MODELING COMMUNITY STRUCTURE AND ABUNDANCE USING OBSERVER DATA FOR THE U.S. GULF OF MEXICO DEEPWATER REEF FISHERY

A Thesis

by

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ABSTRACT

Fishery observer data collected in the Gulf of Mexico deepwater reef fish fishery from July 2006 through December 2013 were examined for community structure using hierarchical cluster analyses to quantify species relationships and reveal stratifications in the fishery. The correlation measure of dissimilarity with average agglomerative linkage was the most efficient method using randomly fake species as a comparison tool between dissimilarity and linkage choices. This approach in combination with a multiscale bootstrapping revealed distinct stratifications and probabilities indicating the strength of species relationships in the fishery. For deepwater species managed under the individual fishing quota (IFQ) system, cluster analyses findings detected patterns in species co-occurrence on fishing sets that may be of interest to managers. Additionally, delta-lognormal boosted regression tree and zero-inflated negative binomial predictive models were compared for standardizing spatial abundance for the fishery. Delta-lognormal boosted regression tree models were superior in representing fine-scale variations, however, zero-inflated negative binomial models were more representative in abundance observed on a larger spatial scale. An examination of the deepwater IFQ-managed species also found evidence for size selection of discards and differences in retention rates for some species managed under the same allocation category.

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NOMENCLATURE

AU	Approximately Unbiased
AUC	Area Under the Curve for the Receiver Operating Characteristic
CPUE	Catch Per Unit Effort
Delta-BRT	Delta-lognormal Boosted Regression Tree
GMFMC	Gulf of Mexico Fishery Management Council
HCA	Hierarchical Cluster Analysis
IFQ	Individual Fishing Quota
NMFS	National Marine Fisheries Service
NOAA	National Oceanographic and Atmospheric Administration
SEFSC	Southeast Fisheries Science Center
SERO	Southeast Regional Office
ZINB	Zero-Inflated Negative Binomial

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1. INTRODUCTION

The incidental captures of undersized or non-target species (bycatch) are of great concern to fishery managers due to the overexploitation of stocks not only in the Gulf of Mexico (Gulf), but worldwide (Sissenwine et al. 2014). In November 1984, the Gulf of Mexico Fishery Management Council (GMFMC) implemented the Reef Fish Fishery Management Plan to rebuild declining stocks of reef fish (GMFMC 1984). Since that time, the GMFMC has used size limits, area closures, and quota systems to regulate the fisheries; however, this management has been met with conflicting opinions on their effectiveness (Coleman et al. 2000; Nieland et al. 2007; Cowan et al. 2011). Some of the various management options have resulted in the at-sea discarding of fish that may have been caught at depths that correlate with immediate mortality (Render and Wilson 1994; Bartholomew and Bohnsack 2005; Rudershausen et al. 2007; Stephen and Harris 2010). The Gulf reef fishery is a multi-species fishery primarily targeting groupers (*Epinephelus* sp. and *Mycteroperca* sp.) and snappers (*Lutjanus* sp.) using two primary gear types, bottom longline and vertical line. Based on Gulf observer program coverage from 2006 through 2009, Scott-Denton et al. (2011) identified 183 taxa captured with bottom longline and 178 taxa with vertical line gear. While species diversity was high, only 17 species accounted for 90% of the number of captures recorded.

Modeling fishery observer data on a large spatial scale for the Gulf deepwater reef fish fishery provides an opportunity to examine the current quota management system that has undergone many changes in the past decade. The most recent change has been a shift from a "derby" style fleet-wide quota system to an individual fishing quota (IFQ) allocation for each permit holder based on historical landings for a number of species. IFQ management aimed to reduce the overcapacity in the commercial fishery and eliminate problems affiliated with derby fishing. Derby fishing or the "race to fish" is when fishermen try to catch fish as fast as possible once a fishing season is open with a fleet-wide quota. Branch (2009) examined how individual transferrable quotas affected various fisheries worldwide for a number of factors including high-grading for single species and discards for multi-species fisheries finding both often declined, but may increase without effective enforcement or if the catches are not counted against the quota. High-grading refers to differing retention rates by fishers for a species usually influenced by price differences based on fish size, e.g., increased discards of less valuable fish sizes. High-grading can also occur due to price differentials between species in multi-species IFQ allocation categories and be observed in changes of retention rates, e.g., retaining more valuable species and discarding less valuable ones. Fishery managers could make better-informed decisions when determining IFQ allocation categories if species relationships could be quantified in the assemblages and any stratification in the fishery could be realized.

Numerous studies have examined fish species assemblages with fishery independent and dependent data (Rogers and Pikitch 1992; Williams and Ralston 2002; Farmer et al. 2010; Cope and Haltuch 2012). Heery and Cope (2014) used observer data to identify groundfish assemblages from trawls off Oregon and Washington, but encountered difficulties in identifying uncommon bycatch species on a large spatial scale. Shertzer and Williams (2008) identified reef fish assemblages off the southeastern United States by analyzing logbook data using hierarchical cluster analysis aggregated by year, month, area, and depth. They found little support for using indicator species as a management tool but supported stratifying species into distinct management units as an achievable goal. One limitation of the approach used by Shertzer and Williams (2008) was that it relied on logbook data, which aggregates only the retained species from the entire fishing trip, not for each specific fishing location. During fishing trips, a vessel may fish in a number of geographical areas across various habitats. Thus, the spatial resolution may not be fine enough for an accurate representation of species co-occurrence in terms of environmental factors. More importantly, the methods in Shertzer and Williams (2008) do not account for species that are discarded during the trip unless they are self-reported by vessel captains. Unlike logbook data, fishery observer data from the Gulf deepwater reef fish fishery include bycatch and site specific information. Analyses of the observer data provides relevant insights that are of special interest due to the high discard mortality associated with the depths fished.

Furthermore, fishery observer data could assist management goals for this fishery by building predictive models of abundance on different spatial scales through incorporating environmental variables shown to influence marine communities. Catch per unit effort (CPUE) is a widely used proxy of abundance derived from both fishery-dependent and fishery-independent sources. The interpretation of CPUE from fishery-dependent, e.g., fishery observer data, is often disputed when viewed as a linear time-series index of abundance due to confounding factors such as spatial variation in effort, gear selectivity, and seasonal variations. However, using fishery observer data for quantifying spatial distributions of CPUE provides a fine-scale management tool by identifying spatial patterns and providing confidence in the relationships observed. Using commercial fishing landings data from northwest Mexico, Erisman et al. (2011) identified patterns in the species composition for different regions by applying multivariate analyses and explained how the results could be incorporated into a more localized ecosystem-based management approach. For this thesis CPUE predictions derived from delta-lognormal boosted regression tree (delta-BRT) and zero-inflated negative binomial (ZINB) models will be compared. These approaches have been shown to equal or outperform the traditional techniques of generalized additive and linear models in predictive capabilities (Abeare 2009; Froeschke and Drymon 2013; Mateo and Hanselman 2014; Walsh and Brodziak 2014).

The objectives of this research were: (1) to examine the deepwater IFQ-managed species for size selection of discards and differences in retention rates for multi-species allocations under the current management system: (2) to compare modeling approaches for identifying relationships in species assemblages on a large spatial scale: and (3) to predict spatial abundance for the IFQ-managed species by area, depth, and gear type. Since the management in this fishery has shifted to IFQ allocations, realizing interspecific relationships in species assemblages and predicting spatial abundance may provide an option to explore distinct management units in the future. A comparison of methods for modeling observer data on a large scale will be of interest to researchers desiring holistic perspectives on a fishery.

2. RESEARCH METHODS

2.1 Observer Data

In 2005, the GMFMC dictated mandatory fisheries observer coverage (GMFMC 2005). In July 2006, the National Marine Fisheries Service (NMFS) Southeast Fisheries Science Center (SEFSC) initiated a mandatory observer program to characterize the commercial reef fish fishery in the Gulf. Prior to that, the only observer coverage was a voluntary NMFS observer program conducted from 1993 through 1995. The mandatory program incorporates a randomized selection process to select federally permitted commercial reef fish vessels for coverage stratified by season, gear, and region (Scott-Denton et al. 2011). Only fishery observer data collected on vessels from 2006 through 2013 using bottom longline and vertical line gear from depths ≥ 100 m were included in the analyses to limit the spatial scale of the study. While onboard the fishing vessels, observers collected detailed information such as location, depth, gear, and capture information for each set (NMFS 2015). Scott-Denton et al. (2011) and Scott-Denton and Williams (2013) provide detailed descriptions of the protocol for the reef fish observer program's data collection methodology.

Only data that conformed to confidentiality rules specified by the Magnuson-Stevens Fishery Conservation and Management Act were included in the analyses (NMFS 2007). The bottom longline fishing sets consisted of a mainline with variable length with baited hooks attached (gangions). For the vertical line fishery, a set was a specific fishing location, e.g., anchored, attached to an oil rig, motor fishing, or drifting. Any movement to a new location by the vessel resulted in a new set, which represented a finer spatial scale than the bottom longline fishery. Additionally, sets for vertical line gear can be broken up by time, e.g., a vessel stops fishing for a significant amount of time and resumes fishing at a later time at the same location. Fishing sets from vessels trolling were excluded from the analyses because these sets typically cover a large area and are not targeting bottom fish. Finally, fishing sets with no catch were removed from the analyses. All analyses in this study were performed using R statistical software (version 3.1.1; R Core Team 2014).

2.2 Species Managed Under the IFQ System

We first compared pre- and post-IFQ retention rates for the seven species managed under the current deepwater grouper and tilefish IFQ quota management systems. The deepwater grouper IFQ allocation is not for a single species, but instead comprises four different grouper species: snowy grouper (*Epinephelus niveatus*), speckled hind (*Epinephelus drummondhayi*), warsaw grouper (*Epinephelus nigritus*), and yellowedge grouper (*Epinephelus flavolimbatus*). The tilefish IFQ allocation comprises three different species: blueline tilefish (*Caulolatilus microps*), goldface tilefish (*Caulolatilus chrysops*), and golden tilefish (*Lopholatilus chamaeleonticeps*). Specifically, abundance data before and after the grouper-tilefish IFQ start date of January 1, 2010 were examined for changes in retention rates, i.e. number of fish retained out of the total number captured. Differences in retention rates between the time periods were examined with Fisher's exact test. To detect if high-grading by size selection of discards for a species was occurring under the IFQ management program, the fork lengths of the discards were compared to those of the retained fish using a one-tailed Kolmogorov-Smirnov test. For significant differences, the length measurements of the discarded and retained fish were plotted to determine the relative distribution of each. Prior to the implementation of the IFQ system, an open season was used to manage the tilefish and deepwater grouper quotas until they were filled. Both seasons opened on January 1 for a given year; however, the closures did not always coincide (SERO 2015). We compared the retention rates with observer data to detect differences in discard rates between the staggered seasons.

2.3 Cluster Analysis

The hierarchical cluster analyses (HCA) were conducted for both gear types combined and subsets for each gear type, bottom longline and vertical line, to investigate patterns in species relationships. Only species groupings with observations ≥ 50 were used in the cluster analyses as rare species may distort patterns in the species assemblages (Koch 1987). The reef fish capture data were tabulated into counts of species groupings, e.g. abundance, for individual fishing sets. Count data were converted to a presence-absence matrix for each fishing site prior to the examination of species associations. The species managed under the IFQ management system were also separated by disposition into two groups of retained and discarded, e.g., retained and discarded blueline tilefish, to analyze patterns in retention rates for each fishing set. Since HCA requires no *a priori* assumptions, it is critical to validate the final results using additional approaches (Borcard et al. 2011). For this study, both the correlation (*1 - cor(X)[j,k])* and Bray-Curtis dissimilarity measures were compared for each grouping of the analysis. For each measure of dissimilarity, the distance was calculated with both the average agglomerative linkage and Ward's linkage to compare the results between the two for consistent groupings. The HCA was done using the package 'pvclust' in R with 1,000 multiscale bootstraps to create probabilities between the relationships in the species groupings (Suzuki and Shimodaira 2011). The approximately unbiased (AU) probability was used because it provided a more accurate approximation of the strength of the relationships in the dendrogram (Liu et al. 2012). Since the fishing sets should not be considered independent observations, the AU probabilities were used to evaluate the strength of the relationships between the species in each of the clusters rather than statistical significance.

Cope and Haltuch (2012) used a technique of incorporating fake species into the analyses with a 0.5 probability of occurrence to identify the significance of the clusters formed by HCA. The idea behind this method of validating clusters was that random groupings of species would be less equivalent than the fake species. The Bray-Curtis measure and average agglomerative linkage were the only methods used by these authors to detect patterns in species assemblages. However, the use of fake species with presence or absence data and the Bray-Curtis measure is unnecessary as the measure is of compositional dissimilarity between counts of species at each sampling location (Bray and Curtis 1957). When count data are transformed to presence or absence information, the exact probability of co-occurrence can be determined by examining the dissimilarity in the resulting dendrogram. For instance, the fake species in the dendrograms will always result in a dissimilarity of 0.5 with a 0.5 probability of occurrence using presence or absence data with the average agglomerative linkage method. To overcome this in our study, the optimal method for dissimilarity measure and linkage were chosen when the fake species had the highest dissimilarity in the resulting dendrograms. We compared clusters formed by each method using the dendrograms of significant clusters species grouping with an AU probability ≥ 95. For the best combination of methods, the probability of occurrence of fake species was increased in the presence-absence matrix until they significantly clustered with real species to further evaluate the strength of the species relationships in the results.

2.4 CPUE Prediction Models

Only fishing sets that captured at least one IFQ-managed species were used in the analyses to examine spatial variations in abundance. Initial examination indicated the catch data for the IFQ-managed species was zero-inflated and possessed long tails, as a small number of fishing sets had larger than expected catch. To account for this, two different predictive approaches were used to model abundance and compared on different spatial scales. The first predictive model used a delta-lognormal approach (Lo et al. 1992) with boosted regression trees (delta-BRT) to standardize CPUE with a binomial model fit for the probability of occurrence and a log-normal model fit to the catch positive fishing sets for each species. Each sub-model was combined to form the full delta-BRT model of CPUE for each IFQ-managed deepwater species. The delta-

BRT of abundance for each species was calculated as the product of probability of occurrence times the unlogged CPUE value from catch positive model (Froeschke and Drymon 2013). Boosted regression trees are a powerful method for cross-validating predictor variables compared with traditional tree regression by applying a model averaging technique where the influence of predictor variables is determined using stochastic gradients (De'ath 2007; Elith et al. 2008).

The predictor variables included in each delta-BRT sub-model were latitude, longitude, depth, and gear type. For each sub-model, the relative importance for each predictor variable was reported as their contribution scaled to 100. The Area Under the Curve (AUC) value for the Receiver Operating Characteristic was used to select the best binomial sub-models and the lowest predicted deviance was used for evaluating the lognormal catch positive models. The AUC value is a measure of overall model accuracy with 0.5 considered random and 1.0 a perfect fit interpreted as the predicted values of presence versus absence for each site (Phillips et al. 2006). The tuning parameters of the learning rate (0.05-0.001), bag fraction (0.5-0.75), and tree complexity (3-7) were adjusted in the model fitting process. To prevent overfitting, the data were divided into 10 subsets and cross-validation was used to determine the optimal number of trees for minimizing the holdout deviance with the gbm.step function in the ‘dismo’ and ‘gbm’ packages of R with a Gaussian distribution for the catch positive models (Hijmans et al. 2013; Ridgeway 2013). For model validation, the residuals for both sub-models were plotted using a histogram to detect model fit and a QQ-plot was used to examine normality of the theoretical quantiles for the lognormal sub-models.

The second predictive modeling approach used a zero-inflated negative binomial (ZINB) with the same initial variables as the delta-BRT models of latitude, longitude, depth, and gear type. The initial analyses encountered problems with convergence when the interactions between the variable were included. Therefore, the decision was made to not include any interactions in the model fitting process. Model selection for each species removed insignificant variables with backwards regression for each sub-model using the likelihood ratio test to drop insignificant variables (Zuur et al. 2009). The significance for each variable remaining in the final models was reported using the χ^2 test on the difference of log likelihoods when the variable was not included in the model. Overall model significance was tested using the χ^2 test on the difference in log-likelihoods between the null and final models. Models diagnostics included plotting the Pearson residuals versus the fitted values and comparing the residuals for each explanatory variable to detect poor fits.

The final models for each IFQ-managed deepwater species were used to predict indices of abundance as CPUE per fishing set by area and depth of capture. The areas in the Gulf were generated using NMFS statistical zones (Patella 1975) to represent the following regions: 1-3 Florida Keys, 4-7 West Florida, 8-9 Northwest Florida, 10-12 Alabama/Mississippi, 13-17 Louisiana, and 18-21 Texas (Figure 1). Since no statistical method is available to directly compare the performance of each respective predictive model type, the raw mean CPUE was examined against the predicted mean CPUE from the delta-BRT and ZINB models as a comparison tool for model accuracy on different spatial scales. For each area, 95% bootstrapped confidence intervals (n=1,000) were generated for the observed and predicted mean CPUE from each model to compare the results on a large spatial scale (Efron and Tibshirani 1986). To examine predictive model performance on finer spatial scales, observed and predicted CPUE loess regression lines were compared for depth ranges observed for each Gulf region. The patterns observed for the IFQ-managed species in the cluster analyses were expected to be evident in differing spatial abundance for the observed and predicted observations.

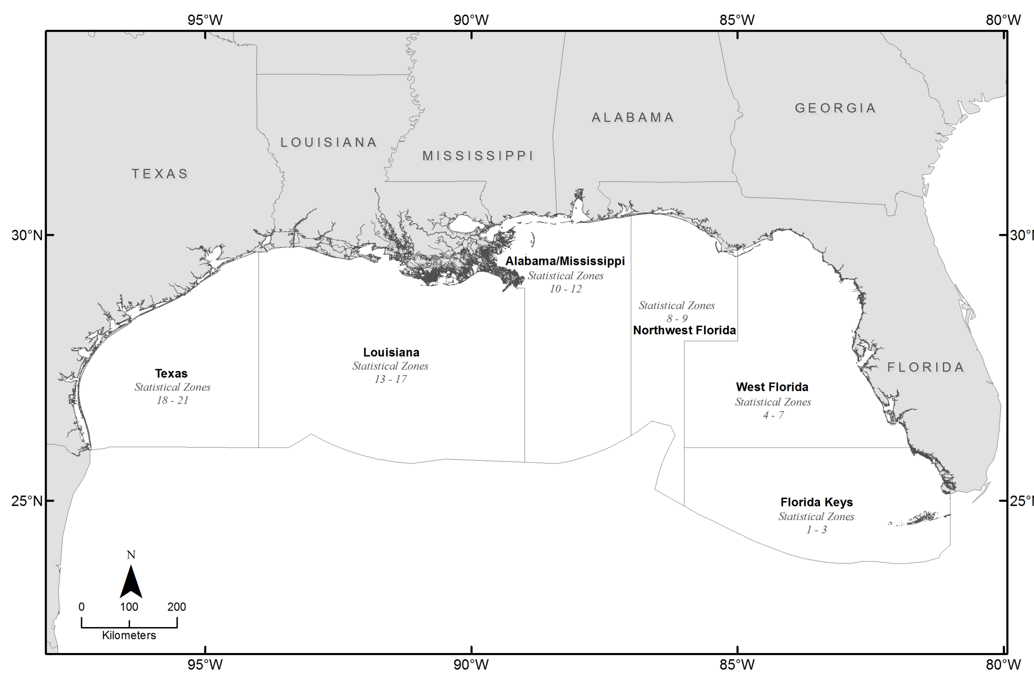

Figure 1. Aggregation of statistical zones used by the NMFS fishery observer program in the Gulf of Mexico.

3. RESEARCH RESULTS

From 2006 through 2013, in depths ≥ 100 meters, observers recorded a total of 117,702 captures of finfish. Of these captures, 99,510 fish were recorded from vessels using bottom longline gear, and 18,192 from vertical line gear. A total of 200 unique species groupings were recorded for both gear types combined, of which 173 groupings occurred with vessels using bottom longline gear and 106 groupings for vertical line gear. For both gear types, 64 species groupings were included in the analyses when captures with $n < 50$ observations were removed (Table 1). Yellowedge grouper ($n = 26,047$), golden tilefish ($n = 22,841$) , and blueline tilefish ($n = 10,545$) were the three most abundant species observed and were primarily captured using bottom longline gear. Vermilion snapper (*Rhomboplites aurorubens*) was the most common species recorded for vertical line gear with 7,150 captures. A total of 3,194 fishing sets with captures recorded were observed for both gear types, of which 1,978 were bottom longline sets, and 1,216 were vertical line sets. A small number of species groupings dominated the catch with the 10 most abundant species accounting for > 78% of the number of captures observed, and the 3 most abundant comprising > 50% (Table 1).

Table 1. The number of captures observed at depth (≥ 100 m) with observations (n > 50) and percentage by gear type bottom longline (BLL) and vertical line (VL) recorded by the observer program from 2006 through 2013 in the Gulf reef fish fishery.

Common Name	Scientific Name	# of Captures	% BLL	% VL
Yellowedge Grouper	*Epinephelus flavolimbatus*	26,047	98.9%	1.1%
Golden Tilefish	*Lopholatilus chamaeleonticeps*	22,841	99.6%	0.4%
Blueline Tilefish	*Caulolatilus microps*	10,545	97.9%	2.1%
Vermillion Snapper	*Rhomboplites aurorubens*	7,200	0.7%	99.3%
King Snake Eel	*Ophichthus rex*	6,193	99.8%	0.2%
Snowy Grouper	*Epinephelus niveatus*	4,840	88.3%	11.7%
Cuban Dogfish	*Squalus cubensis*	4,286	99.8%	0.2%
Red Porgy	*Pagrus pagrus*	4,029	21.2%	78.8%
Smooth Dogfish	*Mustelus canis*	3,989	99.0%	1.0%
Red Snapper	*Lutjanus campechanus*	2,467	46.1%	53.9%
Atlantic Sharpnose Shark	*Rhizoprionodon terraenovae*	1,899	99.1%	0.9%
Scamp Grouper	*Mycteroperca phenax*	1,761	60.0%	40.0%
Greater Amberjack	*Seriola dumerili*	1,652	65.0%	35.0%
Southern Hake	*Urophycis floridana*	1,291	99.6%	0.4%
Spiny Dogfish (genus)	*Squalus* sp.	1,158	99.5%	0.5%
Spotted Hake	*Urophycis regia*	1,135	99.6%	0.4%
Gag Grouper	*Mycteroperca microlepis*	1,110	31.1%	68.9%
Speckled Hind	*Epinephelus drummondhayi*	1,074	72.3%	27.7%
Blacktail Moray	*Gymnothorax kolpos*	1,006	99.3%	0.7%
Hake (genus)	*Urophycis* sp.	992	99.4%	0.6%
Grouped Sharks	*General sharks*	944	90.5%	9.5%
Chub Mackerel	*Scomber japonicus*	914	0.1%	99.9%
Spinycheek Scorpionfish	*Neomerinthe hemingwayi*	779	98.3%	1.7%
Silk Snapper	*Lutjanus vivanus*	774	32.7%	67.3%
Dogfish (genus)	*Mustelus* sp.	560	99.3%	0.7%
Pale Spotted Eel	*Ophichthus puncticeps*	523	100.0%	0.0%
Red Grouper	*Epinephelus morio*	511	97.7%	2.3%
Bearded Brotula	*Brotula barbata*	484	98.6%	1.4%
Almaco Jack	*Seriola rivoliana*	411	41.4%	58.6%
Blackedge Moray	*Gymnothorax nigromarginatus*	353	98.6%	1.4%

Table 1. Continued

Common Name	Scientific Name	# of Captures	% BLL	% VL
Purplemouth Moray	*Gymnothorax vicinus*	305	91.8%	8.2%
Gulf Hake	*Urophycis cirrata*	287	98.3%	1.7%
Queen Snapper	*Etelis oculatus*	260	69.6%	30.4%
Blackfin Tuna	*Thunnus atlanticus*	255	95.7%	4.3%
Blackfin Snapper	*Lutjanus buccanella*	236	19.1%	80.9%
Warsaw Grouper	*Epinephelus nigritus*	226	62.8%	37.2%
Scalloped Hammerhead	*Sphyrna lewini*	222	99.5%	0.5%
Sandbar Shark	*Carcharhinus plumbeus*	212	100.0%	0.0%
Moray Eel (genus)	*Gymnothorax* sp.	208	95.7%	4.3%
Blacktip Shark	*Carcharhinus limbatus*	203	94.6%	5.4%
Silky Shark	*Carcharhinus falciformis*	175	48.0%	52.0%
Bigeye Sixgill Shark	*Hexanchus nakamurai*	164	100.0%	0.0%
Dolphin Fish	*Coryphaena hippurus*	160	90.6%	9.4%
Night Shark	*Carcharhinus signatus*	159	100.0%	0.0%
Wenchman	*Pristipomoides aquilonaris*	140	55.0%	45.0%
Little Tunny	*Euthynnus alletteratus*	131	87.8%	12.2%
Shortspine Dogfish	*Squalus mitsukurii*	128	100.0%	0.0%
Tiger Shark	*Galeocerdo cuvier*	126	99.2%	0.8%
Blackbelly Rosefish	*Helicolenus dactylopterus*	110	76.4%	23.6%
Sharpnose Sevengill Shark	*Heptranchias perlo*	103	100.0%	0.0%
Sixgill Shark (genus)	*Hexanchus* sp.	101	99.0%	1.0%
Snake Eel (family)	*Ophichthidae*	99	100.0%	0.0%
Spotted Moray	*Gymnothorax moringa*	94	100.0%	0.0%
Longtail Bass	*Hemanthias leptus*	76	15.8%	84.2%
Conger Eel	*Conger oceanicus*	74	98.6%	1.4%
Great Barracuda	*Sphyraena barracuda*	69	76.8%	23.2%
Dogfish Shark (order)	*Squaliformes*	67	100.0%	0.0%
Jack (genus)	*Seriola* sp.	65	90.8%	9.2%
Hammerhead Shark (genus)	*Sphyrna* sp.	64	100.0%	0.0%
Chain Dogfish	*Scyliorhinus retifer*	63	100.0%	0.0%
Barrelfish	*Hyperoglyphe perciformis*	60	31.7%	68.3%
Green Moray	*Gymnothorax funebris*	58	100.0%	0.0%
Rough Scad	*Trachurus lathami*	52	0.0%	100.0%
Lesser Amberjack	*Seriola fasciata*	51	15.7%	84.3%

Significant differences were found in the retention rates for five of the seven IFQ-managed species in the deepwater reef complex (Table 2). All tilefish species had lower retention rates when compared to the IFQ grouper species; however, only 43 captures were observed for goldface tilefish indicating it is a rarely encountered species. The species with the greatest difference relative to the number of fish discarded after the implementation of the IFQ system was golden tilefish with a post-IFQ retention rate of 80.3%, compared with 97.1% prior to the IFQ implementation. Blueline tilefish had the highest percentage (> 44%) of discards under IFQ management but were less commonly captured than golden tilefish thus representing a smaller overall number of discards observed. Yellowedge, snowy, and warsaw grouper species all had retention rates > 96% under IFQ management indicating little evidence of high-grading among these species managed under the same IFQ allocation category. For warsaw grouper and goldface tilefish, no analyses were conducted to compare the size of the discarded and retained fish under the IFQ system due to limited length data, and because no significant difference in retention rates were observed, $p = 0.24$ and $p = 0.39$ respectively.

Size selection of discards under IFQ-management was also apparent for four of the five species that had different retention rates with discards being significantly smaller for golden tilefish, yellowedge grouper, snowy grouper, and speckled hind (Figure 2). For example, the 90th percentile of discarded golden tilefish lengths was approximately equivalent to the 50th percentile of the length of fish retained. Of these 4 species, the results are of greatest concern for golden tilefish that had both the largest number and the highest percentage of discards recorded under the IFQ system. Blueline tilefish was the only species with a different retention rate that had a marginally significant difference (p = 0.06) between the size of discarded and retained fish. Prior to the IFQ system when fishery observer data were available, there is evidence that most (> 96%) tilefish were retained under the derby system when the season was open (Table 3). A high percentage (> 98%) of discarding occurred only when the tilefish and deepwater grouper closures did not coincide.

Table 2. Retention rates for the IFQ-managed deepwater reef fish species using fishery observer data from 2006 through 2013.

Species	Number Retained		Number Discarded		Retention Rate		Fisher's Exact Test P-value
	Pre-IFQ	Post-IFQ	Pre-IFQ	Post-IFQ	Pre-IFQ	Post-IFQ	
Golden Tilefish	2,169	16,464	65	4,042	97.1%	80.3%	< 0.001
Blueline Tilefish	1,723	3,863	1,761	3,062	49.5%	55.8%	< 0.001
Goldface Tilefish	4	12	3	24	57.1%	33.3%	0.39
Yellowedge Grouper	6,834	18,925	41	233	99.4%	98.8%	< 0.001
Snowy Grouper	105	3,968	13	75	89.0%	98.1%	< 0.001
Speckled Hind	392	583	6	93	98.5%	86.2%	< 0.001
Warsaw Grouper	98	115	8	4	92.5%	96.6%	0.24

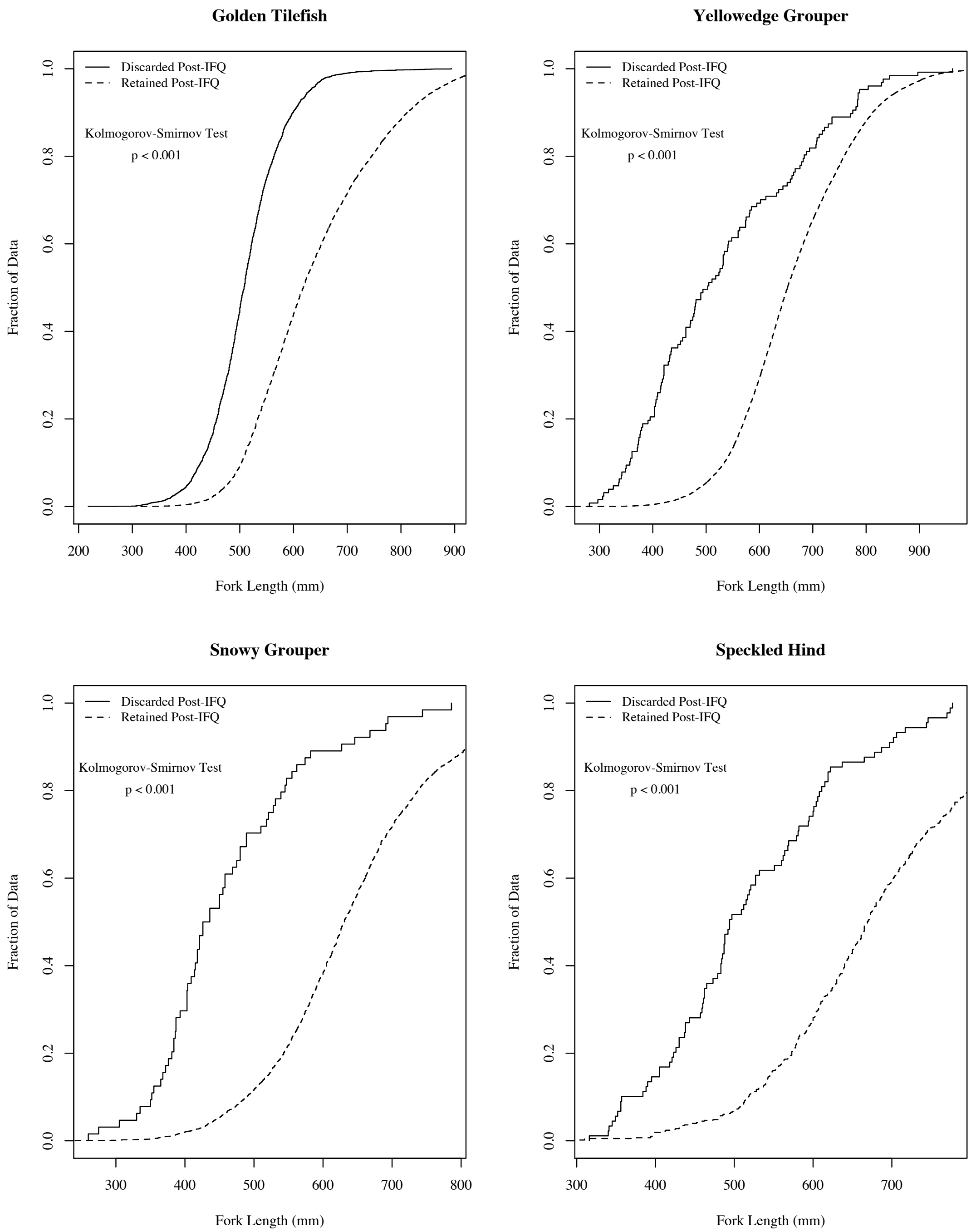

Figure 2. Empirical cumulative distribution of lengths for IFQ-managed deepwater reef fish species with significant differences based on the Kolmogorov-Smirnov test from 2010-2013.

Table 3. Retention rates for most common tilefish species pre-IFQ for time periods before and after aggregated deepwater grouper closure.

Fishing Season	2007 Open, 1/1-4/18	2007 Closed, 4/19-6/2	2008[a] Open, 1/1-5/10	2009 Open, 1/1-5/15	2009 Closed, 5/16-6/27
Golden Tilefish					
Number Kept	44	0	211	1,913	1
Number Discarded	0	5	8	22	30
Retention Rate	100.0%	0.0%	96.3%	98.9%	3.2%
Blueline Tilefish					
Number Kept	3	9	155	1,555	1
Number Discarded	0	589	0	57	1,115
Retention Rate	100.0%	1.5%	100.0%	96.5%	0.1%

[a] In 2008 the deepwater grouper closure coincided with the tilefish closure.

For examining community structure on large spatial scale, the most consistent method for filtering out the fake species across all subsets of the data was using the correlation measure of dissimilarity with average agglomerative linkage (Figure 3). For all subsets, the fake species never had a dissimilarity measure less than 0.9 with a 0.5 probability of co-occurrence. The correlation measure of dissimilarity in combination with the average linkage resulted in the fake species being absent from all significant clusters (AU ≥ 95). The correlation measure of dissimilarity did not perform as well with Ward's linkage because the fake species consistently clustered with real species. Using the Bray-Curtis measure of dissimilarity with both average and Ward's linkage resulted in species at a higher co-occurrence than the fake species for all subsets of the data, which may indicate it is inefficient at determining species relationships on a large spatial scale with this type of dataset (Figures 4 and 5).

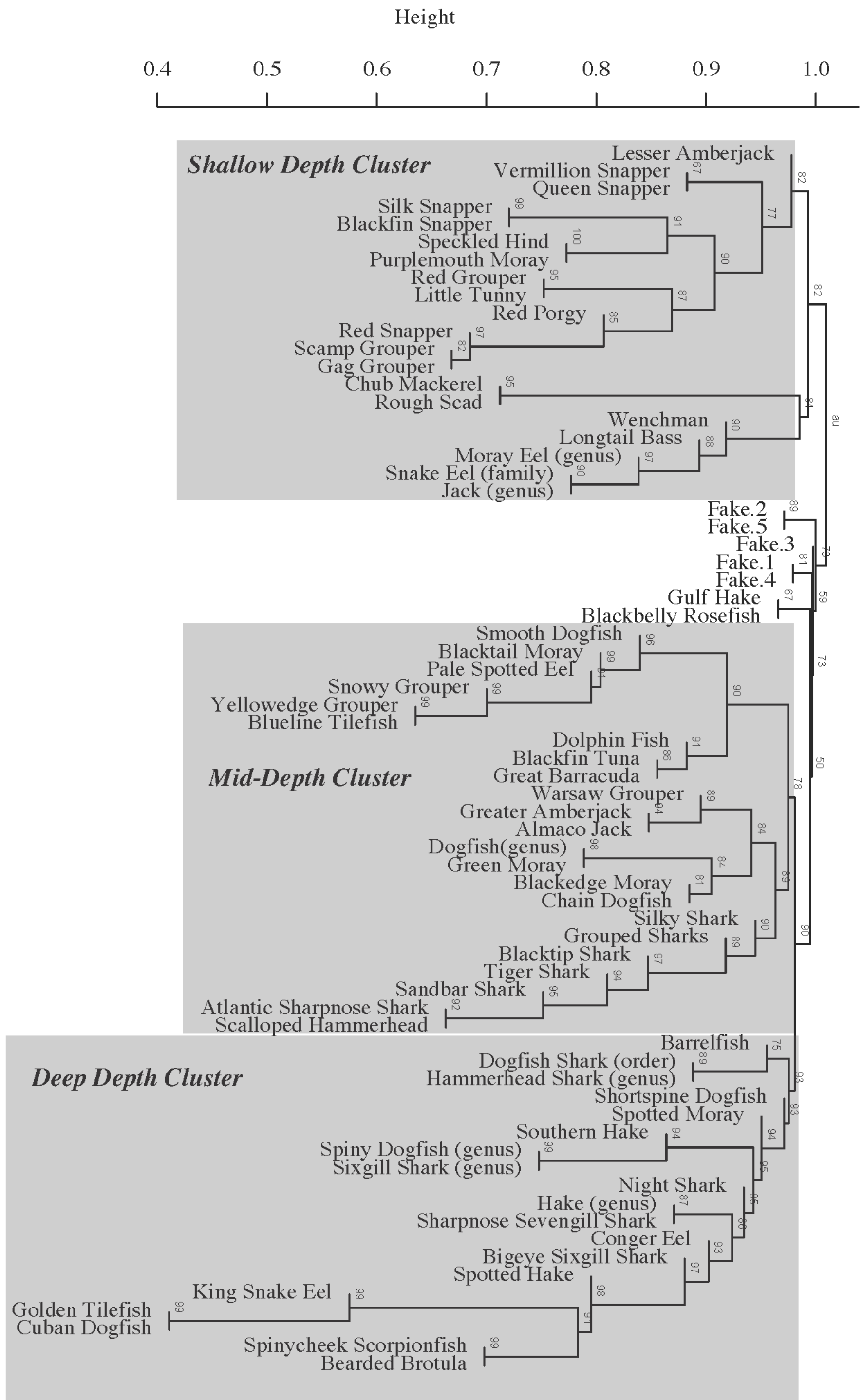

Figure 3. Dendrogram of species clusters for gear types combined using the correlation measure of dissimilarity with average agglomerative linkage.

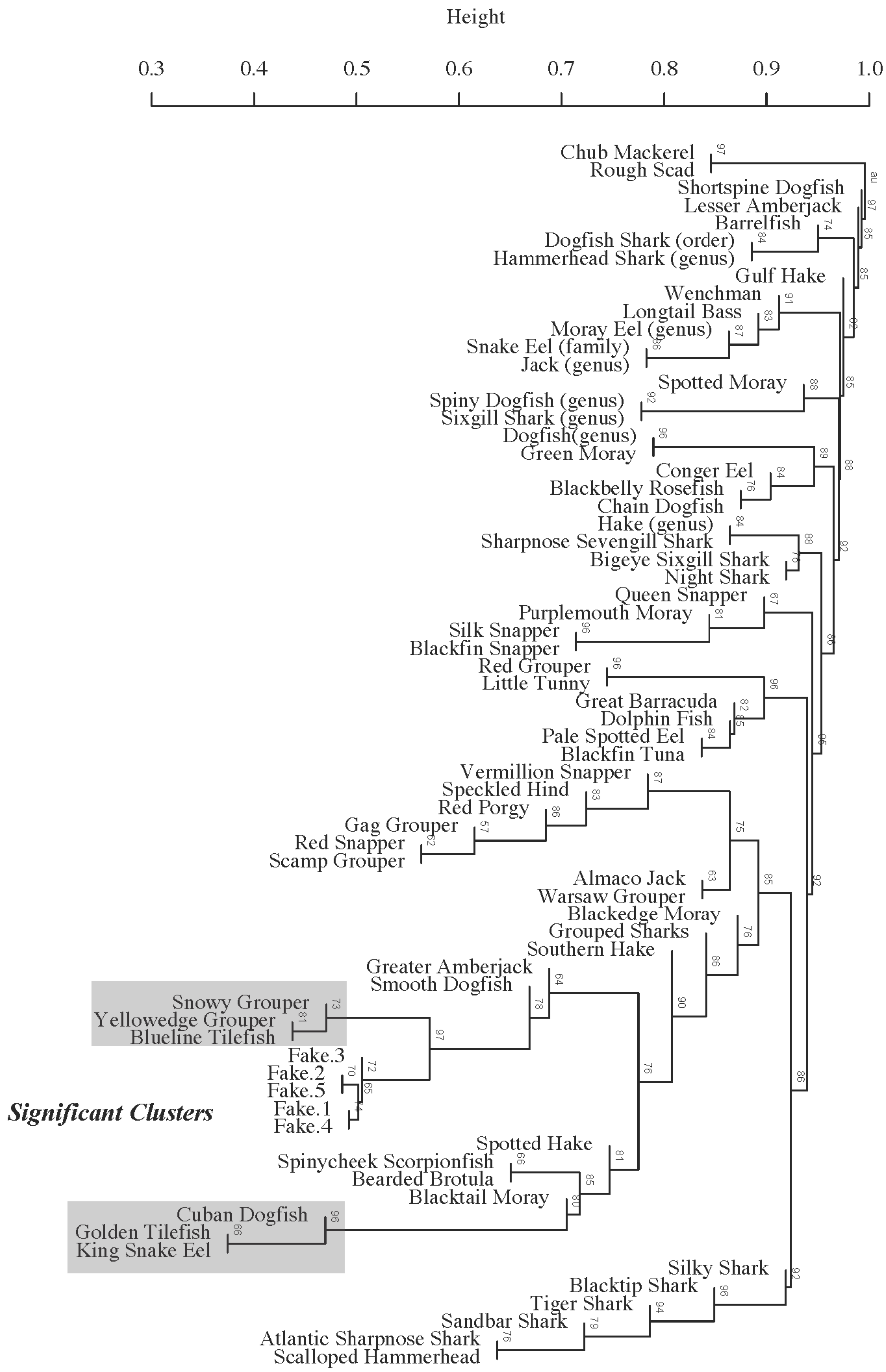

Figure 4. Dendrogram of species clusters for gear types combined using the Bray-Curtis dissimilarity measure and average agglomerative linkage.

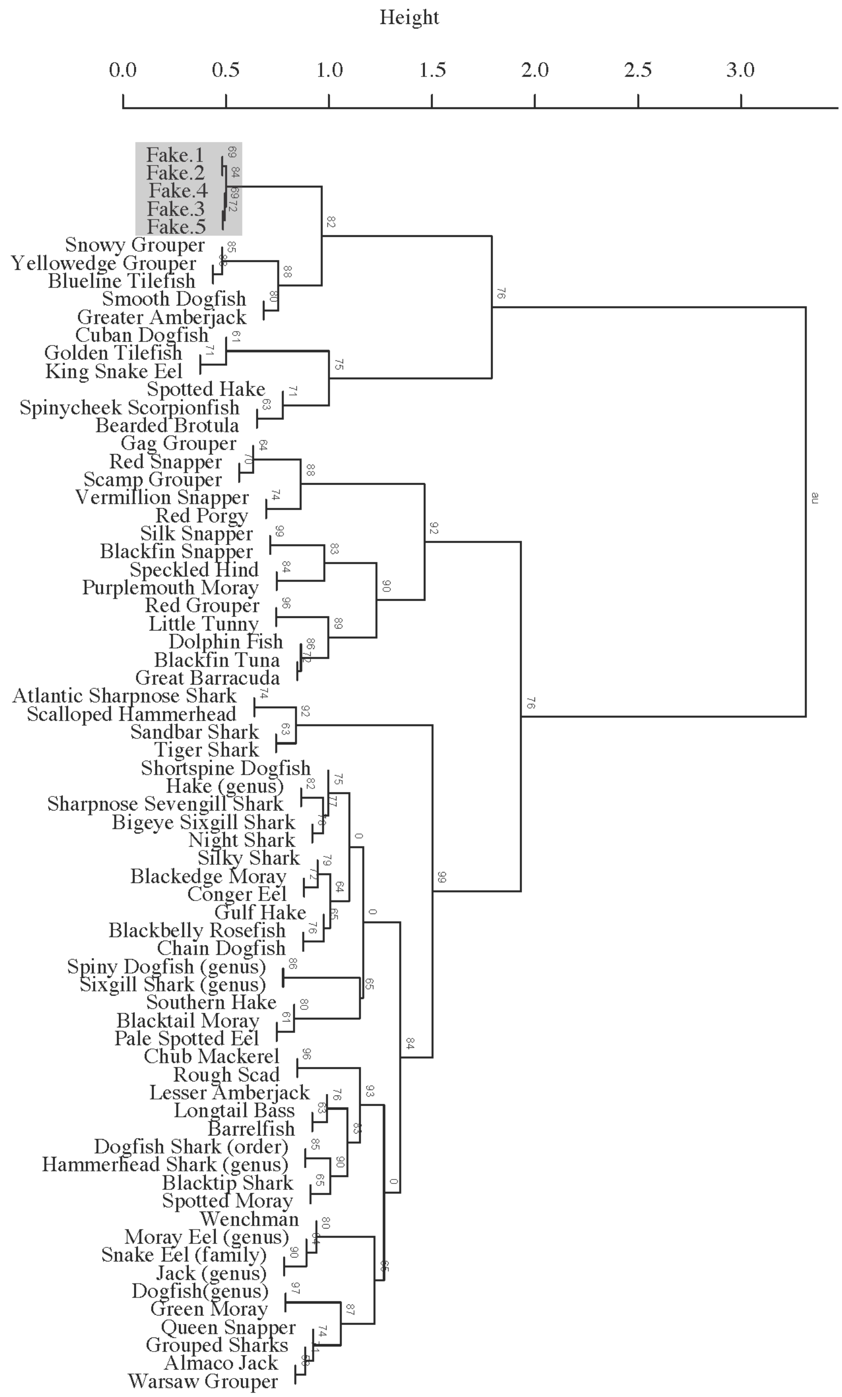

Figure 5. Dendrogram of species clusters for gear types combined using the Bray-Curtis measure of dissimilarity with Ward's linkage.

To validate the correlation measure of dissimilarity with average linkage on this type of dataset, the probability of random occurrence for fake species was increased until they clustered with real species by 0.05 increments. For the entire dataset, the fake species did not cluster with real species until the probability of occurrence was increased to 0.8. For subsets of the data with bottom longline and vertical line gears, the fake species clustered with some of the rarely caught species, but the dissimilarity was never less than 0.95. In the analysis for species with observations > 1,000 (Figure 6), the fake species did not cluster significantly with any real species until the probability of random occurrence was increased above 0.95 in the species matrix. This indicates that the correlation measure in combination with average linkage is even more robust than random associations on groupings when less likely encountered species are removed.

The IFQ-managed species of blueline tilefish, yellowedge grouper, and snowy grouper consistently clustered together for all subsets of the data (Figures 3 and 6). Golden tilefish only clustered with the other IFQ species for the vertical line subset of the data when few observations were present, indicating co-occurrence on fishing sets capturing other IFQ-managed species is not common. When the IFQ-managed species disposition was added for cluster analysis, the same previous relationships were evident (Figure 7). Retained and discarded golden tilefish clustered significantly, but not with any other IFQ species. Yellowedge, snowy, and speckled hind grouper being retained significantly clustered with blueline tilefish retained and discarded. Discarded yellowedge, snowy, and speckled hind grouper significantly clustered together indicating that they are not being retained on the same fishing sets.

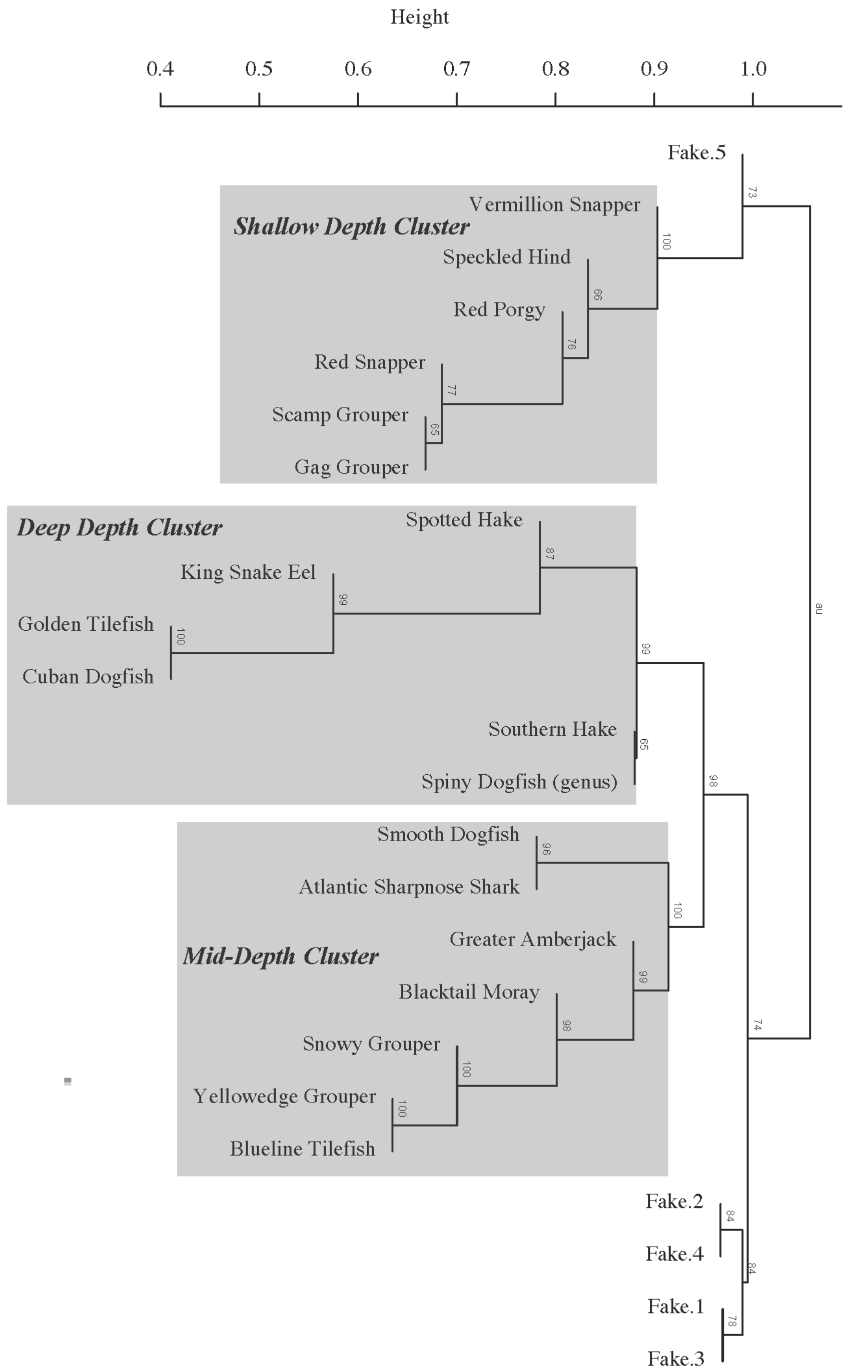

Figure 6. Dendrogram of species clusters with > 1,000 captures recorded using the correlation dissimilarity measure and average agglomerative linkage.

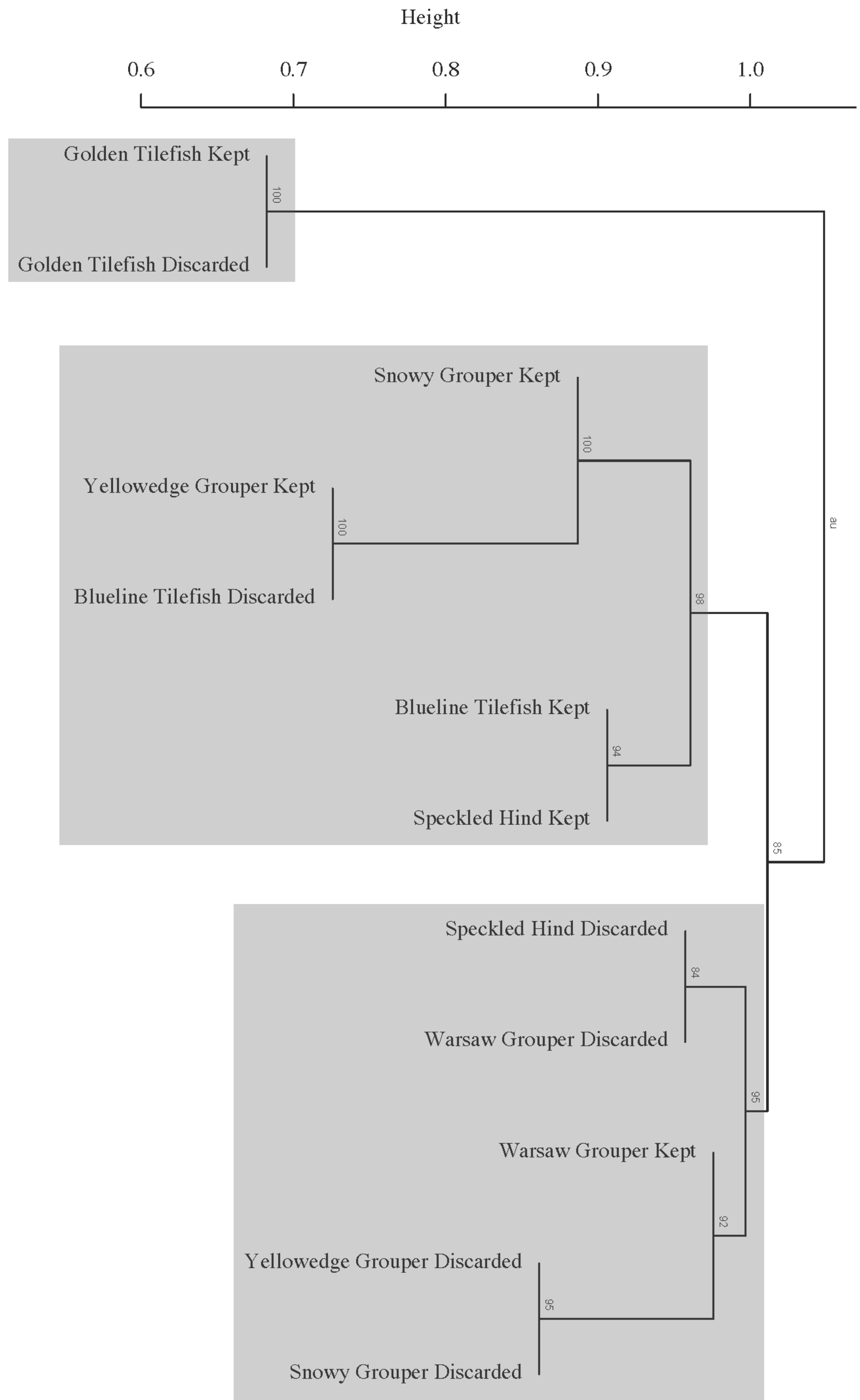

Figure 7. Dendrogram of clusters for IFQ species kept or discarded using the correlation dissimilarity measure and average agglomerative linkage.

Catch information from 2,414 fishing sets was used for both predictive model types with yellowedge grouper as the most common (> 74%) and warsaw grouper the least common (6%) species observed on the fishing sets used in the analyses (Table 4). The delta-BRT binomial sub-models indicated good fits for each species with excellent AUC (> 0.9) and explained deviance > 50% for 4 of the 6 IFQ-managed species. The best binomial sub-models were for the tilefish species which both had > 63% of the deviance explained. Longitude had the greatest and gear type the least importance as predictor variables for each species except for golden tilefish. For the catch positive lognormal sub-models, the explained deviance was higher for each tilefish species when compared to the 4 grouper species. The relative importance for each variable was not consistent between the IFQ-managed species, with latitude and longitude the most important only for blueline tilefish, snowy grouper, and speckled hind. Depth was the most important variable for golden tilefish and the second most important for warsaw grouper but was the least important for yellowedge grouper. Yellowedge grouper was the only species that did not have gear type as the least important variable.

Table 4. Results from the delta-BRT models for each IFQ-managed deepwater species with the AUC score for the binomial model, percent of explained deviance, and the relative importance of latitude, longitude, depth, and gear to each sub-model.

Species	Golden Tilefish	Blueline Tilefish	Yellowedge Grouper	Snowy Grouper	Speckled Hind	Warsaw Grouper
Binomial Model						
AUC	0.97	0.96	0.96	0.83	0.94	0.8
Explained Deviance	75.9%	63.7%	59.7%	25.7%	51.8%	21.0%
Latitude	12.1%	14.7%	14.9%	32.8%	27.5%	16.3%
Longitude	51.7%	62.2%	25.9%	37.8%	47.8%	46.4%
Depth	30.7%	13.6%	28.1%	25.8%	23.4%	33.9%
Gear	5.5%	9.5%	31.1%	3.6%	1.3%	3.4%
Catch Positive Log-Normal Model						
% CPS [a]	35.9%	35.6%	74.3%	39.4%	15.8%	6.0%
Explained Deviance	65.1%	50.4%	46.8%	26.2%	22.5%	1.0%
Latitude	24.4%	37.6%	20.8%	37.3%	33.8%	35.2%
Longitude	25.4%	24.6%	36.4%	31.6%	32.6%	29.1%
Depth	46.5%	23.6%	17.0%	28.9%	21.4%	30.7%
Gear	3.7%	14.2%	25.8%	2.2%	12.2%	5.0%

[a] Percentage of catch positive sets out of all fishing sets with an IFQ-managed species captured.

Statistically significant ZINB models ($p < 0.0001$) were generated for each IFQ-managed species with noticeable differences in the variables selected compared to the delta-BRT models (Table 5). For example, latitude was a very important variable in each catch positive delta-BRT sub-model, but was insignificant in each ZINB count model for all the species except for blueline tilefish. Blueline tilefish was the only species with all 8 variables retained in the final models compared with yellowedge and warsaw grouper that only had the fewest (3) variables in the final models. Depth was significant in all the zero-inflation models and most of the count models for each species, but was of varying importance in the delta-BRT sub-models. Model validation for the delta-BRT and ZINB models showed excellent fits for every species except for warsaw grouper that had some non-normality in the residuals for the count and catch positive sub-models, most likely due to the small number (226) of captures observed.

Table 5. The results from the final ZINB model for each IFQ-managed deepwater species with the overall significance. The probabilities for each variable area were calculated using the χ^2 statistic and degrees of freedom (df) when not included in the model.

Species	**Golden Tilefish**	**Blueline Tilefish**	**Yellowedge Grouper**	**Snowy Grouper**	**Speckled Hind**	**Warsaw Grouper**
Pr >|χ^2|	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
χ^2	2055.9	1951.4	1409.7	374.2	874.9	159.7
Final Model df [a]	9	11	6	9	10	6
Negative Binomial Count Model						
Latitude	NS [b]	0.0003	NS	NS	NS	NS
Longitude	NS	0.0111	NS	<0.0001	<0.0001	0.0114
Depth	<0.0001	<0.0001	0.0031	<0.0001	<0.0001	NS
Gear Type	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	NS
Zero-Inflation Model						
Latitude	<0.0001	<0.0001	NS	<0.0001	<0.0001	NS
Longitude	<0.0001	<0.0001	NS	0.0158	<0.0001	0.0013
Depth	<0.0001	0.0176	<0.0001	<0.0001	<0.0001	<0.0001
Gear Type	<0.0001	<0.0001	NS	NS	0.0276	NS

[a] The χ^2 statistic is based on the difference between the null with 3 df and the df in the final model.
[b] NS = Not significant at 0.05 level.

On a large spatial scale, the ZINB models were a better fit to the observed values for each area compared with the delta-BRT models that consistently underfit CPUE for each region (Figure 8). For all delta-BRT models, the underfitting was improved from the initial results by increasing the bag fraction from 0.50 to 0.75 to capture some of the fishing sets with extreme observations. On a finer spatial scale, the delta-BRT models continued to underfit the abundance observed, but were superior to the ZINB models in capturing the variation observed at different depths for each region (Figures 9, 10, and 11). The relationships observed for the IFQ-managed species with cluster analyses were evident with both predictive models. The most notable spatial differences were between golden and blueline tilefish. Blueline tilefish were primarily captured in the Florida Keys and West Florida region in depths < 250 m while golden tilefish consistently showed up in the other 4 regions of the Western Gulf in depths > 250 m. Differences between speckled hind and warsaw grouper were evident with similar depth of capture, but marked differences in the location as speckled hind only occurred in the Florida Keys and West Florida region while warsaw grouper were found mostly in the western Gulf off Louisiana and Texas. Yellowedge grouper were distributed across the Gulf in a wide range of depths, but snowy grouper were more common in the eastern Gulf with a diminishing chance of occurrence in the western Gulf.

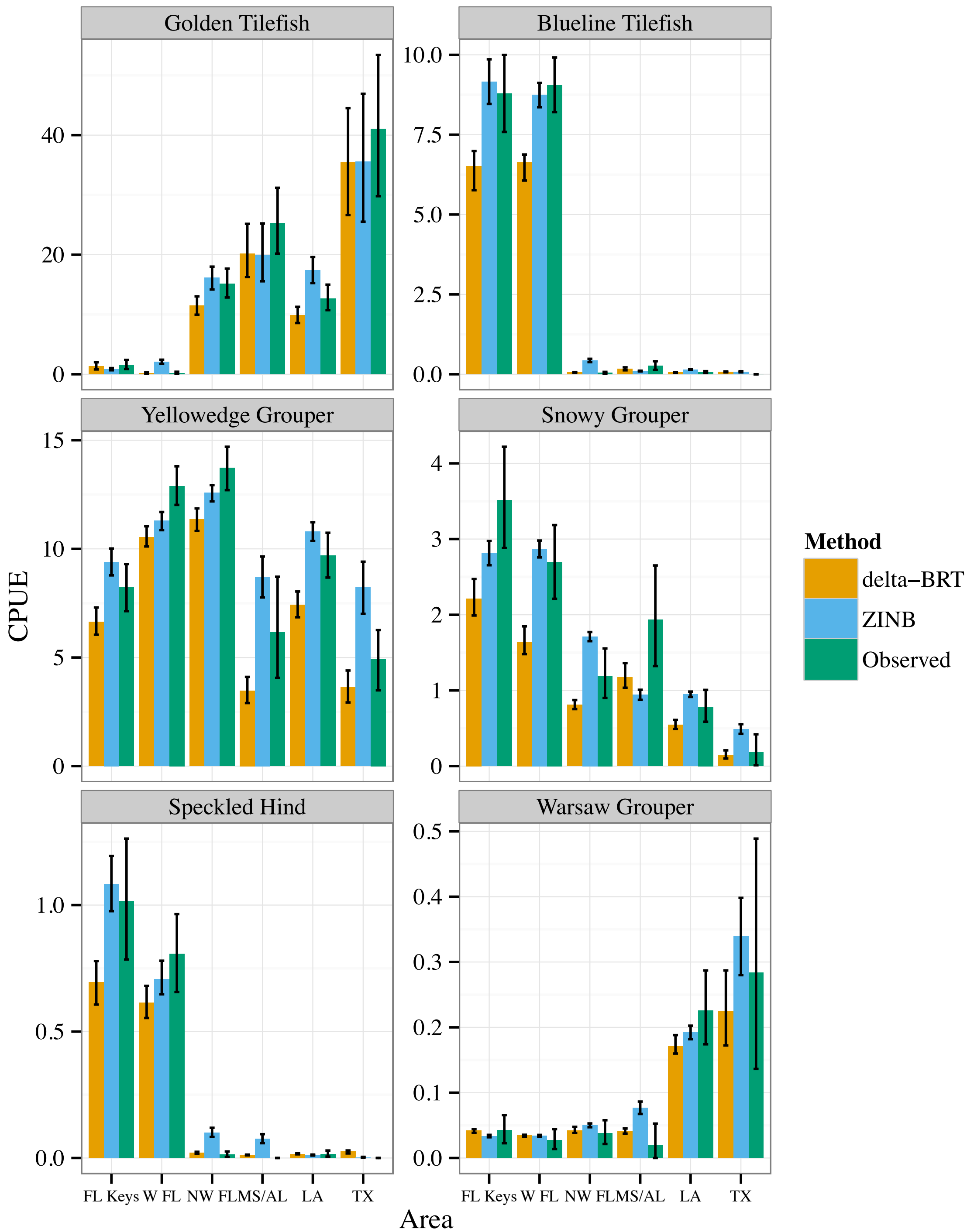

Figure 8. The mean CPUE by area for observed, boosted regression tree (BRT), and zero-inflated negative binomial (ZINB) models with 95% bootstrapped confidence intervals for IFQ-managed species.

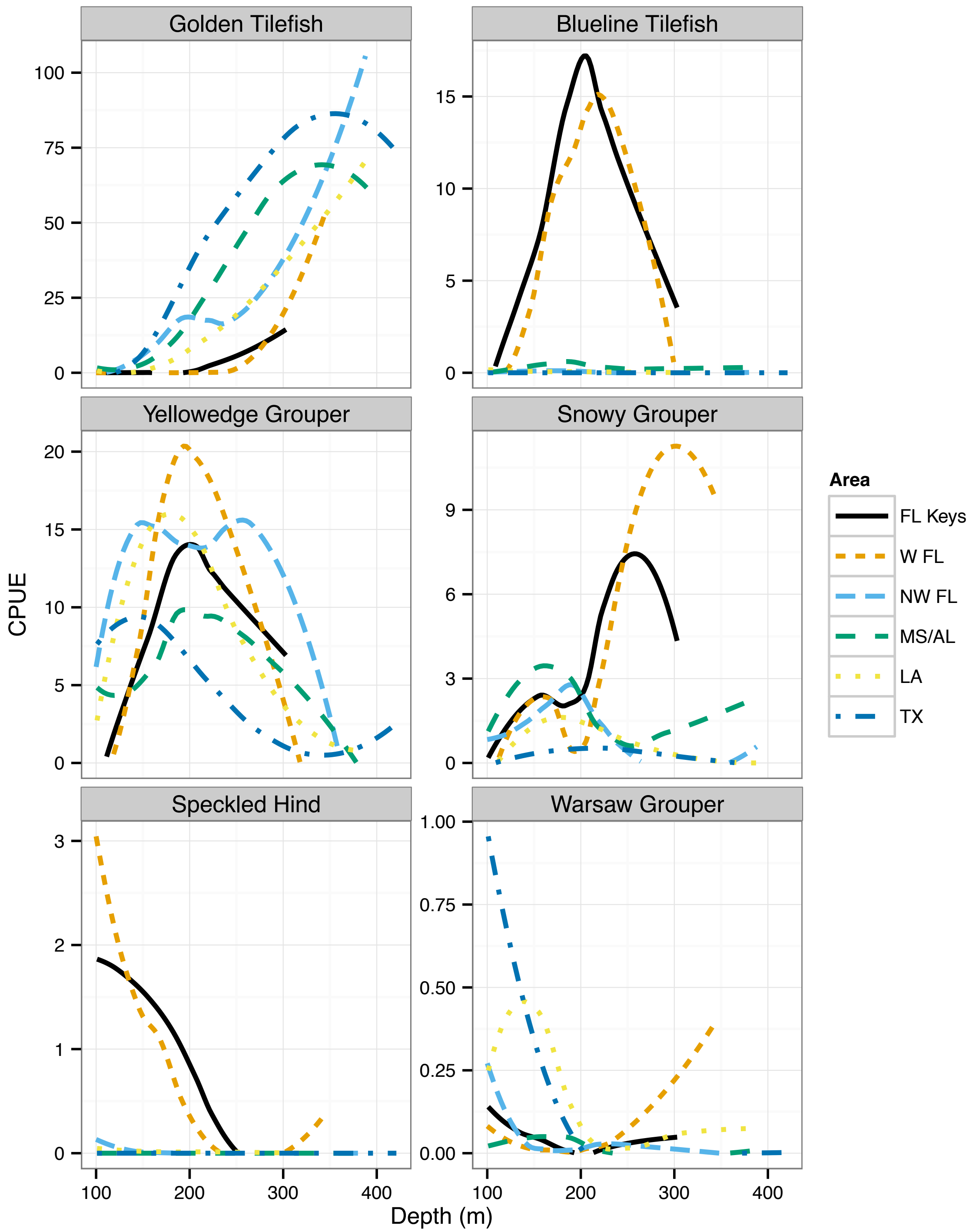

Figure 9. The observed CPUE per fishing set by area and depth for IFQ-managed species.

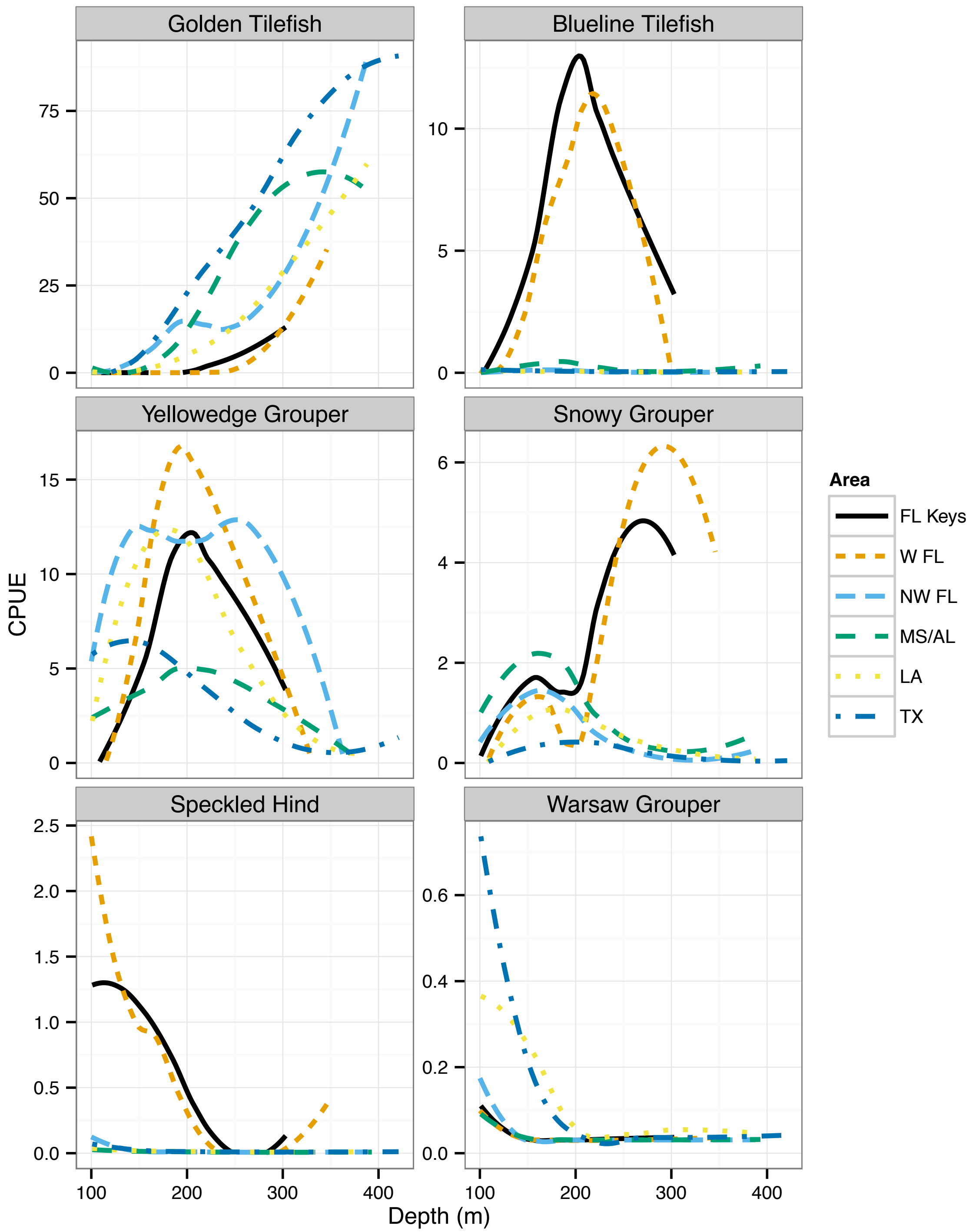

Figure 10. The predicted CPUE per fishing set using delta-BRT models by area and depth for IFQ-managed species.

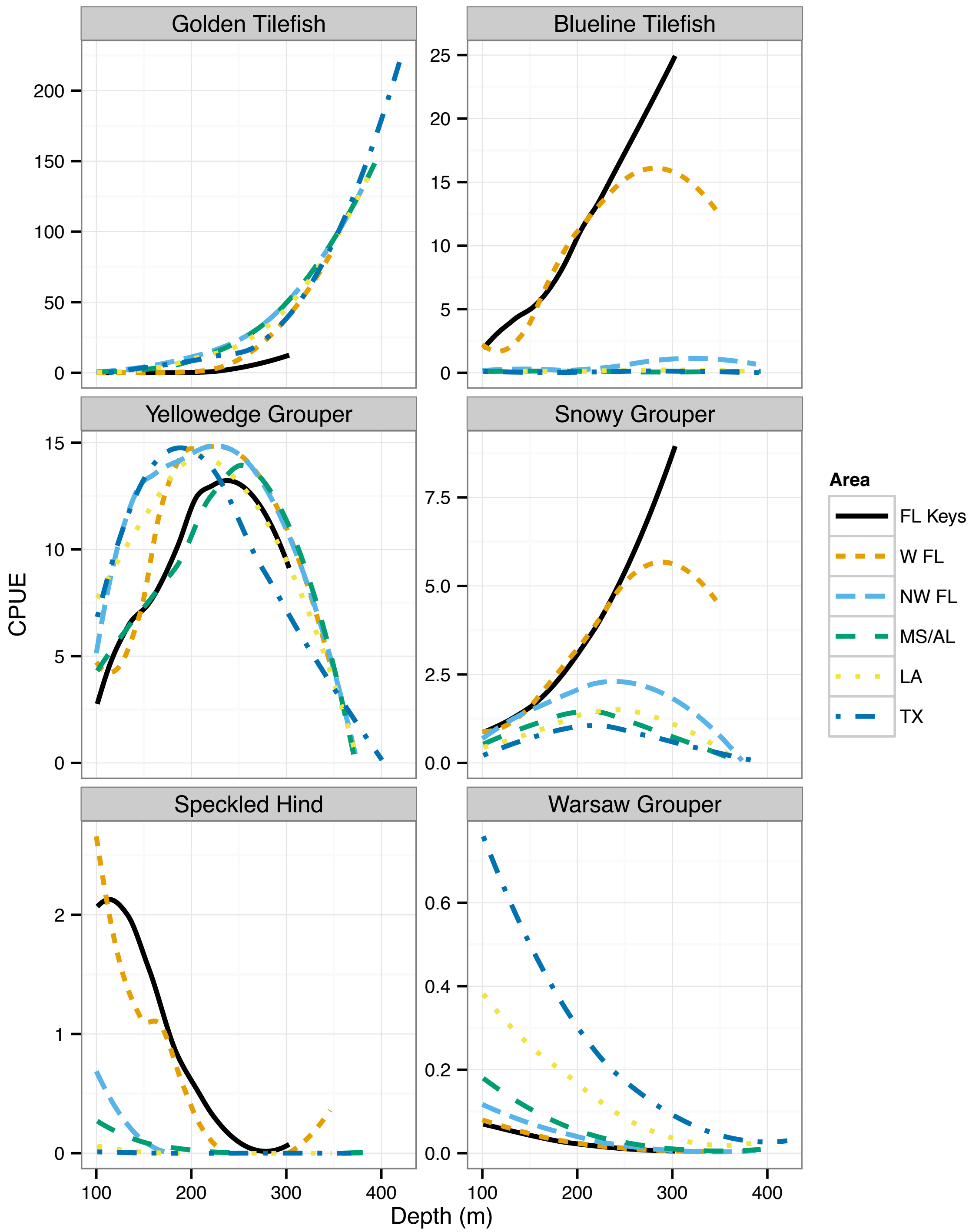

Figure 11. The predicted CPUE per fishing set using ZINB models by area and depth for IFQ-managed species.

4. CONCLUSIONS

The results from this study are of primary interest to research for modeling fishery-dependent data on a large spatial scale. The modeling techniques presented can provide the information needed to stratify target and non-target species into distinct management units based on their species co-occurrence in the fishery. Using the IFQ-managed tilefish species as an example, a refinement of the current allocation category (i.e., blueline and golden tilefish) may be warranted since evidence exists that these species have separate spatial distributions and differing retention rates. Blueline tilefish are most commonly associated with vessels capturing yellowedge and snowy grouper in the eastern Gulf while golden tilefish are more common in the western Gulf. Differences in retention rates among the species may be due to price differentials. For example, in 2012 blueline tilefish ex-vessel price was \$1.32/lb, while golden tilefish was higher at \$2.50/lb possibly explaining the higher retention rate for that species (SERO 2013). Another possible reason for the difference in retention rates is that vessels fishing in the eastern Gulf may have insufficient tilefish IFQ allocation available to retain all the blueline tilefish captured when targeting grouper species. The blueline tilefish retention rate of 55.8% under the current IFQ management scheme through 2013 indicated a high amount of discarding and represents an inefficient use of this fishery resource. Size selection of discards was evident for 4 of the 7 species of interest under the current management strategy and is most likely due to lower prices for smaller sized fish.

Golden tilefish was the species of greatest concern due to the high number and percentage of discards observed.

Methodologically, Bray-Curtis may be a robust measure of composition for species assemblages in other ecological contexts, but for fishery data on a large spatial scale using presence or absence information, we found that the correlation measure was superior. Fake species have often been used as a null model for evaluating the significance of species relationships since first being introduced by Strauss (1982). However, only a limited number of ecological studies have applied the techniques as a comparison tool between the dissimilarity and linkage choices available in combination with a bootstrap approach. Our findings indicated that the correlation method of dissimilarity outperformed the Bray-Curtis measure substantially by filtering out the random fake species introduced in the species matrix for all subsets of the data. The correlation measure in combination with average linkage was even more robust when less likely encountered species were removed indicated by the high probability (> 0.95) needed for fake species to significantly cluster with real species. Future studies using count data, instead of the presence or absence information, would benefit by comparing the same measures of dissimilarity and linkage used in this study to discover whether similar results could be obtained.

Applying the Bray-Curtis measure with fake species as a null model, only two defined clusters would be considered valid in this study: (1) blueline tilefish, yellowedge grouper, and snowy grouper, and (2) golden tilefish, king snake eel (*Ophichthus rex*), and cuban dogfish (*Squalus cubensis*) (see Figure 4). However, under the assumption that the correlation measure of dissimilarity is a better choice for determining valid clusters of species assemblages on a large spatial scale, three distinct groups were present. These represent a shallow water component consisting of snapper species, a mid-depth component including yellowedge and snowy grouper with blueline tilefish, and a deeper depth component of golden tilefish, cuban dogfish, and king snake eel. Additionally, the stratification of the fishery into smaller sub-units may allow more accurate determinations of bycatch levels or provide insight into other species of concern. For instance in the mid-depth cluster, many of the large shark species clustered together indicating that these may be captured on fishing sets with extended soak times, certain bait types, or other unknown factors that are influencing their capture. In addition, the four most commonly discarded IFQ-managed grouper species significantly clustered separately from those being retained possibly due to insufficient IFQ allocations.

In the present study, two methods of dissimilarity and linkage were examined using fishery observer data on a large spatial scale. Jackson et al. (2010) examined cluster analysis and ordination commonly used by community ecologists and found that the field has been slow to adopt recent advances such as the bootstrap or Bayesian methods. The authors advocated using the bootstrap approach with the caveat that the underlying independence of the samples cannot be assumed and therefore the probabilities should represent the degree of association between species instead of statistical significance. This precaution was given due to interspecific relationships existing between sampling locations underlying independence. While the lack of a significant relationship does not mean that none exists between species, a significant relationship suggests that future ecological studies warrant exploration of these species associations.

Our research revealed that the correlation dissimilarity with average linkage for cluster analysis complemented the results from both predictive models, confirming that spatial distributions and community structure can be modeled using fishery observer data. The predictive models for the dominant two tilefish and some grouper species confirmed clear separation between depth and area captured. Latitude, longitude, and depth were important variables for both modeling approaches. Incorporation of other environmental or temporal variables may be able to increase predictive performance. Boosted regression trees are a relatively new technique for analyzing ecological data, but have been used to predict the spatial distribution of fish in coral reefs using bathymetry data and the incidental catch of wahoo, *Acanthocybium solandri*, in the Mexican tuna purse-seine fishery (Pittman and Brown 2011; Martinez-Rincon et al. 2012). If algorithms using a negative binomial or Gamma distribution become available for boosted regression trees, future research could compare the predictive performance of these distributions to the delta-BRT models used in this study. It is possible one of these distributions may eliminate some of the model underfitting observed with the lognormal transformation used for catch positive fishing sets. On a fine spatial scale, the delta-BRT models were superior to the ZINB models in representing the variations observed, but the ZINB models appeared to better represent abundance fishing sets when they were aggregated on a large spatial scale.

Specific determinations of stock status are one of the driving forces of current fishery management schemes and managers are often forced to rely on limited data sources. A recent report on the status of the Gulf of Mexico ecosystem found that abundance indices for tilefish and some of the grouper species in our research have been in decline since the 1980's, while some of the primary species of commercial and recreational importance such as red snapper (*Lutjanus campechanus*) and red grouper (*Epinephelus morio*) in the region have increased in abundance (Karnauskas et al. 2013). These authors suggest the pattern may be due to greater attention applied to the species of higher importance, or that fishers may be targeting the secondary species to compensate for increased regulation on other species. Since many fisheries interact with multiple species, a clear understanding of patterns in species composition as revealed in our research will allow for a more accurate representation of the potential impacts of changes for management.

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