000
DummyYear3	53.469	10.833	0.000
DummyYear4	63.233	8.230	0.000
DummyYear5	65.516	7.910	0.000
DummyYear6	85.308	7.915	0.000
DummyYear7	112.801	8.149	0.000
DummyYear8	117.545	7.894	0.000
DummyYear9	127.141	8.488	0.000

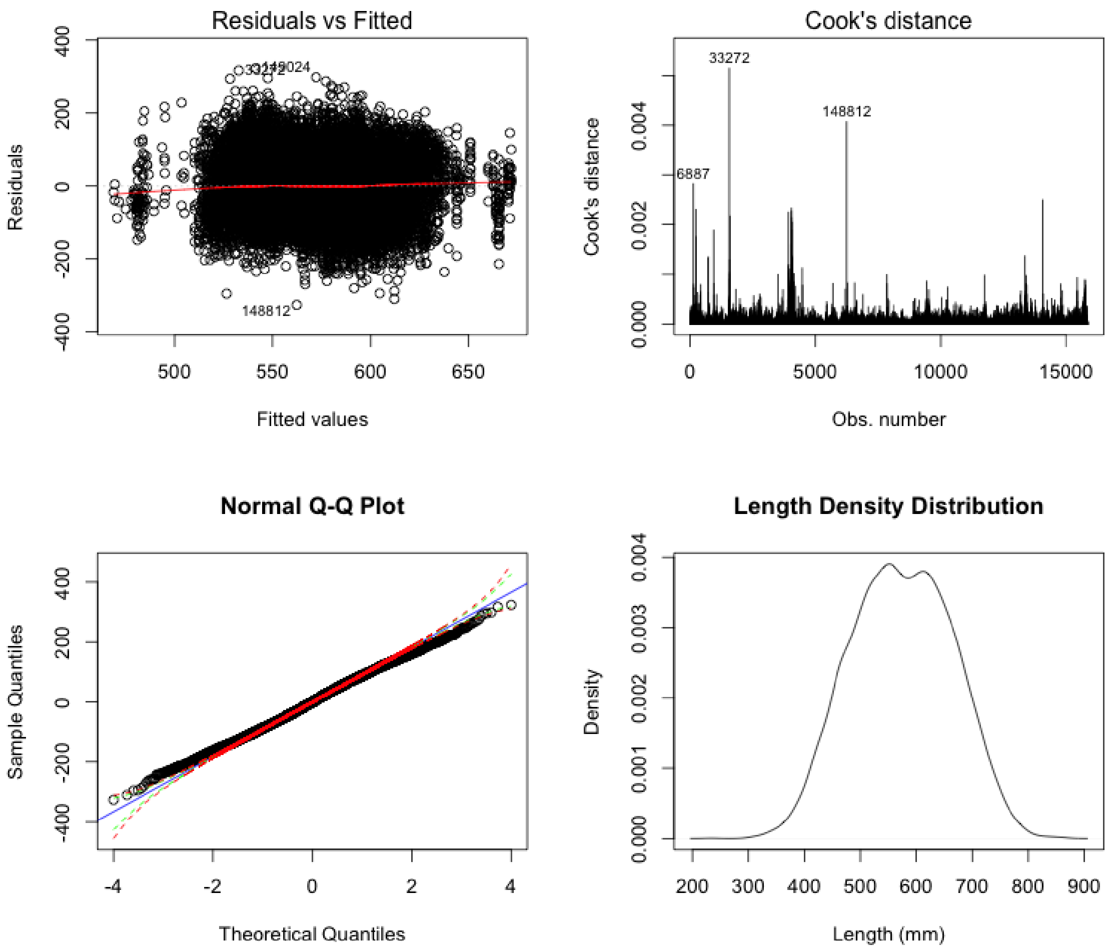

Figure 16. Diagnostic plots for the results of the red snapper ordinary least squares linear model. The residuals vs. fitted plot indicates the model is predicting length well across all sizes, and no influential points are present in the Cook's distance plot. The normal Q-Q plot and density distribution suggest sufficient normality.

2.3.6 Mutton Snapper

Gangion length, month, and their interaction were the best factors for predicting mutton snapper length. The model was significant overall ($p < 0.01$) and explained a large portion of the length variance ($R^2_{adj} = 0.187$) (Table 20). Gangion length, some months, and some interactions were significant for predicting mutton snapper length (Table 20). Diagnostics do not indicate any issues with the model (Figure 17).

Table 20. The results of the top linear model with interaction for mutton snapper by BIC. $R^2_{adj} = 0.183$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	720.055	29.524	0.000
Ganglion Length	-13.383	3.741	0.000
MonthAug	-32.137	84.197	0.703
MonthDec	27.959	16.627	0.093
MonthFeb	-116.309	41.188	0.005
MonthJan	58.935	50.115	0.240
MonthJul	-22.245	30.528	0.466
MonthJun	-334.859	35.518	0.000
MonthMar	160.826	82.815	0.052
MonthMay	-217.322	42.206	0.000
MonthNov	-72.789	150.242	0.628
MonthOct	-1713.555	533.292	0.001
MonthSep	-184.075	60.492	0.002
Ganglion Length:MonthAug	8.804	10.844	0.417
Ganglion Length:MonthFeb	18.005	5.425	0.001
Ganglion Length:MonthJan	-0.538	6.948	0.938
Ganglion Length:MonthJul	4.361	3.826	0.255
Ganglion Length:MonthJun	44.900	4.713	0.000
Ganglion Length:MonthMar	-28.929	12.745	0.023
Ganglion Length:MonthMay	32.201	7.588	0.000
Ganglion Length:MonthNov	17.305	18.903	0.360
Ganglion Length:MonthOct	197.549	64.562	0.002
Ganglion Length:MonthSep	22.951	6.290	0.000

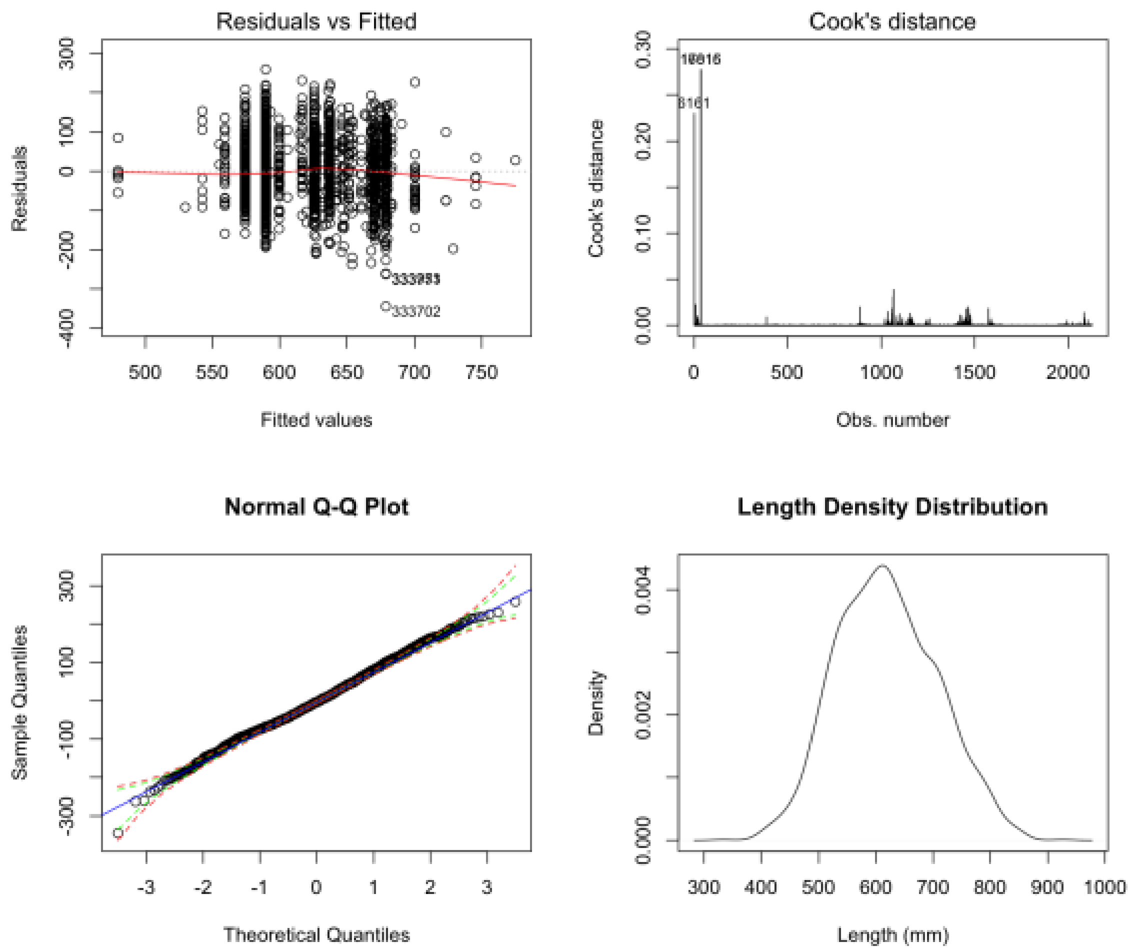

Figure 17. Diagnostic plots for the top linear model with interaction by BIC for mutton snapper. The residuals vs. fitted plot indicates the model is predicting length well across all sizes, and no influential points are present in the Cook's distance plot. The normal Q-Q plot and density distribution suggest sufficient normality.

The strongest ordinary least squares linear model by BIC for mutton snapper explains length using year, fishing depth, mainline length, and month (Table 21). Some years, some months, and mainline length were significant within the model (Table 21). No diagnostic issues are apparent, and the model explains 15.2% of the variance in length, and is significant overall ($p < 0.01$) (Figure 18). However, the OLS model ranks lower than the interaction model by BIC.

Table 21. The top ordinary least squares linear model by BIC for mutton snapper. $R^2_{adj} = 0.152$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	348.060	34.174	0.000
DummyYear2	95.296	22.720	0.000
DummyYear4	26.083	26.709	0.329
DummyYear5	106.270	19.964	0.000
DummyYear6	144.888	21.243	0.000
DummyYear7	92.634	51.273	0.071
DummyYear8	155.415	20.411	0.000
DummyYear9	166.380	24.706	0.000
Fishing Depth	0.200	0.083	0.017
Mainline Length	18.965	2.295	0.000
MonthAug	8.549	15.543	0.582
MonthDec	145.772	23.400	0.000
MonthFeb	12.471	16.552	0.451
MonthJan	49.189	20.058	0.014
MonthJul	-0.799	10.317	0.938
MonthJun	-36.820	10.594	0.001
MonthMar	-2.981	17.191	0.862
MonthMay	-19.630	18.511	0.289
MonthNov	94.175	17.411	0.000
MonthOct	-69.307	30.507	0.023
MonthSep	43.896	16.248	0.007

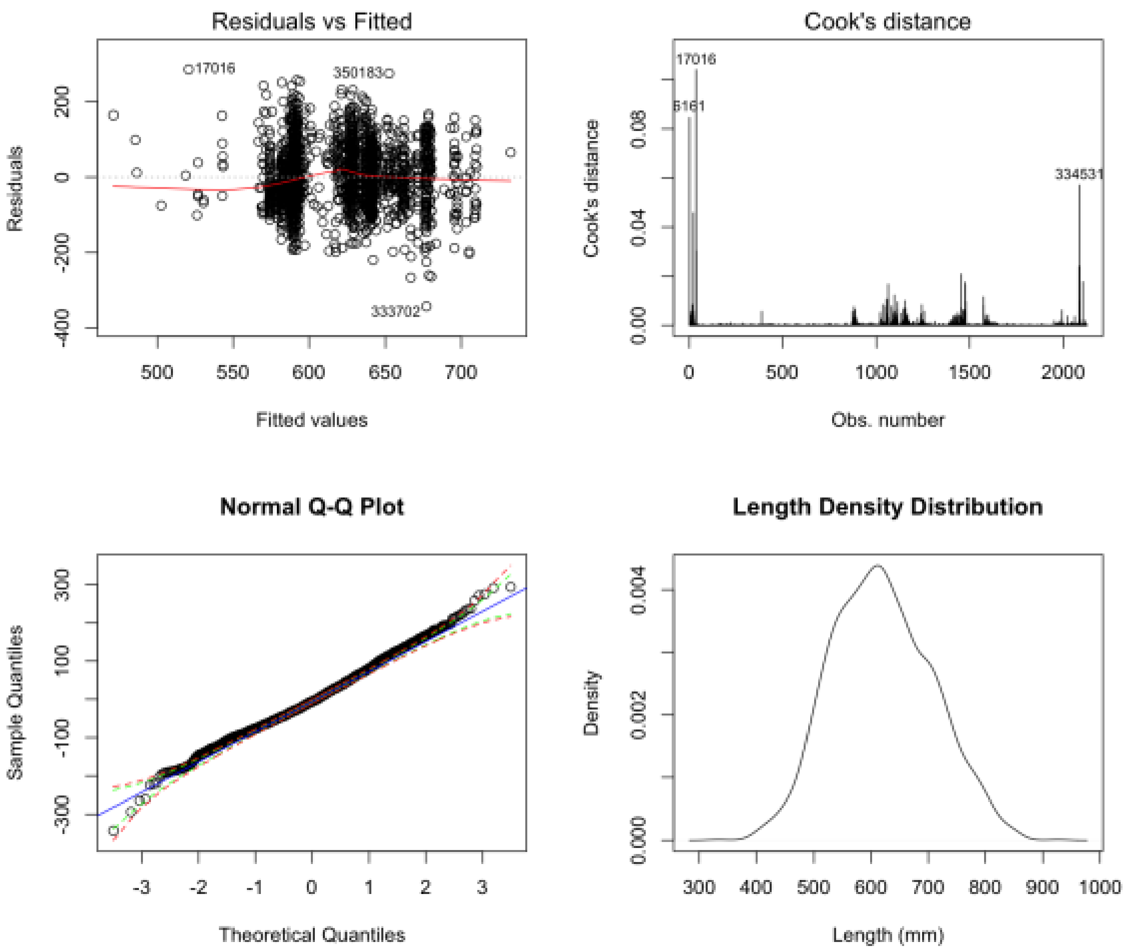

Figure 18. Diagnostic plots for the results of the mutton snapper ordinary least squares linear model. The residuals vs. fitted plot suggests the model is predicting length adequately across the model. There are no issues with Cook's distance, and the Q-Q plot and density distribution suggest sufficient normality.

2.3.7 Scamp

Month, year, and their interaction were the best factors for predicting scamp length. The model was significant overall ($p < 0.01$) but explained only a small portion of the length variance ($R^2_{adj} = 0.095$) (Table 22). Within the model, some years, some months, and some interactions were significant factors for explaining scamp length (Table 22). Diagnostics do not indicate any issues with the model fit (Figure 19).

Table 22. The results of the top linear model with interaction for scamp by BIC. $R^2_{adj} = 0.095$, $p < 0.01$. Year:Month interactions with no observations have been removed.

	Estimate	Std. Error	*p*-value
(Intercept)	570.706	27.665	0.000
MonthAug	-57.311	8.905	0.000
MonthDec	-30.432	10.629	0.004
MonthFeb	10.255	25.836	0.691
MonthJan	65.954	28.751	0.022
MonthJul	-19.830	8.611	0.021
MonthJun	-55.270	8.039	0.000
MonthMar	14.664	11.009	0.183
MonthMay	-24.651	9.473	0.009
MonthNov	106.544	51.620	0.039
MonthOct	-106.019	31.666	0.001
MonthSep	-18.956	11.500	0.099
DummyYear2	9.195	29.831	0.758
DummyYear4	20.738	30.100	0.491
DummyYear5	52.627	37.395	0.159
DummyYear6	-24.430	28.147	0.386
DummyYear7	60.614	31.279	0.053
DummyYear8	58.390	26.628	0.028
DummyYear9	11.027	34.844	0.752
MonthAug:DummyYear2	-4.561	17.718	0.797
MonthDec:DummyYear2	-2.470	88.513	0.978
MonthJul:DummyYear2	-32.571	63.223	0.606
MonthJun:DummyYear2	86.368	88.239	0.328

Table 22 continued.

	Estimate	Std. Error	*p*-value
MonthSep:DummyYear2	19.721	27.627	0.475
MonthFeb:DummyYear4	-16.128	36.754	0.661
MonthJan:DummyYear4	-59.307	36.231	0.102
MonthJun:DummyYear4	19.201	33.984	0.572
MonthMar:DummyYear4	-61.209	31.962	0.056
MonthMay:DummyYear4	13.594	17.288	0.432
MonthNov:DummyYear4	-93.337	54.041	0.084
MonthAug:DummyYear5	-66.022	91.156	0.469
MonthDec:DummyYear5	15.394	29.506	0.602
MonthFeb:DummyYear5	-53.357	36.443	0.143
MonthJan:DummyYear5	-132.062	38.584	0.001
MonthJul:DummyYear5	-7.514	28.170	0.790
MonthMar:DummyYear5	-62.401	28.064	0.026
MonthMay:DummyYear5	-86.827	27.695	0.002
MonthNov:DummyYear5	-124.175	58.574	0.034
MonthOct:DummyYear5	80.616	41.167	0.050
MonthSep:DummyYear5	-2.217	28.931	0.939
MonthAug:DummyYear6	71.492	17.980	0.000
MonthFeb:DummyYear6	24.208	26.741	0.365
MonthJan:DummyYear6	-31.235	29.804	0.295
MonthJul:DummyYear6	71.954	15.467	0.000
MonthJun:DummyYear6	58.860	11.650	0.000
MonthMar:DummyYear6	6.892	13.966	0.622
MonthMay:DummyYear6	94.232	15.885	0.000
MonthOct:DummyYear6	188.742	45.989	0.000
MonthSep:DummyYear6	27.288	17.554	0.120
MonthDec:DummyYear7	-53.506	22.657	0.018
MonthJul:DummyYear7	25.976	23.878	0.277
MonthMar:DummyYear7	-3.686	24.890	0.882
MonthNov:DummyYear7	-94.174	56.032	0.093
MonthOct:DummyYear7	178.556	47.970	0.000
MonthNov:DummyYear8	-177.669	51.616	0.001
MonthOct:DummyYear8	88.388	32.412	0.006

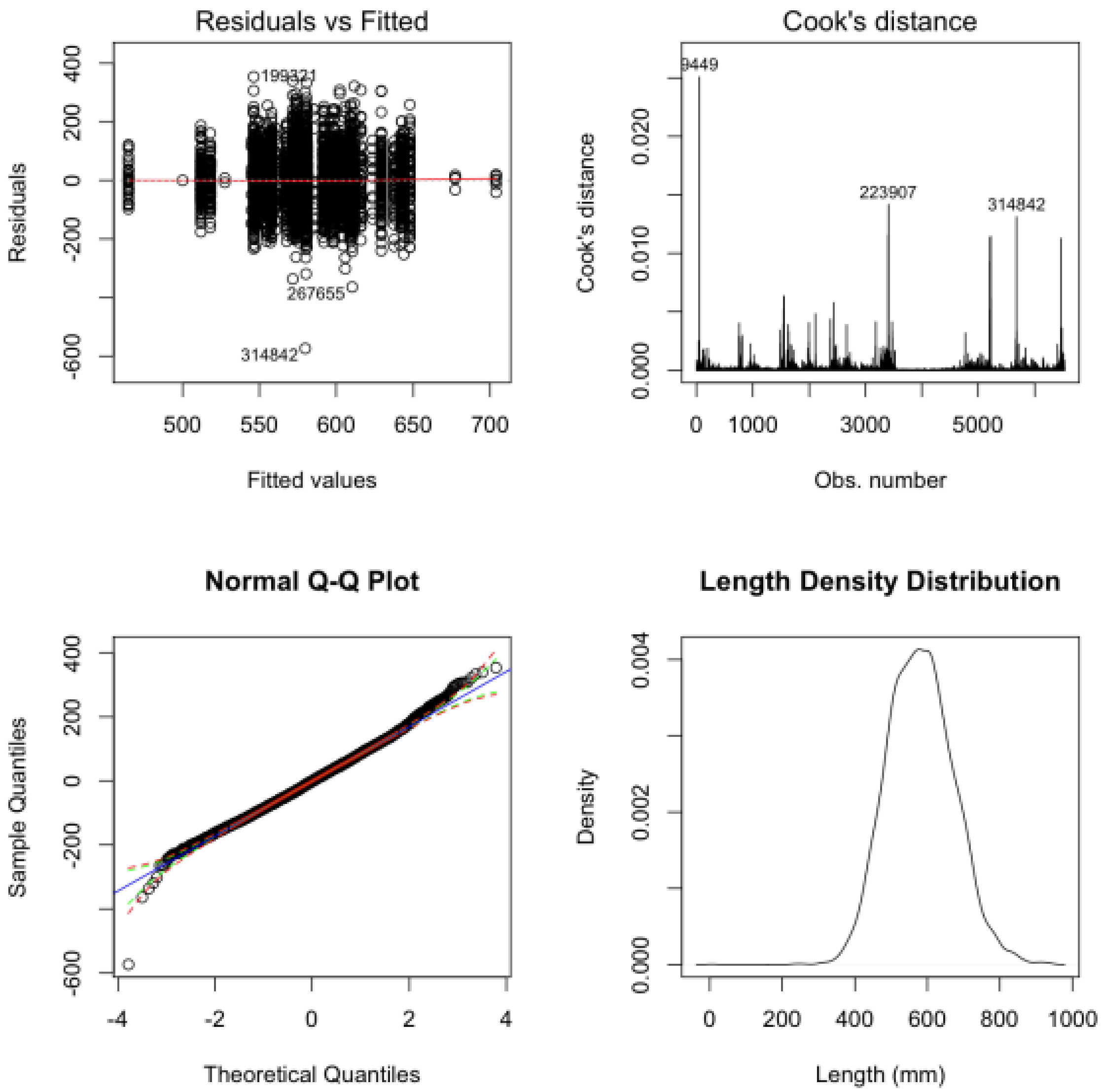

Figure 19. Diagnostic plots for the top linear model with interaction by BIC for scamp. No issues are apparent with the model. The residuals vs. fitted plot indicates a good fit across the model and no influential points are apparent. The distribution has a long left-hand tail in the Q-Q plot and density distribution, but adequate normality.

The strongest ordinary least squares linear model by BIC for scamp explains length as a function of year, fishing depth, gangion length, hook distance, and month (Table 23). All years, fishing depth, gangion length, hook distance, and some months were significant within the model (Table 23). No diagnostic issues are apparent and the model is significant overall (Figure 20, Table 23). However, the model explains only 8.1% of the variance in length (Table 23). The OLS model ranks above the interaction model by BIC.

Table 23. The top ordinary least squares linear model by BIC for scamp. $R^2_{adj} = 0.081$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	590.964	16.113	0.000
Fishing Depth	-0.309	0.034	0.000
Ganglion Length	-5.732	0.503	0.000
Hook Distance	0.741	0.114	0.000
MonthAug	-24.188	6.019	0.000
MonthDec	-21.513	6.645	0.001
MonthFeb	18.972	5.275	0.000
MonthJan	14.589	5.630	0.010
MonthJul	24.543	5.568	0.000
MonthJun	-11.491	5.095	0.024
MonthMar	9.756	5.587	0.081
MonthMay	-22.195	5.576	0.000
MonthNov	-3.022	6.748	0.654
MonthOct	9.788	7.314	0.181
MonthSep	12.909	6.507	0.047
DummyYear2	86.322	15.184	0.000
DummyYear4	89.646	14.235	0.000
DummyYear5	81.832	13.227	0.000
DummyYear6	70.749	13.383	0.000
DummyYear7	104.377	13.927	0.000
DummyYear8	104.822	13.208	0.000
DummyYear9	100.244	14.582	0.000

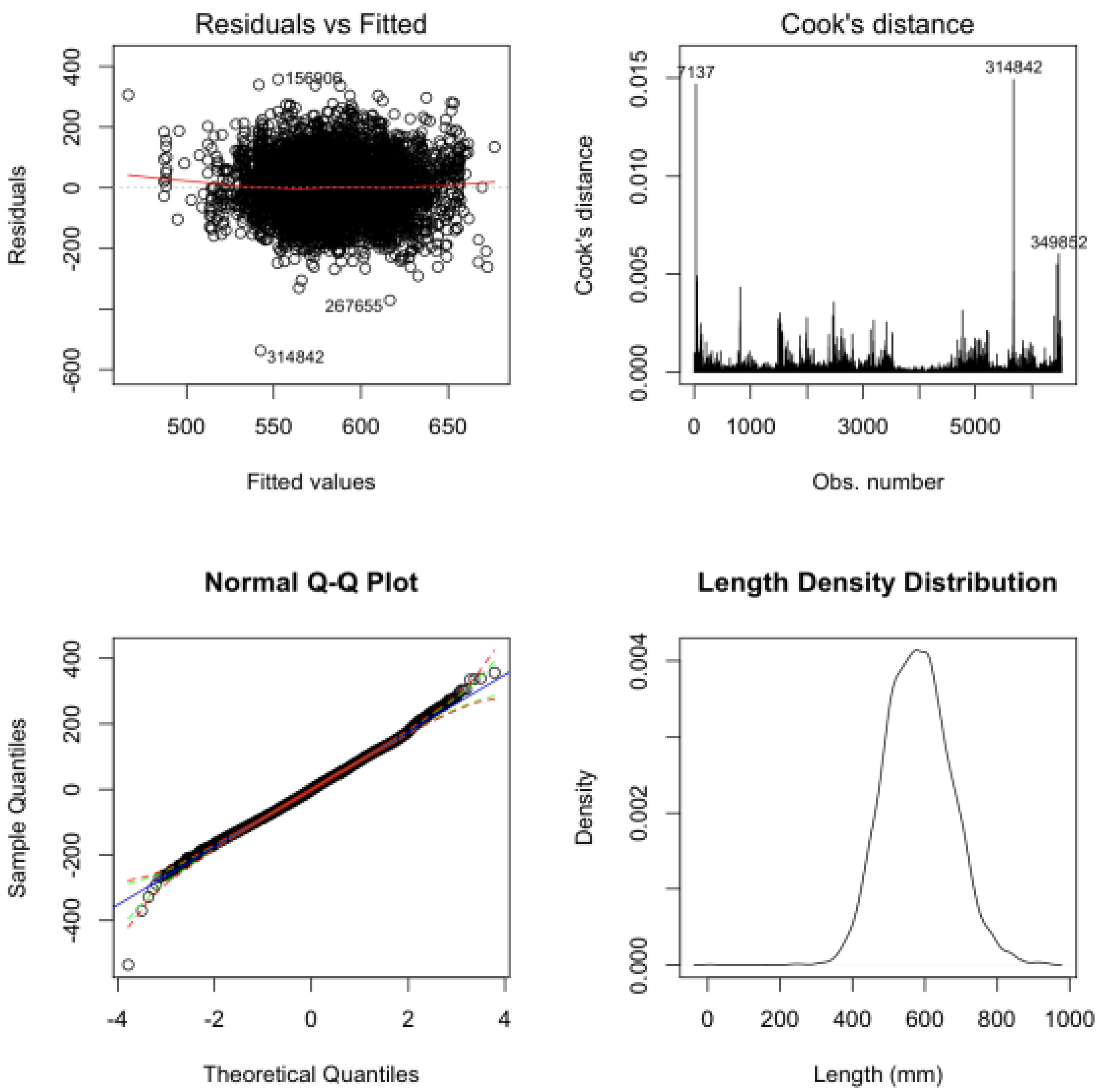

Figure 20. Diagnostic plots for the results of the scamp ordinary least squares linear model. No issues are apparent with the model. The residuals vs. fitted plot indicates a good fit across the model and no influential points are apparent. The distribution has a long left-hand tail in the Q-Q plot and density distribution, but adequate normality.

2.3.8 Gag Grouper

Year, fishing depth, and their interaction were used to generate a linear model for gag grouper that was significant overall ($p < 0.01$) and explained 16.4% of the length variance (Table 24). Within the model, fishing depth, some years, and some interactions were significant predictors of gag grouper length (Table 24). Diagnostics indicate a good model fit (Figure 21). The interaction model ranks above the OLS model, but only slightly (BIC difference < 2).

Table 24. The results of the top linear model with interaction for gag grouper by BIC. $R^2_{adj} = 0.164$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	615.916	52.579	0.000
Fishing Depth	0.861	0.268	0.001
DummyYear2	210.966	63.273	0.001
DummyYear3	461.975	472.734	0.329
DummyYear4	-196.466	60.618	0.001
DummyYear5	-28.934	57.679	0.616
DummyYear6	-32.443	54.454	0.551
DummyYear7	-1.928	61.901	0.975
DummyYear8	73.470	54.485	0.178
DummyYear9	114.052	59.020	0.053
Fishing Depth:DummyYear2	-0.793	0.300	0.008
Fishing Depth:DummyYear3	-3.084	3.101	0.320
Fishing Depth:DummyYear4	0.857	0.306	0.005
Fishing Depth:DummyYear5	0.078	0.287	0.787
Fishing Depth:DummyYear6	-0.149	0.277	0.590
Fishing Depth:DummyYear7	-0.027	0.306	0.931
Fishing Depth:DummyYear8	-0.301	0.276	0.275
Fishing Depth:DummyYear9	-0.438	0.297	0.141

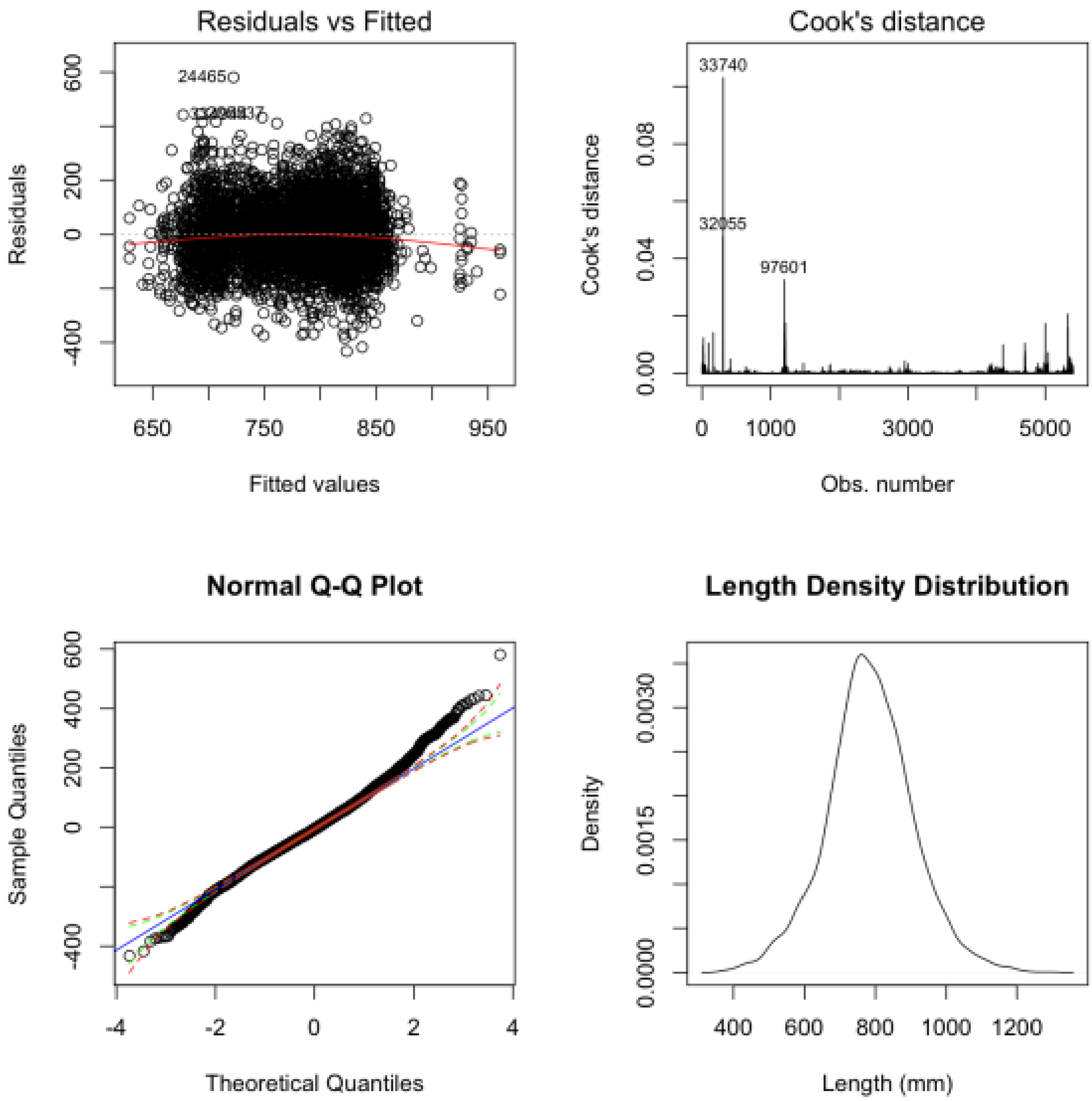

Figure 21. Diagnostic plots for the top linear model with interaction by BIC for gag grouper. The residuals vs. fitted plot suggests that the model is under-predicting length slightly for large individuals. There are no issues with influential points in the Cook's distance plot and the distribution is sufficiently normal.

The strongest ordinary least squares linear model by BIC for gag grouper explains length as a function of fishing depth, year, and mainline length (Table 25). Some years, fishing depth, and mainline length were significant within the model (Table 25). The model is significant overall ($p < 0.01$) and explains 15.5% of the variance in gag grouper length (Table 25). Diagnostics indicate that this model is slightly under-predicting length for very large gag grouper (Figure 22).

Table 25. The top ordinary least squares linear model by BIC for gag grouper. $R^2_{adj} = 0.155$, $p < 0.01$.

	Estimate	Std. Error	Pr(>|t|)
(Intercept)	617.575	18.335	0.000
DummyYear2	11.725	18.351	0.523
DummyYear3	-2.748	53.049	0.959
DummyYear4	-30.328	17.565	0.084
DummyYear5	4.449	16.646	0.789
DummyYear6	-51.514	16.346	0.002
DummyYear7	9.685	17.549	0.581
DummyYear8	21.583	16.311	0.186
DummyYear9	37.306	17.558	0.034
Fishing Depth	0.651	0.037	0.000
Mainline Length	6.201	1.238	0.000

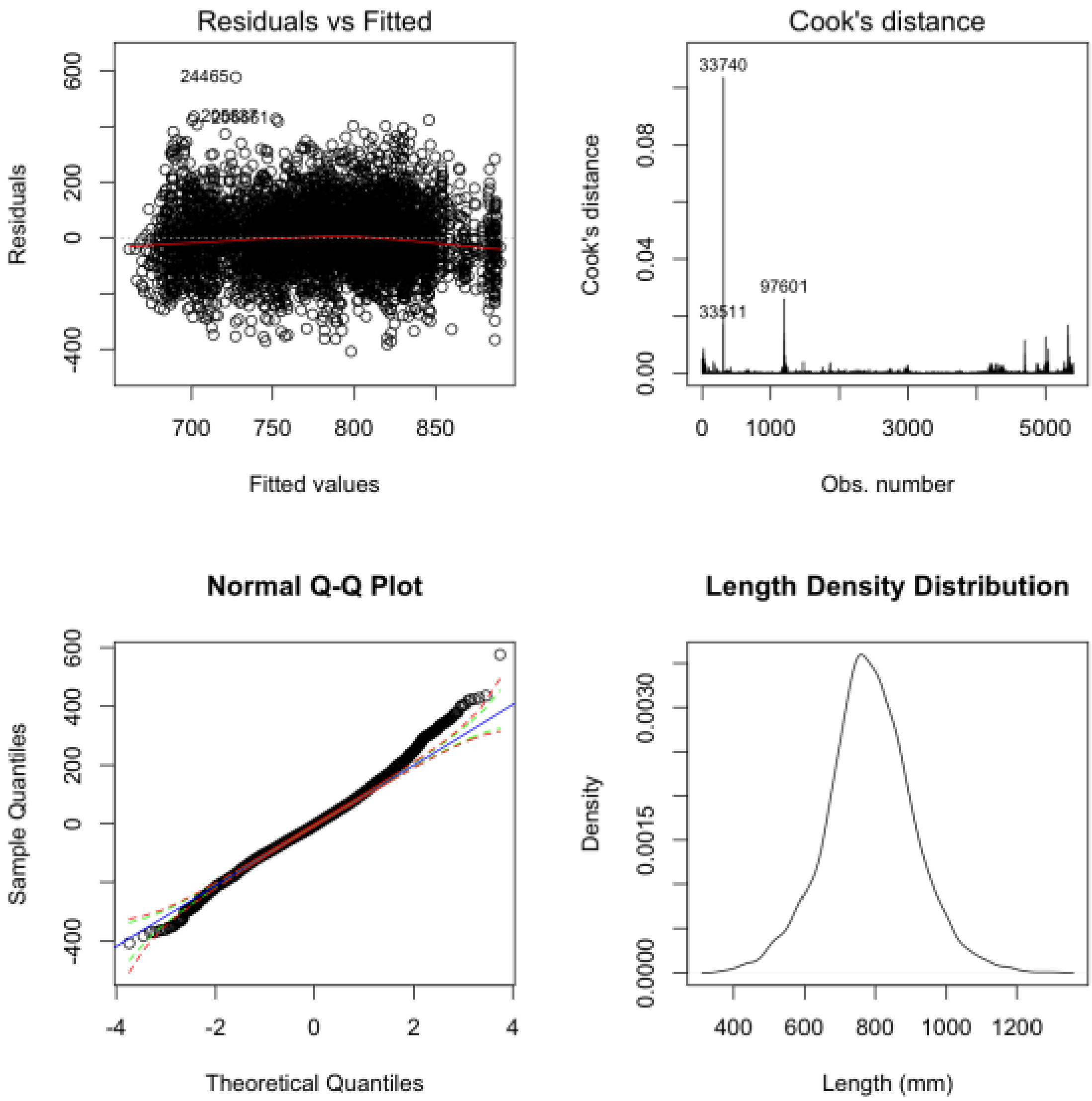

Figure 22. Diagnostic plots for the top gag grouper ordinary least squares model. The model is under-predicting for very gag grouper, but no other issues are apparent with influential points in the Cook's distance plot or normality in the Q-Q plot or distribution.

2.3.9 Red Porgy

Fishing depth, month, and their interaction were the strongest linear model with interaction by BIC for red porgy. The model was significant overall ($p < 0.01$) and explained a sizeable portion of the variance ($R^2_{adj} = 0.219$), but within the model only the month of June and interactions in January and June were significant predictors of red porgy length (Table 26). Diagnostics indicate that the model is slightly over-predicting length for large red porgy (Figure 23). The distribution has a long right tail, but otherwise adequately fits the assumption of normality (Figure 23).

Table 26. The results of the top linear model with interaction for red porgy by BIC. $R^2_{adj} = 0.219$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	296.687	30.348	0.000
Fishing Depth	0.151	0.132	0.256
MonthAug	50.861	65.393	0.437
MonthDec	-85.437	104.708	0.415
MonthFeb	-90.606	51.108	0.077
MonthJan	117.939	52.695	0.026
MonthJul	-119.393	75.862	0.116
MonthJun	-184.532	55.611	0.001
MonthMar	78.636	43.406	0.070
MonthMay	66.167	43.396	0.128
MonthNov	-19.858	57.386	0.729
MonthOct	53.012	50.648	0.296
MonthSep	7.015	46.703	0.881
Fishing Depth:MonthAug	0.029	0.276	0.917
Fishing Depth:MonthDec	0.455	0.455	0.318
Fishing Depth:MonthFeb	0.519	0.208	0.013
Fishing Depth:MonthJan	-0.624	0.234	0.008
Fishing Depth:MonthJul	0.543	0.311	0.081
Fishing Depth:MonthJun	0.890	0.229	0.000
Fishing Depth:MonthMar	-0.141	0.189	0.456
Fishing Depth:MonthMay	-0.350	0.202	0.084
Fishing Depth:MonthNov	0.215	0.258	0.406
Fishing Depth:MonthOct	-0.114	0.247	0.645
Fishing Depth:MonthSep	0.250	0.213	0.241

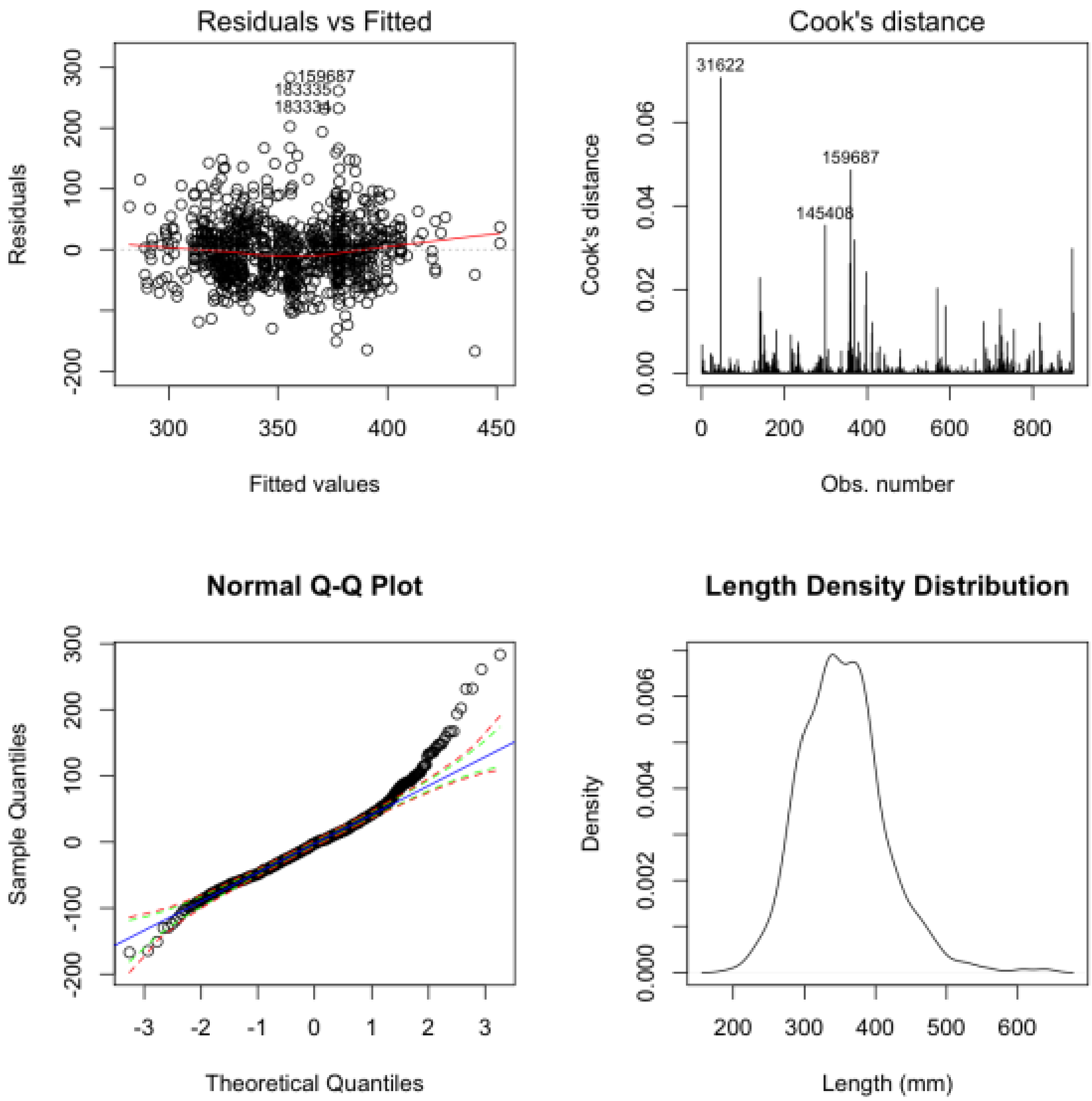

Figure 23. Diagnostic plots for the top linear model with interaction for red porgy. The distribution has a long right-hand tail, but overall fits the assumption of normality. The model is slightly over-predicting red porgy length for large individuals per the residuals vs. fitted plot. No influential points are apparent in the Cook's distance plot.

The strongest ordinary least squares linear model by BIC for red porgy explains length as a function of fishing depth, hook distance, and month (Table 27). Within the model, fishing depth, hook distance, and some months were significant, and the model is significant overall ($p < 0.01$) (Table 27). The model explains 18.9% of the variance in red porgy length and ranks above the interaction model by BIC (Table 27). Diagnostics indicate that the model is predicting fish length more precisely though the distribution has a long right-hand tail (Figure 24).

Table 27. The top ordinary least squares linear model by BIC for red porgy. $R^2_{adj} = 0.189$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	291.672	13.482	0.000
Fishing Depth	0.248	0.054	0.000
Hook Distance	-0.783	0.221	0.000
MonthAug	59.629	8.786	0.000
MonthDec	17.884	15.721	0.256
MonthFeb	41.833	7.898	0.000
MonthJan	-16.209	8.470	0.056
MonthJul	9.713	7.725	0.209
MonthJun	33.881	6.812	0.000
MonthMar	43.205	7.565	0.000
MonthMay	-1.843	7.206	0.798
MonthNov	25.405	10.653	0.017
MonthOct	37.181	9.698	0.000
MonthSep	58.634	10.343	0.000

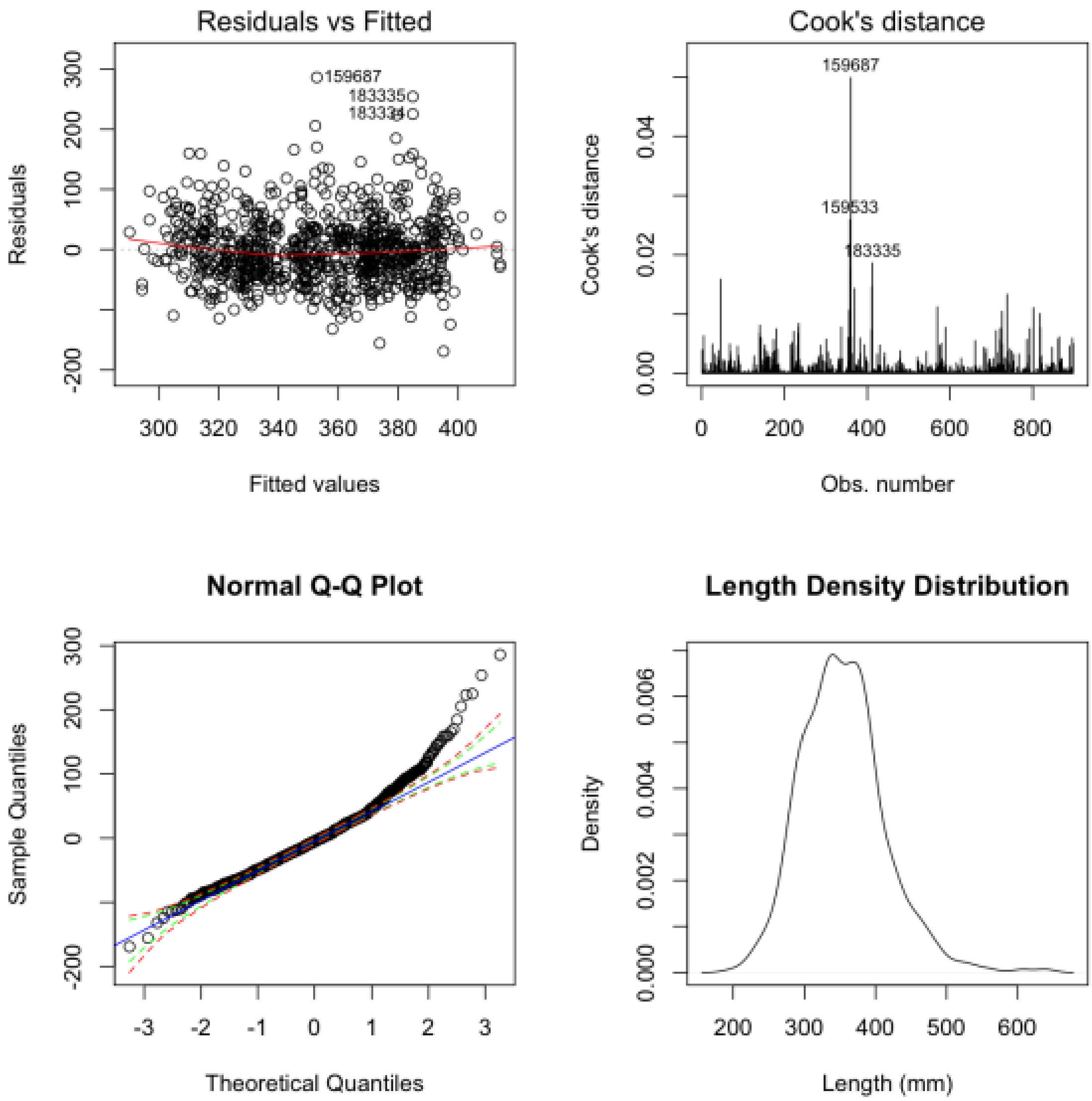

Figure 24. Diagnostic plots for the top ordinary least squares linear model for red porgy by BIC. The long right tail is present, but the model is predicting red porgy length more precisely than the linear model with interaction and no influential points are apparent.

3.2.10 Leopard Toadfish

The strongest linear model for leopard toadfish predicted length as a function of mainline length, month, and their interaction (Table 28). The model was significant overall ($p > 0.01$), but the R^2_{adj} value (0.074) indicates a weak overall performance from the strongest detected model. Within the model, no variables were significant. Diagnostics indicate that the model is under-predicting length for large leopard toadfish and the distribution has a long right-hand tail but is otherwise adequately normal (Figure 25).

Table 28. The top linear model with interaction by BIC for leopard toadfish. R^2_{adj} = 0.074, p < 0.01.

	Estimate	Std. Error	*p*-value
(Intercept)	319.222	24.358	0.000
MonthAug	66.887	39.758	0.093
MonthDec	45.857	55.532	0.409
MonthFeb	26.284	35.343	0.457
MonthJan	29.471	78.403	0.707
MonthJul	63.192	62.612	0.313
MonthJun	87.027	52.393	0.097
MonthMar	-70.060	40.147	0.082
MonthMay	-15.877	30.316	0.601
MonthNov	-86.388	46.354	0.063
MonthOct	-68.261	67.170	0.310
MonthSep	17.470	39.377	0.658
Mainline Length	9.332	5.003	0.063
MonthAug:Mainline Length	-16.864	7.329	0.022
MonthDec:Mainline Length	-15.177	10.814	0.161
MonthFeb:Mainline Length	-9.746	7.283	0.181
MonthJan:Mainline Length	-2.134	16.079	0.895
MonthJul:Mainline Length	-14.932	12.804	0.244
MonthJun:Mainline Length	-20.479	10.436	0.050
MonthMar:Mainline Length	12.045	8.692	0.166
MonthMay:Mainline Length	-1.516	5.684	0.790
MonthNov:Mainline Length	14.655	9.533	0.125
MonthOct:Mainline Length	5.068	13.427	0.706
MonthSep:Mainline Length	-9.990	8.386	0.234

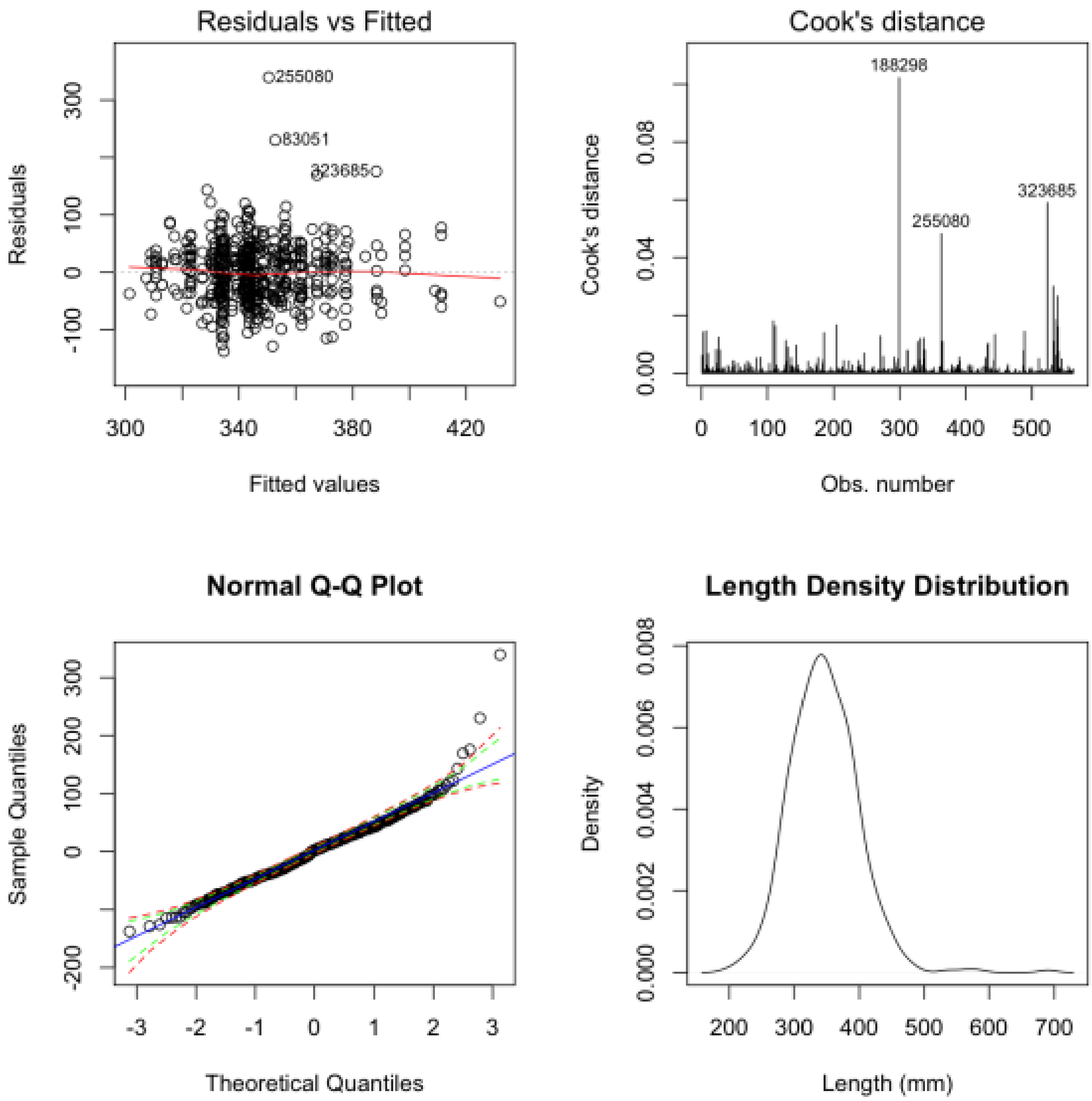

Figure 25. Diagnostic plots for the top linear model with interaction for leopard toadfish by BIC. The long right tail is present in the Q-Q plot and density distribution. The residuals vs. fitted plot suggests the model is under-predicting for large fish. No influential points are apparent.

The strongest ordinary least squares model predicts leopard toadfish length as a function of soak time, fishing depth, hook count, and mainline length. This model was significant overall ($p < 0.01$), but explained only 5.9% of the variance (Table 29). All variables within the model were significant predictors of leopard toadfish length (Table 29). The distribution has a long right-hand tail accounting for some non-normality, but the model fits well overall across all lengths (Figure 26). The OLS model ranks above the interaction model by BIC.

Table 29. The results of the top ordinary least squares linear model for leopard toadfish by BIC. $R^2_{adj} = 0.059$, $p < 0.01$.

	Estimate	Std. Error	Pr(>|t|)
(Intercept)	332.921	13.793	0.000
Soak Time	-5.656	2.060	0.006
Fishing Depth	0.177	0.045	0.000
Hooks	-0.040	0.011	0.000
Mainline Length	7.397	1.758	0.000

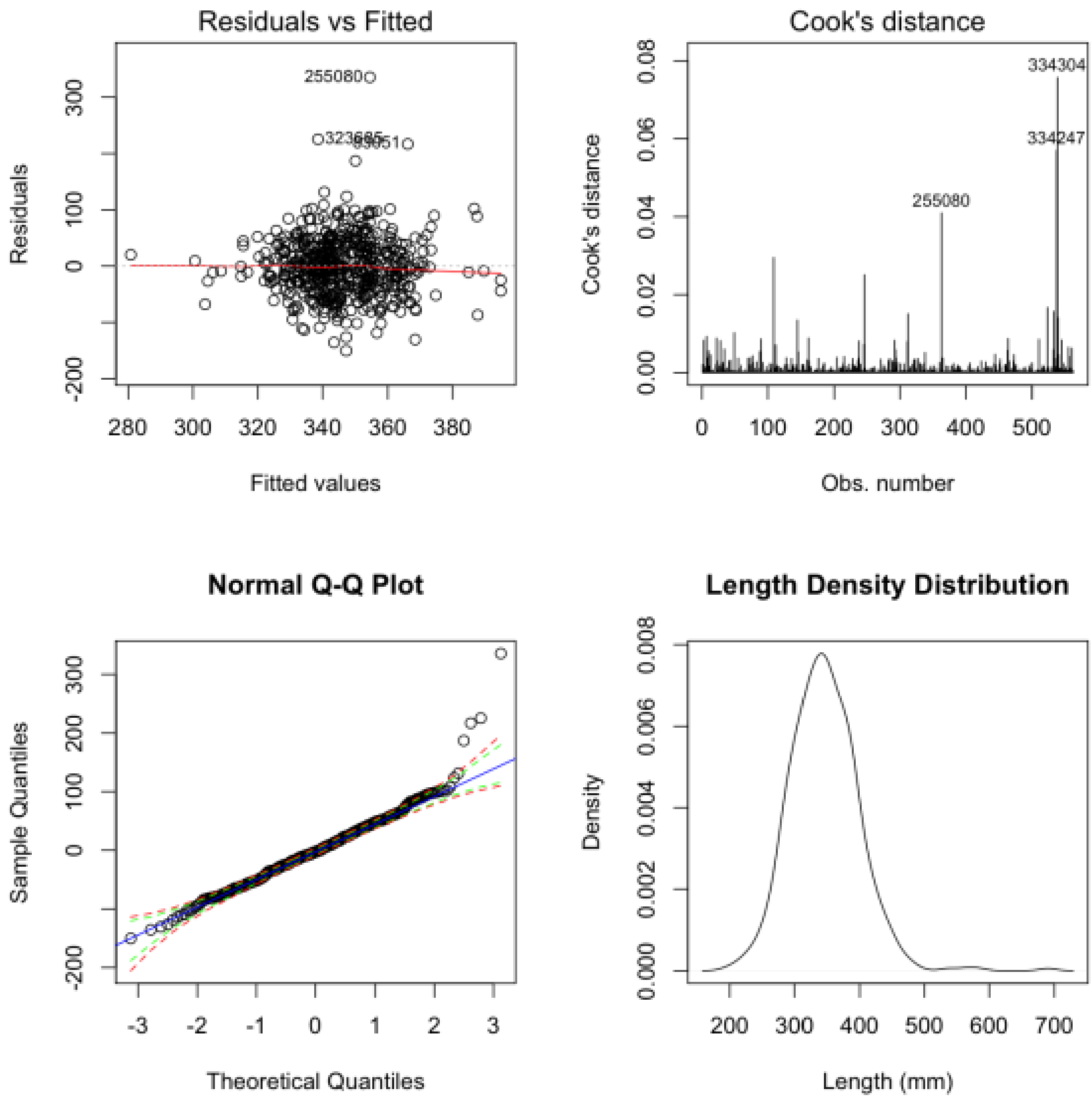

Figure 26. Diagnostic plots for the top ordinary least squares linear model for leopard toadfish. The distribution has a long right-hand tail, but otherwise fits well across all lengths. No influential points are apparent.

3.2.11 Atlantic Sharpnose Shark

The strongest linear model with interaction for Atlantic sharpnose shark length by BIC included month, year, and their interaction. The model was significant overall ($p < 0.01$) and accounted for a sizeable portion of the variance ($R^2_{adj} = 0.317$) (Table 30). Within the model, several months, years, and interactions were significant predictors of Atlantic sharpnose shark length (Table 30). Diagnostics indicate that the distribution has long tails, but otherwise satisfies assumptions (Figure 27).

Table 30. The top linear model with interaction by BIC for Atlantic sharpnose shark. $R^2_{adj} = 0.317$, $p < 0.01$. Year:month interactions with no observations have been excluded.

	Estimate	Std. Error	*p*-value
(Intercept)	730.529	13.094	0.000
MonthAug	70.027	30.738	0.023
MonthDec	-78.859	11.516	0.000
MonthFeb	-17.771	13.980	0.204
MonthJan	-48.570	11.054	0.000
MonthJul	48.113	20.082	0.017
MonthJun	74.065	13.221	0.000
MonthMar	-19.130	6.316	0.003
MonthMay	14.946	9.140	0.102
MonthNov	-31.167	7.524	0.000
MonthOct	87.548	20.956	0.000
MonthSep	53.790	8.400	0.000
DummyYear2	-109.612	27.836	0.000
DummyYear3	-36.593	13.196	0.006
DummyYear4	-13.007	14.652	0.375
DummyYear5	168.360	30.738	0.000
DummyYear6	75.258	13.904	0.000
DummyYear7	-49.773	27.086	0.066
DummyYear8	142.247	12.443	0.000
DummyYear9	173.412	15.350	0.000

Table 30 continued.

	Estimate	Std. Error	*p*-value
MonthDec:DummyYear2	163.443	64.932	0.012
MonthJul:DummyYear2	124.185	38.780	0.001
MonthFeb:DummyYear3	51.596	21.386	0.016
MonthFeb:DummyYear4	212.049	20.315	0.000
MonthJan:DummyYear4	152.843	13.666	0.000
MonthMar:DummyYear4	-34.132	13.002	0.009
MonthMay:DummyYear4	113.190	18.045	0.000
MonthNov:DummyYear4	145.127	13.481	0.000
MonthAug:DummyYear5	-87.916	93.158	0.345
MonthDec:DummyYear5	-77.459	30.866	0.012
MonthFeb:DummyYear5	-14.779	32.109	0.645
MonthJan:DummyYear5	-72.372	32.844	0.028
MonthJul:DummyYear5	-9.202	50.683	0.856
MonthMar:DummyYear5	-70.974	29.096	0.015
MonthMay:DummyYear5	96.666	65.856	0.142
MonthNov:DummyYear5	-127.039	29.018	0.000
MonthOct:DummyYear5	-136.910	35.587	0.000
MonthSep:DummyYear5	-76.335	29.491	0.010
MonthAug:DummyYear6	-93.413	48.567	0.055
MonthFeb:DummyYear6	-19.179	15.497	0.216
MonthJan:DummyYear6	17.410	13.747	0.205
MonthMar:DummyYear6	-23.271	9.455	0.014
MonthMay:DummyYear6	14.993	18.586	0.420
MonthOct:DummyYear6	-86.572	22.331	0.000
MonthSep:DummyYear6	-40.412	13.204	0.002
MonthDec:DummyYear7	258.199	33.677	0.000
MonthFeb:DummyYear7	172.780	31.498	0.000
MonthJan:DummyYear7	256.815	55.789	0.000
MonthJul:DummyYear7	204.132	89.631	0.023
MonthMar:DummyYear7	132.431	27.370	0.000
MonthNov:DummyYear7	138.803	32.083	0.000
MonthAug:DummyYear8	-21.886	38.836	0.573
MonthOct:DummyYear8	-123.863	21.979	0.000

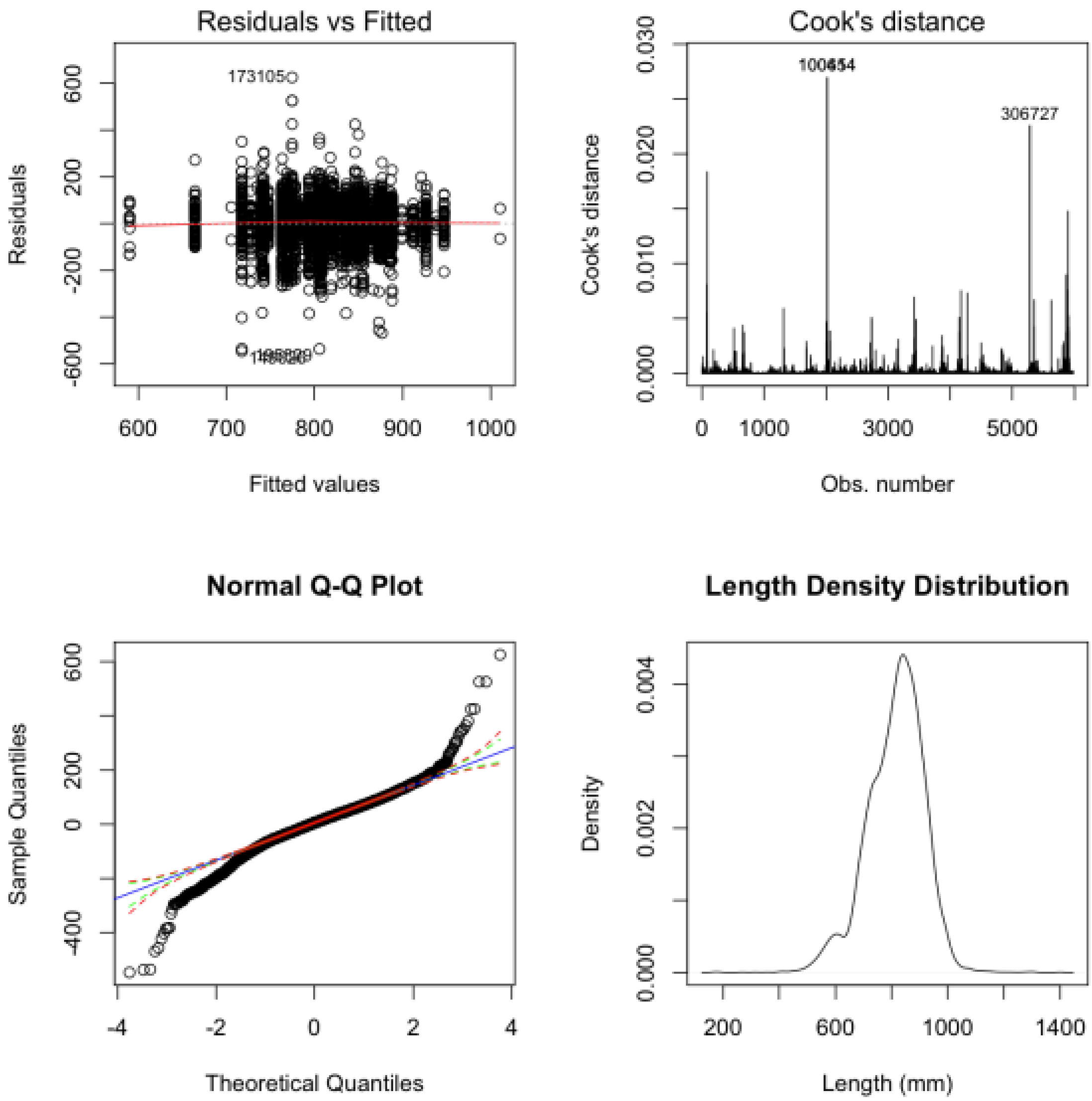

Figure 27. Diagnostic plots for the top linear model with interaction for Atlantic sharpnose shark. The distribution has long tails, but overall fits the assumption of normality and fits the data well across all lengths.

The strongest ordinary least squares linear model by BIC for Atlantic sharpnose sharks explains length as a function of year, fishing depth, gangion length, hook count, mainline length, and month (Table 31). Within the model, some years, some months, fishing depth, gangion length, and hook count are significant predictors of Atlantic sharpnose shark length (Table 31) The model is significant overall ($p < 0.01$) and explains 30.7% of the variance in Atlantic sharpnose shark length (Table 31). Diagnostics indicate a long-tailed distribution, but a good model fit overall (Figure 28). The OLS model is superior to the interaction model by BIC.

Table 31. The results of the top ordinary least squares linear model for Atlantic sharpnose shark by BIC. $R^2_{adj} = 0.317$, $p < 0.01$.

	Estimate	Std. Error	p-value
(Intercept)	712.788	14.269	0.000
DummyYear2	-94.387	20.225	0.000
DummyYear3	-137.518	12.592	0.000
DummyYear4	-33.725	10.918	0.002
DummyYear5	-4.602	10.419	0.659
DummyYear6	-17.997	10.208	0.078
DummyYear7	29.207	11.057	0.008
DummyYear8	67.603	10.161	0.000
DummyYear9	84.317	10.706	0.000
Fishing Depth	0.631	0.028	0.000
Ganglion Length	2.277	0.501	0.000
Hooks	-0.058	0.006	0.000
Mainline Length	6.623	0.879	0.000
MonthAug	-27.742	17.070	0.104
MonthDec	-58.678	6.584	0.000
MonthFeb	-15.479	4.866	0.002
MonthJan	-34.055	5.019	0.000
MonthJul	49.474	15.502	0.001
MonthJun	36.082	13.197	0.006
MonthMar	-27.259	3.982	0.000
MonthMay	26.324	7.186	0.000
MonthNov	-55.635	4.578	0.000
MonthOct	11.295	5.084	0.026
MonthSep	63.068	4.963	0.000

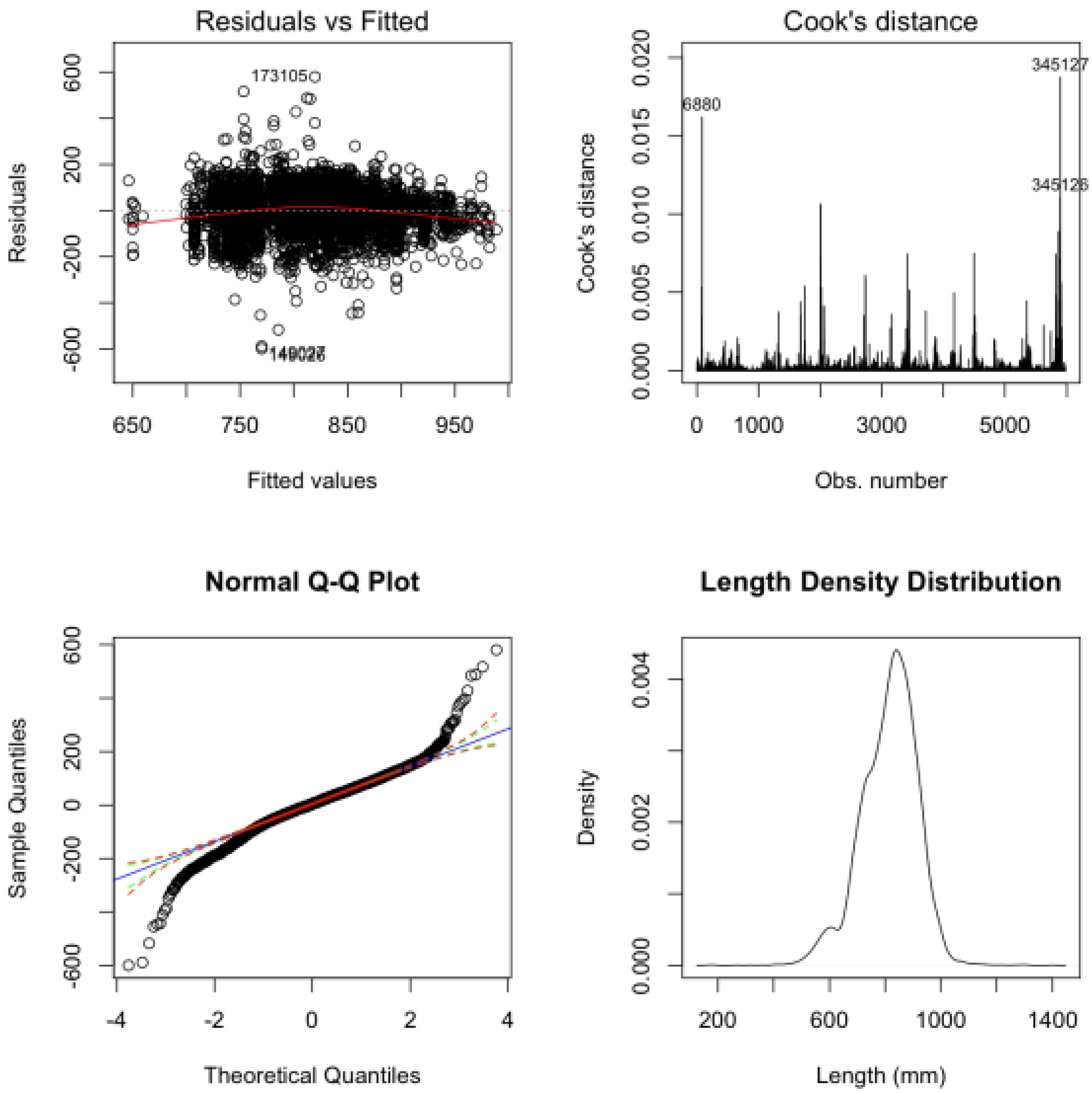

Figure 28. The results of the top ordinary least squares model for Atlantic sharpnose shark by BIC. The distribution is long-tailed, but otherwise satisfies assumptions. The model fits the data well across all lengths, though the model is slightly under-predicting length for very large and very small individuals (data poor regions).

2.4 Discussion

2.4.1 General Trends

These results indicate that fishing gear may explain a significant, albeit small, portion of the variance in length for some Gulf of Mexico reef fish species. While previous research has focused on gear fish size selectivity at a fishery level (Løkkeborg and Bjordal 1992; Erzini et al. 1996; Løkkeborg and Pina 1997; Huse and Soldal 2000), the results of this study suggest that size selectivity of longline gear may function at a species level instead. Evaluating gear selectivity at only fishery level may fail to capture trends that exist within each individual species. Additionally, this study indicates that previously unassessed parameters, such as those pertaining to hook placement (e.g. gangion length, hook distance), may play a role in size selectivity for some species.

Fishing depth was a factor in ordinary least squares models in explaining length for all but one species (jolthead porgy), and resulted in a significant positive increase in length for every species except mutton snapper (not significant) and scamp (negative). The trend of increasing fish length with depth has been well documented across several reef fish species and regions, and holds for most of the reef fish species analyzed here (Bell 1983; Macpherson and Duarte 1991; Wraith 2007; Jaxion-Harm and Szedlmayer 2015). For all species except scamp, fish length increased with increasing depth. Scamp are territorial and prefer complex structure (Gilmore and Jones 1992). Because the data analyzed are only for hooked fish, it is possible that fishers are unable to drop gear safely close enough to the complex structure preferred by the larger, more territorial fish and therefore the relationship between fish size and depth for the catch data does not reflect biological reality. For speckled hind, fishing depth was the only variable in the OLS model. Little is known about speckled hind life history, but the relationship between speckled hind length and depth has been previously established (Ross 1988), and is confirmed here. Further studies that do not rely on catch data (e.g. Wraith 2007) may elucidate the relationship between fish length and depth.

Temporal variables (month and year) were included in a number of models. Month was a significant explanatory variable in the OLS models for blacknose shark, red grouper, red snapper, mutton snapper, scamp, and red porgy. The months during which fish are largest varied across species, suggesting that there are optimal times during the year to catch large fish depending on the species targeted. Using this information to set seasons for fishing for each target species may help minimize undersize bycatch. For species that are not desired, avoiding seasons where the fish were largest, if practicable, may allow the largest individuals of the species to continue breeding so as to not disrupt the ecosystem. Year was included in the OLS models for blacknose shark, red grouper, red snapper, mutton snapper, scamp, gag grouper, and sharpnose shark. Year was relatively neutral in the blacknose shark and gag grouper models, with only one year showing significantly smaller catches. For red grouper, red snapper, mutton snapper, scamp, and sharpnose sharks, however, an overall trend towards larger fishes in later years is observed. While initially this might be attributed to legislation increasing legal size limits, the only legislation pertaining to size limit for these species after 2006 is Gulf of Mexico Reef Fish Fishery Management Plan

Amendment 27, which *reduces* red snapper minimum length. This suggests that several reef fish species in the Gulf of Mexico are attaining larger sizes before being caught, and other species are remaining at constant lengths. Such a result suggests that fishery management in the Gulf of Mexico in the past decade has been highly effective.

While prior studies have focused on the effects of the type and size of hook used on selectivity (Millar 1992; Piovano et al. 2010), the placement of hooks relative to each other was a significant factor for explaining length in several species. Gangion length and hook distance were significant in explaining the length of blacknose sharks, red grouper, red snapper, scamp, red porgy, and sharpnose sharks. Of these species, red snapper and red porgy generally school (Rodger and von Zharen 2011), while the remainder are solitary (Rodger and von Zharen 2011; Bacheler and Shertzer 2015; Florida Museum of Natural History 2016). For the schooling species, hook distance and gangion length had a significant negative impact on length, suggesting that placing hooks closer together is beneficial for catching the largest possible individuals, which should be part of the school. Hook distance was a significant positive predictor of length for blacknose shark, red grouper, and scamp, which are solitary and may avoid the fishing area if other fish are already present. Gangion length had a negative impact on blacknose and scamp length, both solitary species that may be larger when gangions allow for more space between hooks; a positive effect was documented for sharpnose, which did not follow the trend observed (Rodger and von Zharen 2011; Bacheler and Shertzer 2015; Florida Museum of Natural History 2016). While further research is necessary to confirm, this may be because the sharks are competing directly for prey.

Long gangions may drift toward each other during fishing, effectively putting the hooks closer together and contributing to avoidance of the area by other fish. Further research is necessary to clarify the influence and importance of hook placement parameters on fish length.

2.4.2 Commercially Important Species

Of the species analyzed, the following were targeted or captures by fishers between 2006-2014: general sharks (e.g. sharpnose, blacknose), red grouper, mutton snapper, red snapper, gag grouper, and scamp. Using the models derived herein to guide fishing practices may increase the mean length of fish caught, while also minimizing undersized bycatch of target species. Special attention should be focused on these species so as to guide future decision making.

Blacknose and sharpnose sharks were included in the general sharks category. Blacknose sharks caught during the month of January were 42.6 mm smaller; those in November, 140.2 mm smaller; and in December, 80.5 mm smaller than those caught in April (the baseline). Blacknose sharks caught in 2007 (year 3) were significantly smaller, but the size stabilized after this year. For sharpnose, smaller sharks were caught during years 2-4, but larger sharks during years 7-9. Particularly in the case of blacknose, fishing during the summer months may contribute to catching the largest possible fish and avoiding the smaller individuals in the winter season. While blacknose shark size seems to have stabilized, sharpnose sharks appear to be getting larger.

The grouper complex consists of red, scamp, and gag grouper. A strong seasonal effect was apparent for red grouper and scamp; month was not included in the gag grouper model. In general, scamp and red grouper were smallest during the late summer and into the fall, and largest during the winter months. For red grouper, fishing in deep water using long main lines and hooks spaced far apart appears to be the most effective combination for catching large fish. Fishing for gag grouper using long mainlines in deep water may contribute to catching larger fish. Scamp can be best targeted by fishing in shallower water using shorter gangions and hooks spaced further apart; such a configuration may allow the hooks to get closer to the complex structure favored by this species.

Red and mutton snapper were both included in the analysis. No consistent seasonal trend exists for these two species. Red snappers were smallest in January, and larger in the spring and fall into winter. Mutton snapper were largest in September and December but smaller in June. Using long mainlines for mutton snapper appears to be the most effective strategy, while red snapper fishers should increase soak time and fishing depth, and decrease gangion length.

These models are of considerable use for commercially targeted species. While this particular set of models accounts for size (and not species) selectivity, altering fishing gear to best target the largest individuals of the desired species may ultimately prove financially beneficial to fishers, and beneficial to managers working to minimize discard mortality.

2.4.3 Conclusions and Future Directions

Altering fishing practices to better suit the desired target species may contribute to catching larger individuals. Reduction of bycatch of undersized fish may allow more fish to survive to reproductive maturity. For managers, minimizing catch of undersized fish is also desirable. Fishing regulations must account for the potential mortality of undersized fish after being discarded. Changing fishing practices in accordance with the models here may minimize this uncertainty and allow populations to continue to grow, and eventually increase the population's maximum sustainable yield.

This study is the first to account for the influences of hook placement and proximity on size selectivity. While previous studies have evaluated the influences of hook size, the results have been inconclusive (Løkkeborg and Bjordal 1992; Erzini et al. 1996; Huse and Soldal 2000). Hook placement parameters (gangion length and/or hook distance) were significant predictors of fish length for six of 12 species analyzed here, indicating that hook placement may be an important factor in size selectivity of bottom longline gear. Future research in other areas should consider including these parameters, to determine whether the relationship between fish behavior and hook placement is consistent in other regions.

Further study is necessary to fully capture the size selectivity of longline gear and develop best fishing practices. Monitoring of reef fish catches will continue through the Southeast Fisheries Science Center (SEFSC) Galveston Reef Fish Observer Program, and these models should be tested against new data as it becomes available, and continually updated to best reflect the status of the fishery. The results of this study may also be provided to fishers as suggestions for modifying fishing practices, and the catches of fishers who choose to update their methods can be compared against those that have retained previous fishing practices. If considerable changes are observed, new gear regulations may be considered to minimize undersized bycatch. Further assessment of hook size and bait size may also prove beneficial in assessing size selectivity.

Ultimately, the results of this study suggest that manipulations in gear and set parameters may have a major influence on the size of the fish caught on longline gear. In the interest of maintaining a thriving longline reef fishery in the Gulf of Mexico, fishers should implement the recommendations provided here as soon as possible. Undersized bycatch cannot be avoided completely, but mitigating its impacts may have broad implications for both angling success and the strength of the fishery as a whole. While these recommendations are not a formula for catching only large fish (and should not be approached as such), minimizing undersized bycatch may be possible using the models derived.

3. TARGET SPECIES SUCCESS AS A FUNCTION OF GEAR AND SET METHODOLOGY*

3.1 Introduction

3.1.1 Bycatch Concerns

In the past few decades, fishery management has begun to adopt a holistic, ecosystem-based focus in favor of the traditional species-by-species management approach. This management style requires consideration of prey and predator species, environmental impacts, and interactions of these components (Kennelly and Broadhurst 2002; Pikitch et al. 2004). Once managers have identified the extent to which these considerations factor into their ecosystem of interest, managers must attempt to integrate these components into a cohesive management plan. While longline fishing imposes less environmental damage than more invasive methods like dredging, managers must still be aware of potential risks including disruption of trophic interactions (Chuenpagdee et al. 2003). While catches of target species are closely regulated, catches of non-target species may have unexpected impacts. The intent of this study is to assess gear configurations that contribute to increased probability of successfully catching the intended species.

Bycatch of non-target species is a concern in longline fishery management. Herein, bycatch is defined per Alverson (1999) as "…the capture of any species, size of

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species, or sex of species that is not the primary target(s) of a fishing activity." A significant portion of the literature focuses on avoiding bycatch of species outside the fishery (e.g. turtles, marine mammals, and seabirds) (Belda and Sánchez 2001; Southwood et al. 2008; Piovano et al. 2010). Incidental capture of these species has contributed to population declines in several instances, and requires further study (Lewison et al. 2004). However, bycatch of fishes that are not retained also carries significant negative consequences and serves as the major concern of this research. Discarded fish may experience physical injury or stress contributing to later negative impacts to the individual, lowering their fitness and potentially resulting in mortality (Alverson 1999; Davis 2005). While measures can be taken to minimize the adverse effects of catching and handling fish, configuring gear to minimize the potential for non-target fish catch may ultimately prevent stress or injury prior to its occurrence.

NOAA Fisheries (2016) aims to, "promote productive and sustainable fisheries and improve the recovery and conservation of protected resources," through an ecosystem-based management approach to its national bycatch reduction strategy. While several federal laws mandate bycatch prevention (e.g. Magnuson-Stevens Fishery Conservation and Management Act, Marine Mammal Protection Act, Endangered Species Act), each quantifies and manages bycatch differently. The national bycatch reduction strategy aims to unify these approaches through strengthening monitoring efforts, clarifying research needs, improving discard and take estimates, improving management measures, strengthening the effectiveness of law enforcement, and improving communication within NOAA Fisheries and with stakeholders (NOAA

Fisheries 2016). One strategy identified for improving management measures to reduce bycatch is to develop and implement species-specific bycatch reduction measures (NOAA Fisheries 2016). Through evaluating the most effective means of catching target species in the longline fishery, this research may ultimately provide the basis for species-specific bycatch reduction through altering fishing techniques.

3.1.2 Management of Species of Evaluated, 2006-2014

Fishing success must be considered in the context of the relevant management regulations. The Gulf of Mexico Fishery Management Council is responsible for preparing fishery management plans for federal waters. The federal commercial fishing regulations for several species studied herein mandate minimum length limits and catch quotas which may influence fishing success.

Two porgy species, two snapper species, and four grouper species were included in this study. Of the species studied, red porgy and jolthead porgy are not included in the Gulf of Mexico Reef Fish Fishery Management Plan (GMRFFMP) (Gulf of Mexico Fishery Management Council 2015). Mutton snapper have been managed simply, under a 12-inch total length minimum (GMRFFMP amendment 5) through the duration of the study period, with no trip catch limits or quotas. While these species may be managed at the state level, federal regulations have not been in effect during the study period. However, both snapper species (mutton and red) and all four grouper species (red, scamp, gag, and speckled hind) have been regulated for the duration of the study period.

Red snappers have been managed by total length limits and catch quotas throughout the study period. In 2006 and 2007, a class 1 or class 2 license allowed trip limit catches of 2,000 pounds for the former or 200 pounds for the latter, with a 15-inch minimum length. The fishery was closed in January, and opened from noon on the 1^{st} to noon on the 10^{th} of each month until the sub-quota of 3.06 million pounds (mp) was filled (via a March 1997 regulatory amendment). The remainder of the total 4.65-million-pound quota was released starting in October, following the same pattern until December 31^{st}. In 2008, the fishery transitioned to an individual fishing quota (IFQ) system, with a 13-inch total length limit and a total quota of 2.55 mp (GMRFFMP amendment 27). These regulations remained in effect in 2009. In 2010, 2012, and 2013, the quotas were increased to 3.542 mp (2010 regulatory amendment for red snapper), 3.664 mp (2011 regulatory amendment for red snapper), and 4.121 mp for 2012 and 4.257 mp for 2013 (both via 2012 regulatory amendment for red snapper) with the 13-inch length limit retained throughout.

Gag grouper are also managed under length and catch limits. From 2006-2008, gag groupers were subjected to a 24-inch total length limit, and managed under the shallow water grouper overall quota of 8.80 mp gw, with seasonal closures from February 15 to March 15 annually (Secretarial Amendment 1, 2004). A separate gag grouper quota (included under the total shallow water grouper quota) was instated at 1.32 mp for 2009, 1.41 mp for 2010, and 1.49 mp for 2011 (GMRFFMP amendment 30B). In 2011, an emergency interim rule restricted the gag grouper quota to 430,000 pounds of the net quota. The quota was lowered to 0.567 mp in 2012, 0.708 mp in 2013, 0.835 mp in 2014 (GMRFFMP amendment 32). Amendment 32 also lowered the total length minimum to 22 inches.

Scamp have been managed under an IFQ program with composite grouper quotas for the duration of the study period, with a 16-inch total length restriction throughout. From 2006-2008, scamp were included in the shallow water grouper quota of 8.80 mp gw (Secretarial Amendment 1, 2004). The shallow water grouper quota was set to 7.48 mp for 2009, 7.57 mp for 2010, and 7.65 mp in 2011 on (GMRFFMP amendment 30B). In all years, scamp caught after filling the shallow water grouper IFQ can be counted towards the deep-water grouper IFQ.

Red groupers were regulated under a separate quota throughout the study period. Minimum length was set at 20 inches but the length was lowered to 18 inches for the remaining years (Amendment 30B). Seasonal closures from February 15 to March 15 were in effect for 2006-2008 (November 2005 regulatory amendment, removed by amendment 30B). The catch quota was set to 5.31 mp gw for 2006-2008, and subsequently raised to 5.75 mp gw for 2009 (GMRFFMP amendment 30B). A 2010 regulatory amendment lowered the quota to 4.32 mp. From 2012 on, the red grouper quota was set at 6.03 mp (GMRFFMP amendment 32)

Speckled hinds have not been regulated by a minimum size at any point during the study period. From 2006-2009, a trip limit of 6,000 pounds was in effect for groupers, and speckled hinds were managed under the 1.02 mp gw deep water grouper quota (Secretarial Amendment 1, 2004). In 2010 and 2011, speckled hinds were moved into the shallow water grouper quota (GMRFFMP amendment 30B).

3.1.3 Bycatch Reduction Measures

Fishing technology developed with the intent of catching as many fish as possible. Bycatch and discard of fish has been documented as early as biblical times, and legal prohibition of bycatch dates back to the 14th century (Kennelly and Broadhurst 2002). However, the technological advances made during the 20th century allowed humans to extract fish at a rate faster than the population could replace them, ultimately leading to declines in several economically valuable fish stocks (Kennelly and Broadhurst 2002). Management and regulation of fisheries in the United States began in earnest with the institution of the Magnuson Act of 1976, and intensified with stricter laws and management plans through the 1980s (Kennelly and Broadhurst 2002). As public pressure to improve fishery management practices has increased over the last several decades, bycatch reduction strategies have become a focus for managers and industry.

A number of bycatch mitigation methods have been employed in the bottom longline fishery. Altering hook shape and size has proven useful in reducing bycatch of stingrays, and setting lines deeper or at night can reduce seabird hooking and entanglement (Hall et al. 2000; Belda and Sánchez 2001; Piovano et al. 2010). However, hook size selectivity appears to vary between species, with some bycatch reduction for certain species and no apparent effect for others (Erzini et al. 1996). Bait size, though potentially confounded with hook size, did not appear to affect the species and size selectivity of Portuguese red sea breams (Erzini et al. 1998). However, in the Norwegian haddock fishery, increasing bait size successfully reduced bycatch of undersized individuals (Huse and Soldal 2000). Shortening gear soak times may contribute to a decline in shark bycatch, without reducing catches of red grouper or red snapper (Mitchell 2014). Similarly, bycatch of elasmobranch species in the Portuguese artisanal hake fishery was significantly reduced following the removal of hooks set at deeper depths, with only minor reduction of target species catch (Coelho et al. 2003).

While bycatch reduction is a worthwhile goal, fishery managers must be conscientious of bycatch reduction techniques that may negatively impact target catch. For instance, utilizing hooks with inedible plastic bodies successfully reduced bycatch of undersized haddock, but reduced overall catch (Huse and Soldal 2000). Bycatch reduction technologies that negatively impact catch success of the target species are unlikely to be adopted voluntarily by the fishing industry, and will have a negative financial impact on fishers if mandated. Ultimately, bycatch reduction methods should aim to improve selectivity without reducing the catch of the target species.

The objective of this study is to identify fishing gear and set characteristics that favor successfully catching the target species. Prior research has not addressed month-to-month changes in catch success, and has not included hook placement parameters. For the intent of this study, fish that were not legally retained for commercial purposes were considered bycatch. Presumably, fishers are not targeting a species after the required quotas have been filled. Therefore, quota restrictions should have only limited impact on fishing success. However, factors contributing to the lowering of the quota (e.g. population declines) may influence fishing success. For species with length restrictions, success may improve or decline if length restrictions are lowered or raised, and therefore these factors will be considered in addressing the results. Ultimately, the intent of this study is to identify the best fishing practices for each target species. These models will contribute to reducing bycatch (and thereby improve the fishery system), and reduce the economic investment of time and capital which will strengthen the fishing community.

3.2 Methods

Data were collected as described in section 1.2 by observers from the SEFSC Galveston Reef Fish Observer Program between 2006-2014. All statistical analysis was conducted using R version 3.2.3 “Wooden Christmas-Tree” or later.[4] The purpose of the models derived in this chapter is to predict the success of obtaining a given target species as opposed to any other reef fish species. For the purpose of this study, a “success” was considered a fish of the target species of interest that was coded as “kept for consumption purposes” by the fishery observers. A “failure” was considered catch of any other reef fish species or an individual of the target species that was not kept; bycatch of protected species was not included, nor were empty hooks. Only species with more than 500 catches of individuals were considered. Blacknose sharks (7 individuals kept), sharpnose sharks (11 individuals kept), and leopard toadfish (3 individuals kept) were excluded from the analysis due to the limited number of successes. Prior to analysis, data entries with missing values were removed from the dataset as necessitated by the software package. The total number of catches included in the sample after

[4] Mention of trade names or commercial companies is for identification purposes only and does not imply endorsement by the National Marine Fisheries Service, NOAA.

removing entries with missing information was 339,179. The species analyzed and the number of successes are given in Table 32.

As in chapter 2, only variables fishers can manipulate were considered as explanatory variables: soak time in hours; fishing depth in feet; main line length in miles; hooks deployed (actual when available, and approximate otherwise); gangion length in feet; hook distance in feet; and month of the year. Year was included as a measurement of changes over time. Years are numbered from 1 (2006) to 9 (2014).

Table 32. The species names and number of successful catches (coded by observers as kept for consumption).

Common Name	Scientific Name	Number of Successes
Jolthead Porgy	*Calamus bajonado*	1162
Speckled Hind	*Epinephelus drummondhayi*	468
Red Grouper	*Epinephelus morio*	187171
Red Snapper	*Lutjanus campechanus*	5316
Mutton Snapper	*Lutjanus analis*	2147
Scamp	*Mycteroperca phenax*	6446
Gag Grouper	*Mycteroperca microlepis*	3593
Red Porgy	*Pagrus pagrus*	587

Binomial regression models were constructed in R using the complementary log-log link function for all species (except red grouper) to account for the low number of successes out of the total dataset. For red grouper, the log odds link function was used as the success rate was very high. The final model was determined using backwards regression. Variables were tested for significance using the “drop1” command in R, which computes the significance of all single terms in the model. The least significant variable was removed at each step until all variables remaining were significant at $p \leq$

0.01. Models were compared using the Bayesian information criterion (BIC) to verify that the final model was indeed the most suitable for the data. An ANOVA was used to assess the significance of the final model when compared with the null (intercept-only) model.

McFadden's R^2 (R^2_{McF}) was calculated to determine the proportional reduction in error variance using the equation below, where L_M is the log-likelihood of the final model, and L_0, the log-likelihood of the null (intercept only) model (Allison 2014):

$$R^2_{McF} = 1 - \frac{\ln L_M}{\ln L_0}$$

A Cook's distance plot was evaluated for the presence of influential points. For the red grouper log odds model, the coefficients represent the change in the log odds of success associated with the variable of interest, when all other variables are held constant. For all other models, the coefficients represent a change in the complementary log-log odds.

3.3 Results

3.3.1 Jolthead Porgy

The final model for jolthead porgy predicts fishing success as a function of fishing depth, gangion length, hook distance, hook count, month, and year (Table 33). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p < 0.01$). All months except January and October were significant improvements as compared with the April baseline, and all years except year 2 were significant against year 1 (Table 33). Fishing depth, gangion length, and mainline length increases contributed to increased probability of catching jolthead porgy, while increases in hook distance and hook count contributed to declines (Table 33). The model represents an approximately 12.4% improvement over the null model (R^2_{McF} = 0.124).

Table 33. The results of the binomial regression model for jolthead porgy derived by backwards regression. $R^2_{McF} = 0.124$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-11.267	0.478	0.000
Fishing Depth	0.015	0.001	0.000
Ganglion Length	0.037	0.013	0.005
Hook Distance	-0.022	0.003	0.000
Mainline Length	0.183	0.025	0.000
Hooks	-0.001	0.000	0.000
MonthAug	1.133	0.185	0.000
MonthDec	0.811	0.209	0.000
MonthFeb	0.585	0.164	0.000
MonthJan	0.200	0.185	0.281
MonthJul	1.235	0.163	0.000
MonthJun	1.956	0.143	0.000
MonthMar	0.890	0.154	0.000
MonthMay	0.504	0.176	0.004
MonthNov	1.626	0.169	0.000
MonthOct	0.067	0.265	0.801
MonthSep	-0.981	0.315	0.002
DummyYear2	0.277	0.546	0.612
DummyYear3	1.201	0.724	0.097
DummyYear4	2.049	0.434	0.000
DummyYear5	1.214	0.433	0.005
DummyYear6	1.841	0.426	0.000
DummyYear7	1.217	0.442	0.006
DummyYear8	2.020	0.421	0.000
DummyYear9	2.608	0.446	0.000

3.3.2 Speckled Hind

The resulting binomial regression model for speckled hind included fishing depth, hook count, month, and year (Table 34). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p <$ 0.01). Increased fishing depth and hook count contributed positively to successfully catching speckled hind (Table 34). The months of March and October significantly increased the complementary log-log likelihood of catching speckled hind when compared with the April baseline (Table 34). While year was significant within the model, no individual years represented a significant deviation from the year 1 baseline. The model constitutes a 20.4% improvement over the null model ($R^2_{McF} = 0.204$).

Table 34. The results of the binomial regression model for speckled hind derived by backwards regression. $R^2_{McF} = 0.204$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-17.648	1.111	0.000
Fishing Depth	0.036	0.001	0.000
Hooks	0.001	0.000	0.001
MonthAug	0.849	0.242	0.001
MonthDec	0.164	0.330	0.619
MonthFeb	0.298	0.224	0.184
MonthJan	0.569	0.261	0.029
MonthJul	0.501	0.237	0.035
MonthJun	0.529	0.221	0.017
MonthMar	1.010	0.219	0.000
MonthMay	0.319	0.270	0.237
MonthNov	0.792	0.303	0.009
MonthOct	1.250	0.273	0.000
MonthSep	-0.939	0.486	0.053
DummyYear2	1.440	1.066	0.177
DummyYear3	-10.825	162.671	0.947
DummyYear4	2.223	1.026	0.030
DummyYear5	2.587	1.013	0.011
DummyYear6	1.808	1.017	0.075
DummyYear7	1.357	1.033	0.189
DummyYear8	2.208	1.014	0.029
DummyYear9	-0.621	1.109	0.576

3.3.3 Red Grouper

Because of the high number of red grouper catches in the dataset (n = 152,008), the log odds link function was used for the binomial regression model. The final model for red grouper included soak time, gangion length, hook distance, mainline length, hook count, month, and year (Table 35). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p < 0.01$). Increased mainline length and hook count significantly improved catch success of red grouper, whereas soak time, gangion length, and hook distance contributed to decreased success (Table 35). All months except May represented significant changes from the April baseline, with increased success in January, February, September, October, and December, and decreases in March, June, July, August, and November (Table 35). While the model was significantly better than the null model, the final model represents only a 2.3% improvement ($R^2_{McF} = 0.023$).

Table 35. The results of the binomial regression model for red grouper derived by backwards regression. $R^2_{McF} = 0.023$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-0.892	0.028	0.000
Soak Time	-0.030	0.003	0.000
Ganglion Length	-0.021	0.001	0.000
Hook Distance	-0.002	0.000	0.000
Mainline Length	0.061	0.003	0.000
Hooks	0.000	0.000	0.000
MonthAug	-0.101	0.018	0.000
MonthDec	0.163	0.014	0.000
MonthFeb	0.186	0.011	0.000
MonthJan	0.070	0.014	0.000
MonthJul	-0.046	0.016	0.005
MonthJun	-0.065	0.015	0.000
MonthMar	-0.029	0.010	0.006
MonthMay	-0.024	0.013	0.053
MonthNov	-0.049	0.014	0.000
MonthOct	0.041	0.012	0.001
MonthSep	0.069	0.011	0.000
DummyYear2	0.345	0.028	0.000
DummyYear3	0.191	0.041	0.000
DummyYear4	0.296	0.025	0.000
DummyYear5	0.379	0.021	0.000
DummyYear6	0.696	0.021	0.000
DummyYear7	0.714	0.022	0.000
DummyYear8	0.941	0.021	0.000
DummyYear9	0.893	0.023	0.000

3.3.4 Red Snapper

The final model for red snapper predicts fishing success using fishing depth, gangion length, mainline length, hook count, month, and year (Table 36). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p < 0.01$). All months were significantly different from the April baseline, with decreased success in June, July, and August, and increased success in other months (Table 36). While year 2 represented a decline in success and year 7 was not significant, all other years represent a significant increase in catch success (Table 36). Maineline length contributed to a decline in catch success, but fishing depth, gangion length, and hook count were all significantly positive (Table 36). The model represents 5.9% improvement over the null model ($R^2_{McF} = 0.059$).

Table 36. The results of the binomial regression model for red snapper derived by backwards regression. $R^2_{McF} = 0.059$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-7.632	0.173	0.000
Fishing Depth	0.011	0.000	0.000
Ganglion Length	0.059	0.005	0.000
Mainline Length	-0.101	0.013	0.000
Hooks	0.000	0.000	0.000
MonthAug	-0.935	0.132	0.000
MonthDec	1.108	0.064	0.000
MonthFeb	0.433	0.057	0.000
MonthJan	0.512	0.064	0.000
MonthJul	-0.697	0.098	0.000
MonthJun	-1.402	0.110	0.000
MonthMar	0.279	0.060	0.000
MonthMay	0.223	0.068	0.001
MonthNov	0.713	0.066	0.000
MonthOct	0.198	0.075	0.008
MonthSep	0.238	0.063	0.000
DummyYear2	-1.228	0.321	0.000
DummyYear3	2.001	0.177	0.000
DummyYear4	0.799	0.156	0.000
DummyYear5	0.947	0.144	0.000
DummyYear6	0.764	0.145	0.000
DummyYear7	0.041	0.155	0.792
DummyYear8	0.984	0.143	0.000
DummyYear9	0.740	0.154	0.000

3.3.5 Mutton Snapper

The final model for mutton snapper predicts catch success using soak time, fishing depth, gangion length, hook distance, month, and year (Table 37). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p < 0.01$). Months February, March, and November were not significant when compared to the April baseline (Table 37). January, May, June, August, September, October, November, and December had a negative impact on catch success, while June and July were positive contributors (Table 37). Year 3 was not significant, but all other years represented decreased catch success (Table 37). Soak time, fishing depth, gangion length, and hook distance all contributed positively to catch success (Table 37). The model represents a strong 33% improvement over the null model (R^2_{McF} = 0.330).

Table 37. The results of the binomial regression model for mutton snapper derived by backwards regression. $R^2_{McF} = 0.330$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-6.789	0.244	0.000
Soak Time	0.170	0.012	0.000
Fishing Depth	0.008	0.001	0.000
Ganglion Length	0.130	0.012	0.000
Hook Distance	0.017	0.003	0.000
MonthAug	-1.306	0.217	0.000
MonthDec	-0.791	0.212	0.000
MonthFeb	-0.386	0.195	0.048
MonthJan	-0.867	0.209	0.000
MonthJul	3.005	0.130	0.000
MonthJun	2.057	0.133	0.000
MonthMar	-0.442	0.192	0.022
MonthMay	-0.717	0.220	0.001
MonthNov	-0.046	0.169	0.786
MonthOct	-2.660	0.380	0.000
MonthSep	-1.063	0.202	0.000
DummyYear2	-3.314	0.212	0.000
DummyYear3	-13.838	122.987	0.910
DummyYear4	-3.689	0.254	0.000
DummyYear5	-1.984	0.132	0.000
DummyYear6	-3.819	0.149	0.000
DummyYear7	-6.699	0.592	0.000
DummyYear8	-2.354	0.130	0.000
DummyYear9	-1.794	0.205	0.000

3.3.6 Scamp

The final model for scamp predicts catch success with soak time, fishing depth, gangion length, month, and year (Table 38). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p < 0.01$). All months represented a significant increase in success over the April baseline except for September and November, which were not significant (Table 38). Years 3, 6, and 9 were not significantly different from year 1, but years 2, 4, 5, 8, and 9 all represented a significant improvement in catch success (Table 38). Fishing depth and gangion length contributed positively, but soak time significantly decreased catch success (Table 38). The model represents an 18.3% improvement over the null model ($R^2_{McF} = 0.183$).

Table 38. The results of the binomial regression model for scamp derived by backwards regression. $R^2_{McF} = 0.183$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-10.172	0.185	0.000
Soak Time	-0.098	0.012	0.000
Fishing Depth	0.024	0.000	0.000
Ganglion Length	0.099	0.006	0.000
MonthAug	0.327	0.068	0.000
MonthDec	0.394	0.073	0.000
MonthFeb	0.295	0.060	0.000
MonthJan	0.527	0.065	0.000
MonthJul	0.216	0.063	0.001
MonthJun	0.335	0.058	0.000
MonthMar	0.285	0.063	0.000
MonthMay	0.696	0.063	0.000
MonthNov	0.180	0.076	0.018
MonthOct	0.244	0.083	0.003
MonthSep	0.019	0.075	0.801
DummyYear2	0.736	0.176	0.000
DummyYear3	-12.591	67.275	0.852
DummyYear4	0.568	0.166	0.001
DummyYear5	0.897	0.159	0.000
DummyYear6	0.096	0.159	0.547
DummyYear7	0.508	0.164	0.002
DummyYear8	1.039	0.157	0.000
DummyYear9	-0.141	0.171	0.410

3.3.7 Gag Grouper

The model for gag grouper predicts catch success with soak time, fishing depth, gangion length, hook count, month, and year (Table 39). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p < 0.01$). Fishing depth, gangion length, and hook count increased success, and soak time decreased catch success (Table 39). All months were significant improvements over the April baseline (Table 39). Years 3, 6, and 7 were not significant, but all other years represent an increase in fishing success. The model was a 9% improvement over the null model ($R^2_{McF} = 0.090$).

Table 39. The results of the binomial regression model for gag grouper derived by backwards regression. $R^2_{McF} = 0.090$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-8.939	0.192	0.000
Soak Time	-0.097	0.016	0.000
Fishing Depth	0.015	0.000	0.000
Ganglion Length	0.054	0.007	0.000
Hooks	0.000	0.000	0.000
MonthAug	0.750	0.093	0.000
MonthDec	0.918	0.089	0.000
MonthFeb	0.432	0.091	0.000
MonthJan	0.533	0.102	0.000
MonthJul	0.142	0.099	0.153
MonthJun	0.326	0.087	0.000
MonthMar	0.562	0.086	0.000
MonthMay	1.134	0.083	0.000
MonthNov	0.413	0.098	0.000
MonthOct	0.688	0.098	0.000
MonthSep	0.730	0.087	0.000
DummyYear2	1.481	0.169	0.000
DummyYear3	-0.942	0.474	0.047
DummyYear4	0.885	0.167	0.000
DummyYear5	0.846	0.157	0.000
DummyYear6	-0.333	0.161	0.038
DummyYear7	0.116	0.169	0.494
DummyYear8	0.956	0.154	0.000
DummyYear9	0.499	0.174	0.004

3.3.8 Red Porgy

The final model for red porgy predicts success as a function of fishing depth, gangion length, hook distance, mainline length, month, and year (Table 40). No issues with VIF or influential points were identified, and the model was a significant improvement from the null model ($p < 0.01$). Fishing depth and gangion length increases resulted in increased red porgy catch success, whereas hook distance and mainline length were negative contributors (Table 40). Months August, January, November, and September were not significantly different from the April baseline; February and December saw decreased catch success, whereas March, May, June, July, and October resulted in catch success improvement. The model represents an 12% improvement over the null model ($R^2_{McF} = 0.120$).

Table 40. The results of the binomial regression model for red porgy derived by backwards regression. $R^2_{McF} = 0.120$, $p < 0.01$.

	Estimate	Std. Error	*p*-value
(Intercept)	-9.420	0.385	0.000
Fishing Depth	0.022	0.001	0.000
Ganglion Length	0.124	0.019	0.000
Hook Distance	-0.025	0.005	0.000
Mainline Length	-0.131	0.036	0.000
MonthAug	0.424	0.233	0.069
MonthDec	-1.143	0.368	0.002
MonthFeb	-1.198	0.249	0.000
MonthJan	-0.105	0.215	0.624
MonthJul	0.536	0.200	0.007
MonthJun	1.195	0.166	0.000
MonthMar	0.507	0.187	0.007
MonthMay	0.568	0.206	0.006
MonthNov	-0.305	0.303	0.315
MonthOct	0.939	0.228	0.000
MonthSep	-0.287	0.247	0.245
DummyYear2	-2.033	0.485	0.000
DummyYear3	-12.895	195.088	0.947
DummyYear4	-0.721	0.296	0.015
DummyYear5	-1.172	0.250	0.000
DummyYear6	-1.385	0.243	0.000
DummyYear7	-1.006	0.280	0.000
DummyYear8	-1.808	0.244	0.000
DummyYear9	-0.599	0.322	0.063

3.4 Discussion

3.4.1 Porgys

Neither red nor jolthead porgys have been federally regulated with catch or total length limits during the study period. Jolthead porgy catch success was increased with increasing fishing depth, gangion length, mainline length, and hook count. While mainline length had a similar effect on jolthead porgy length (chapter 2), hook count increased the probability of catch success but decreased jolthead porgy length. Soak time, which contributed to decreased jolthead porgy length, was not included in the catch success model. This suggests that fishers may need to balance hook count depending on whether larger fish or more frequent successes are the priority. Neither month nor year were significant in the length model, but both contributed in the catch success model. The months of June, July, and August had significantly reduced catch success when compared to the April baseline, whereas all other months saw significantly greater catch success than April. This result suggests that fishing for jolthead porgys is most successful from September to May, and lower in the summer months. A slight decline in catch success occurred in year 2 (2007), but all other years except year 7 (2012) saw significantly greater catch success than the year 1 (2006) baseline.

Red porgy catch success increased significantly with gangion length and fishing depth, but declined with hook distance and mainline length. Hook distance and fishing depth were also included in the overall length model (chapter 2), and contributed to catch success in the same fashion. Catch success was significantly lower in December and February, and significantly higher in the spring and summer (March, May, June, July, and October). The length model followed a similar trend, except for February where fish were larger although catch success was lower. Year was not a factor in the length model, but the catch success model suggests an overall decline in red porgy catch success, with only years 3 and 9 (2008 and 2014) not significantly lower than year 1. The results of this model suggest that increasing fishing depth and decreasing hook distance are the most important for catching red porgys, as these factors contributed to both overall catch success and length. Spring and summer are the best times to catch large and retainable red porgys. However, the overall decline in catch success from year 1 indicates that either fishers are keeping fewer red porgys, or that overall catch success is declining. Further study is necessary to assess whether a population decline is occurring, and whether federal regulation has become necessary.

3.4.2 Snappers

Throughout the study period, mutton snappers have been regulated with a 16-inch total length minimum but no quotas or trip limits. Fishing depth, soak time, gangion length, and hook distance all contributed to increased catch success. In the length model (chapter 2), fishing depth was included but not significant, and mainline length alone significantly contributed to increased length. August, September, October, December, January, and March, and May saw significantly lower catch success than the April baseline. June and July appear to be the best times for fishing, as these months were the only months with positive coefficients. However, in the length model, fish caught in June were significantly smaller, and the largest fish were caught in the winter months. This suggests that fishers must balance the risks of catching more, smaller fish, or fewer, larger individuals. Additionally, while the annual trend shows an increase in mutton snapper length, the catch success model suggests an overall decline in kept mutton snapper. Further research is necessary to determine whether this is due to fisher selection, or a population decline requiring management intervention.

Red snapper catch success was significantly improved with increasing fishing depth, gangion length, and hook count, and declined with mainline length. In the length model (chapter 2), fishing depth increased length, but gangion length decreased fish length. Soak time was significant in the length model but did not affect catch success. June, July, and August had significantly lower catch success, but all other months were significantly higher than the April baseline. While the smallest fish were caught in January in the length model, in general the largest fish were caught in the fall through spring months. Red snapper have seen significant regulatory change over time, with the initiation of the IFQ system in 2008 and quota increases in 2010, 2012, and 2013, and a decrease in the total length requirement from 15 inches to 13 inches in 2008. While year 2 (2007) had significantly lower catch success, all other years except year 7 (2012) had significantly increased catch success when compared with year 1. In the length model, all years saw significantly increased length. These results suggest that the IFQ system has been extremely effective in regulating red snapper.

3.4.3 Groupers

Speckled hind catch success improved significantly with fishing depth and hook count; fishing depth also contributed significantly in the speckled hind length model (chapter 2). Neither month nor year were included in the length model, but both were significant in the catch success model. The greatest speckled hind success compared with the April baseline was recorded in the months of October, November, and March, indicating that the winter months may be the best time for catching speckled hind. While year was significant within the model, no individual year deviated significantly from the year 1 baseline. Interestingly, speckled hind management has changed dramatically over the study period, with the species being moved from the deep-water grouper to shallow-water grouper quota in 2010, and the quota lowered in 2012. Despite these regulatory changes, catch success of speckled hind has not changed between 2006 and 2014.

Red grouper catch success improved significantly with mainline length and hook count, but declined with fishing depth, gangion length, and hook distance. Mainline length had a positive effect in the length model (chapter 2), but hook distance and fishing depth contributed to larger fish but had a negative impact on catch success. Again, fishers must prioritize fish size or catch success. Seasonality plays an important role in red grouper catch success, with significantly lower success in March, June, July, August, and November, and significantly higher success in September, October, December, January, and February when compared with the April baseline. In the length model, fish were significantly smaller in the summer months, suggesting that red grouper fishing will be most successful in the late fall and winter months. The red grouper catch quota was raised in 2009, and lowered in 2012, with the total length minimum raised in 2008. Despite these changes, all years showed significantly greater catch success when compared with the year 1 baseline, with greater gains in later years.

Scamp catch success improved with fishing depth and gangion length and declined with soak time. Interestingly, scamp length declined with fishing depth and gangion length, indicating that fishers may need to assess whether it is more beneficial to catch more, smaller fish, or fewer, larger fish. Increased hook distance increased scamp length, but did not impact catch success. All months except September and November had significantly higher catch success than the April baseline. In the length model, fish were significantly smaller in May, August, and September, and significantly larger in January, February, and July. Fishing success for scamp may be best in the late winter and early spring. The catch quota for scamp was lowered in 2009, raised in 2010, and lowered again in 2012. Significant increases in catch success when compared with the year 1 baseline were recorded in years 2 (2007), 4 (2009), 5 (2010), 7 (2012), and 8 (2013). This indicates that quota changes did not negatively impact fishing success, as increases were documented in the periods surrounding the quota lowering.

Gag grouper catch success increased significantly with fishing depth, gangion length, and hook count, and declined with soak time. Fishing depth also positively influenced gag grouper length, as did mainline length. Month was not significant within the gag grouper length model, but all months except July had significantly greater catch success than the April baseline. This suggests that while the summer months may be slightly worse for catching gag grouper, in general fishing year-round is successful. The gag grouper total length requirement was lowered in 2013. Gag were given a separate quota in year 4 (2009), which was lowered in 2010. In 2011 an emergency rule limited the total catch to less than half a million pounds, and the quota was lowered dramatically in 2012. Year was significant in the length model, but only year 6 (2011) deviated significantly lower than year 1. Significant increases in catch success were documented in year 2 (2007), 4 (2009), 5 (2010), 8 (2013), and 9 (2014). These increases in catch success in later years indicate that the quota changes effectively improved catch success, though further research is required to assess whether this improvement occurred at the population level or resulted from reduced fishing effort.

3.4.4 Conclusions and Future Directions

The results of this study indicate that altering fishing practices can influence the success of obtaining the target species. Changing fishing practices to reflect the outcome of these models may reduce bycatch of non-target species or individuals of the target species which are not legally retainable. Combining the results of these models with the results of the length maximization models (chapter 2) may ultimately contribute to bycatch reduction and greater fishing success. Through the utilization of these results, fishers can maximize their catch, reducing the time and capital spent to obtain fish. Bycatch reduction may have long term positive environmental impacts.

This study represents the first to include hook placement and proximity influences on species selectivity. Gangion length, hook distance, hook count, or a combination of these factors were included in every size selectivity model derived herein. Future research in longline fishing selectivity should address these factors, as they quantify the spatial proximity of the fish to each other during fishing. Whether species are solitary or schooling, interactions with other fish (caused by hooks located close together, on short gangions, or because of the number of hooks set) may influence species selectivity.

Further study is necessary to quantify whether the changes over time that have been recorded are a result of improved population strength or a function of increased fishing success. However, in general, most species saw an improvement in catch success over time. Two species, red porgy and mutton snapper, saw declines over the study period. Interestingly, these two species have not been federally regulated by catch quotas and only mutton snapper have a total length limit in place. While some state regulations are in place, these declines suggest that federal management intervention may be appropriate to prevent further catch success declines in the future.

The results of this study ultimately indicate that manipulating gear and set parameters and seasonality may have an influence on the ability of fishers to successfully obtain the targeted species. Fishers should consider implementing the gear configuration recommendations contained herein to improve their catch success and reduce the resources spent to catch the desired amount of fish. When considered in tandem with the length maximization models in chapter 2, fishers can make informed decisions regarding the best fishing practices. Although these studies do not guarantee that fishers will always obtain the desired species, using these recommendations as a guide may ultimately contribute to reduced bycatch and improved fishing success.

4. IMPLICATIONS, CONCLUSIONS, AND FUTURE DIRECTIONS

4.1 Research Implications

The best scientific information, without meaningful application, does not actively benefit society. In this instance, the results of this study may be directly applied to fishery management. Indeed, scientific information is required for fishery management plan development. In the United States, such research is federally mandated; all fishery management plans (FMPs) must be based on "the best scientific information available," per National Standard 2 (50 CFR Ch. VI § 600.315). This includes biological, ecological, economic, and social information, and requires thorough analysis by managers before implementing any regulations. However, I suggest that the factors addressed in this mandate are incomplete, and an analysis of existing fishing methods and suggestions for best practices should be included if the fishery is actively being exploited. The results contained herein will enhance the management of Gulf of Mexico longline reef fish fisheries through addressing best fishing practices at a species-specific level. Best fishing practices have been previously understudied and represent an opportunity to enhance management.

There is a distinct lack of understanding regarding the effects of gear on fishing success. Multiple studies have attempted to quantify the effects of hook size and bait size or the fishing conditions (Løkkeborg and Bjordal 1992; Erzini et al. 1996; Huse and Soldal 2000; Ward and Myers 2005a; Watson and Kerstetter 2006), but these studies have failed to address fishing gear and setup methodology in a holistic manner. While studies have focused on individual components of fishing gear (such as hook size or bait type), fishing gear variables do not work independently. Using modeling to assess a range of variables in unison ultimately captures a more complete picture of fishing success.

The results of this research can be used to address how configuration of gear can influence fish size, and may provide recommendations for configuring gear in order to catch the largest individual fish on a species-by-species basis. Modeling allows for consideration of several factors that can be controlled by fishers simultaneously, rather than considering factors in isolation as previous studies have done. Minimizing bycatch of non-target species is also a concern for managers, as discard mortality may negatively impact a population and can be difficult to quantify (Alverson and Hughes 1996). While previous studies have focused on reducing bycatch of specific non-target species (such as sharks, rays, seabirds, and turtles) (Shepherd and Myers 2005; Ward and Myers 2005a, b; Watson et al. 2005; Piovano et al. 2010), there is no information available on how to improve the probability of catching the target species. Finally, while some information on catch-per-unit effort is available for the fishery (Scott-Denton et al. 2011), questions regarding catch distribution over time and space have not been previously addressed. The questions presented in each component of this dissertation advance the understanding of Gulf of Mexico longline reef fish fisheries by addressing factors previously not given sufficient attention.

This study represents a unique opportunity for managers to enhance the education of Gulf fishers, while also increasing engagement with fishery-dependent communities. At first glance, fishers and managers appear to be on opposing sides of a complex problem: fishers want to remove as many fish as possible, and managers want to limit removal. However, healthy and productive fish populations are in the best interest of both groups over the long term. By using the information in this study, fishers should be able to obtain larger individuals (of legal size to retain) of the target species, improving fishing trip efficiency by reducing capital spent to obtain catch. Managers benefit from the minimization of non-target and undersized bycatch, which minimizes uncertainty in setting total allowable catch. This increase in total allowable catch also benefits fishers, who may be able to harvest more fish in future seasons without adversely impacting the population.

Within the fisher population, managers must pay special attention to communities economically dependent on fisheries. Per National Standard 9 (50 CFR Ch. VI § 600.345), FMP management measures must consider the importance of fisheries to communities, and in so far as possible, sustain their participation in the fishery and minimize adverse economic impacts. Through implementing best fishing practices in reef fish fisheries and the anticipated improvements in population health resulting through bycatch reduction, communities dependent on the success of reef fish fisheries should increase their prosperity.

The benefits of this study to society are direct and tangible. National Standard 1 (50 CFR Ch. VI § 600.310) mandates that all FMPs must establish the optimum yield (OY) of a fishery, where the OY is the amount of fish removed that provides the greatest overall benefit to the nation with respect to biological, ecological, economic, and social factors. A large, thriving fishery is in the best interest of stakeholders who are involved directly in the fishery as a fisher, processor or consumer. Through reductions in bycatch, fish stocks may grow and allow for an increase in OY, resulting in even greater economic success in the fishery. Improved fishing success also generates an economic benefit and improved efficiency through reductions in labor and capital required to harvest fish at the current OY. Such economic benefits can bolster fishing communities and the overall economy of the nation. The broader impacts of the research proposed herein are considerable, with benefits to the fishery, fishery communities, and management sectors.

4.2 Future Directions

Broad dissemination of these results to fishers, managers, and the scientific community via publication of scientific papers and fishing guidelines will enhance the understanding of those with a vested interest in Gulf of Mexico longline reef fisheries. Through this study, communication between managers and fishers may be improved as the industry works together with managers to develop the most efficient fishing practices. Educating fishers on best practices for their particular target species will not only benefit fishers economically, but reduce the impact of undesirable impacts on the fishery. Managers interpreting these results and educating fishers on best practices broadens the impact of the study.

Sharing the methods employed with other fishery management councils nationwide should be a priority. This may encourage the development of similar studies for other fisheries and in other regions, and help to enhance the network of fishery management in the United States. If an observer program has not already been implemented, establishing one should be a priority, particularly for economically important and high bycatch risk fisheries. Commercial fishery landings in the United States were worth over $5 billion as of 2015, and investing in enhancing fishing success may increase this total by catching more valuable (e.g. larger) fish and reducing lost capital (e.g. bait lost to non-target catches). Eventually, should such studies prove useful, including a best fishing practices section in fishery management plans for species that are already exploited, may become a common practice. While this dissertation focuses on longline gear for reef fishing, the methods employed can be readily adapted to other gear types.

Testing the gear configuration and set parameter models derived herein is best done through field testing. Because these results have been generated based on government data, it is vital to address the ethical concerns that may arise from preferred field testing methods. Clearly, fishing success has direct and potentially serious consequences to the financial success of fishers. Using government-collected data and providing the results to only a select portion of fishers poses a serious conflict of interest. Thus, distributing the results to only a portion of the fisher population or requesting that fishers alter their fishing methodology for testing purposes is unethical. Fish populations and fishing conditions, however, may vary widely from year to year and are challenging to both predict and describe. To avoid these ethical pitfalls but still produce a valid analysis, a set of recommendations for targeting each species (e.g. shortening soak times, placing hooks closer together, and using longer gangions) could be provided. As compliance with these recommendations would be entirely voluntary, the fishing success results from those who chose to implement the recommendations could be compared against both their documented fishing success in previous years, and against the fishing success of those who made no changes to their fishing practices. This should generate a valid analysis without the ethical challenges presented in a true control and test group analysis.

Long-term, gear regulation may prove useful in bycatch reduction. Once the recommendations have been vetted in the field, fishery managers may opt to require certain gear configurations and fishing parameters such as soak time limits or fishing depth ranges. While changing gear setups requires negligible time and labor, these changes can generally be made at little cost (for instance, moving hook distances or replacing gangions with longer or shorter lines as they become worn). Increasing soak times or using shallower fishing depths has no associated cost. Fishing lines must be replaced over time, so changing mainline or gangion lengths as replacement becomes necessary would not incur any additional cost. These parameters have been largely ignored in existing literature. Though enforcement of gear regulation would prove difficult in some cases, if presented as a means of improving overall catch success, compliance with these standards should be high. Ultimately, should the recommended fishing practices reduce bycatch levels successfully, it may be possible to raise catch quotas – a tangible benefit for compliance with gear guidelines.

This shift in focus from the biotic and abiotic factors in the environment to variables controllable by fishers represents an important step in fishery management. While the study of the environmental variables that contribute to fish population health is critical and should be ongoing, very little can be changed directly to generate conditions favorable for thriving populations. Fishing gear and set configurations, however, can be manipulated with minimal cost or effort. Given the significant commercial fisheries landings value in the United States noted above, even small improvements may have broad reaching economic impacts. Coupled with the ecological benefits of bycatch reduction, the study of best fishing practices is a valuable tool for progressing fishery management in the United States and beyond.

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