Counter intuitive effects of an extreme Indian Ocean Dipole event on a coupled human and natural system in Southern Myanmar.

Krista A. McCoy[1], Iris Segura-García[2,3*], Steve J. Box[4], Michael W. McCoy[2,5]

[1]Florida Oceanographic Society, 890 NE Ocean Blvd, Stuart, FL 34996

[2]FAU-Harbor Branch Oceanographic Institute, 5600 US 1 N, Fort Pierce, FL 34946, USA

[3]Smithsonian Marine Station at Fort Pierce, 701 Seaway Drive, Fort Pierce FL, 34949 USA

[4]Blue Ventures, The Old Library, Trinity Road, Bristol, BS2 0NW, UK

[5]Department of Biology, Florida Atlantic University, Boca Raton FL, 33431, USA

*Corresponding author: (ISG) iseguragarca@fau.edu

Abstract

The Indian Ocean Dipole (IOD) is a major climate cycle that occurs across the tropical Indian Ocean which has become more variable over time substantially influencing weather extremes and broader climate patterns worldwide. Importantly, these large scale global and regional scale climatic events have strong unexpected impacts on coupled human and natural systems at local scales. One of the strongest negative IOD events ever recorded occurred in 2016 and induced downwelling, decreased chlorophyl-a, and reductions in small pelagic fisheries in Java and Sumatra regions of Indonesia. Here, we use a digital daily catch data collection system to characterize the diversity and volume of fish catches coming from the small-scale fisheries of the Myeik archipelago in Myanmar before, during, and after this 2016 IOD. Unlike Java and Sumatra, total catch (Kg) of pelagic, reef, and demersal fishes increased through 2016 as the negative IOD intensified. Demersal fish accounted for a larger increase in catch than pelagic or reef fish in 2016, but total catches from all three habitats began to decrease in January 2017 as the dipole weakened, with many taxa becoming uncommon or absent by the end of 2017. These data are counter intuitive as negative dipole events are typically associated with reduced productivity in the eastern Indian Ocean. However, the Bay of Bengal and Andaman Sea was buffered from the strongest temperature increases. The increase in landings in Myanmar might have stemmed from northern migration of species to cooler more productive waters in the less impacted Andaman Sea. As climate change intensifies, we need to determine how fish populations respond to variable climatic events. The IOD cycle might function as a recurring phenomenon with locally predictable effects that can inform an ecosystem-based approach to fisheries management to help ensure the long-term sustainability of this coupled human and natural system.

Keywords: negative Indian Ocean dipole, small-scale fishery, fishing data, climate, Myanmar, coupled human and natural system

Introduction

Human induced changes to climate dynamics alter temporal variability in air and sea surface temperature as well as rainfall, which have important consequences for ecological and human communities (Alexander, 2016; Fisher et al., 2021; IPCC, 2023; Seneviratne et al., 2014; Thompson et al., 2013). Changing climate dynamics also influence natural climate phenomenon such as the Indian Ocean Dipole (IOD), which describes a dynamic reversal in sea surface temperatures between the Eastern and Western regions of the Indian Ocean (Vinayachandran et al., 2009). Changes in sea surface temperatures and precipitation during an IOD have far reaching impacts on weather patterns in Africa, Southeast Asia, and Australia.

Millennial timescale climate models indicate that human induced climate warming will weaken the average strength and variability of IOD events, but current IOD events are becoming increasingly variable with extreme IOD events becoming more common which makes predictions and forecasting of weather anomalies more difficult (Tiger et al., 2023; Wang et al., 2024). For instance, Myanmar in Southeast Asian is experiencing major climatic changes due to the IOD characterized by increasingly variable and extreme temperature and rainfall events. In fact, based on the number of extreme weather-related events Myanmar was ranked as the second most impacted country in the world for the period from 2000 to 2019 by the Global Climate Risk Index 2021 (Sein et al., 2021). Indeed, April 2016 marked the onset of a severe negative dipole event that resulted in extreme surface air temperatures in southeast Asia that surpassed heat records for the entire region (Thirumalai et al., 2017). The extreme heat exacerbated energy consumption, disrupted agriculture, and caused severe human discomfort. Subsequently, by mid to late 2016 this IOD developed into the strongest negative IOD recorded since 1980 and working in concert with a weak La Niña in the Pacific Ocean induced flood conditions in Indonesia, and devastating drought in East Africa (Lu et al., 2018).

Anthropogenic associated climate change and increasing variation in large scale climatic patterns like the IOD are impacting coupled human and natural systems in ways that challenge the health and stability of both (Fisher et al., 2021; Ojea et al., 2020; Pecl et al., 2017). Indeed, the interconnectedness of human and ecological well-being is particularly paramount in coastal regions of developing countries where the effects of climate change on coastal ecosystems can be severe impacting economic opportunities and access to protein for local populations (e.g. Fisher et al., 2021). An estimated 40 percent of the global fish catch occurs in small-scale and artisanal fisheries, many in developing countries where resource management is absent or under-resourced and data on fisheries and ecosystem health are extremely limited (FAO et al., 2023). Consequently, there is an urgent need to understand how large-scale changes in climatic patterns are influencing small-scale fisheries in developing countries (Ojea et al., 2020; Pecl et al., 2017). For instance, the combined effects of El Niño and strong positive IOD events has been associated with increases in landings of sardines and Bigeye tuna in Indonesia (Lumban-Gaol et al., 2021; Sartimbul et al., 2010). In this study we assess how an extreme negative IOD in 2016 affected the coupled human and natural system (CHANS) in Myanmar using a digital data collection system implemented with community-based fish buyers to quantify the diversity of fishes and volume of fishery catches flowing from small scale inshore fisheries into regional value chains prior to, during, and after the IOD.

Methods

This study focused in the Tanintharyi Region in south Myanmar, a region with high biodiversity and that is a high priority for conservation (Birch et al., 2016). Myanmar has a tropical climate characterized by three distinct seasons: summer (March–April, avg. 27.3 °C), the rainy season (May–October, avg. 27 °C), and winter (November–February, avg. 22.7 °C) (Htoo, 2022; Vivekanandan et al., 2016). Although seasonal temperatures are quite variable across the country, rising temperatures and increased precipitation have been experienced broadly in the last three decades (Htoo, 2022). Myanmar's commercial offshore marine fisheries are among the largest in Southeast Asia (Tezzo et al., 2018), but inshore fisheries are dominated by small scale artisanal fisheries that operate in areas less than 10 nautical miles from the coast (DOF, 2018). The inshore fishery fleets use a wide array of fishing gears and fishing practices targeting both high value fishery stocks like thread fin (Polynemidae), and lower valued taxa that are important for local consumption. These artisanal fisheries support the livelihoods of up to 34 percent of the population living in Myanmar's coastal regions, and almost half of Myanmar's population (48%) live in these coastal areas (DOF, 2016; World Bank, 2019). In this study we focus on understanding how the extreme negative IOD of 2016 affected coupled human and natural systems in the Myeik archipelago of southern Myanmar using daily purchase records across three years (2016-2018) to construct a picture of the species diversity and volume of fishes caught in key coastal habitats.

Landings data were collected during 2016-2018 from community fish buyers from Myeik, the city with the most important fishing activity in the region. We used a digital catch data collection system implemented via the Android app OurFish 1.0.191 (OurFish Ltd. 2019) that was approved by the Myanmar Fisheries Department. The app was customized specifically for this fishing community with pre-configured buying units representing how fish buyers traded different species or groups of species. Each buying unit was denoted by a photo of that taxonomic group and allowed the purchase to be recorded as counts of individuals and biomass. Other data collected included the price and, where relevant, the size or quality of fish. While most buying units represent one or few species in the same genus or family, buyers also trade boxes of several small pelagic and demersal species reported here as "mixed".

Test for differences in fisheries landings over time

To determine if the overall fishery varied over the season or across years, we used a generalized linear mixed effects model (*glmm*) to test whether the total biomass of fish landed varied as a function of month (ordinal predictor variable), year (categorical predictor variable) or as a function of the interaction between month and year. For this analysis we included a composite variable for each month and year as a random effect to account for autocorrelation of catch biomasses reported in the same month. We used a zero-inflated negative binomial model because catch biomasses were rounded to the nearest whole number (i.e., integer data) and the data were over dispersed due to the presence of many zeroes intermixed with periodic large landings. Moreover, the zero-inflation parameter, which models the probability of structural zeros, was estimated as a function of year to account for annual variation in catch probabilities.

To determine if the patterns observed in the fishery were general or driven by landings of species from specific fished habitats we classified the different families into one of three habitat categories—pelagic, reef associated, or demersal. Again, using a zero-inflated negative binomial *glmm* as described above we tested weather catch biomass varied as a function of month, year, habitat, and all interactions between these variables.

Community composition of landings

To determine if changes in catch among years and habitats were driven by changes in the groups of fishes being landed, we subset the data by habitat type and then ran separate permutational multivariate analyses of variance (PerMANOVA) on the families reported in each habitat type as a function of year. For these analyses we summed catches of each taxon by month and then asked if the monthly biomass reported for each family differed among years based on Bray-Curtis Dissimilarity matrix. Next, again using the Bray-Curtis dissimilarity matrix, we tested whether there were differences in the multivariate dispersion of biomasses to determine if differences might be driven by changes in the beta diversity (i.e. turnover in the most represented species each month) of families captured during each month. Differences observed from these tests were visualized by plotting the results of a principal coordinates analyses with 95% confidence ellipses. Finally, to determine which species were contributing most to observed dissimilarities among years we performed similarity percentage analyses (Simper, Clarke, 1993).

All statistical analyses were performed in the R statistical programming environment (Venables & Smith, 2003). Data wrangling, and summaries were performed using the Tidyverse (Wickham et al., 2019), and statistical and graphical summaries were generated using ggplot2 (Wickham, 2016) and the ggeffects (Lüdecke, 2018) packages. Generalized linear mixed models were fit using the glmmTMB packages, and model assumptions were interrogated using the package DHARMa (Hartig, 2022). Analyses of deviance were performed using the car (Fox & Weisberg, 2019) package using a type 3 model of deviance partitioning. All multivariate analyses were performed using the package vegan (Oksanen, 2013).

Results

There was a clear interaction between the monthly catches and year (Type III Wald Chi-square tests: $x^2 = 194.842, \text{df} = 2, \text{p} < 2.2\text{e} - 16$) with a sharp increase corresponding with the IOD event in 2016, followed by sequentially lower overall catches and declining catches in 2017 and 2018 respectively (Figure 1). In addition, there was an increase in the zero-inflation parameter (i.e. probability of structural zeros) from 2016 to 2018 (2016 = $0.447 \pm 0.011\ (se), p = 4e^{-6}$; 2017 = $0.509 \pm 0.014\ (se), p = 1.3e^{-5}$; 2018 = $0.592 \pm 0.020\ (se), p = 1.1e^{-12}$).

Figure 1: Model estimated curves and data for total catch over each month in each year of the study. The extreme 2016 IOD occurred from May to October 2016. Total catch near Myeik increased during the 2016 IOD and then steadily decreased over the next two years back to pre IOD levels. (A) The predicted curves and 95% confidence envelopes (shaded regions) from zero-inflated negative binomial glmm, and (B) The monthly means and boot strap confidence intervals of raw data. Note: means of raw data are biased down relative to fitted curves because of zero-inflation. Solid lines indicate magnitude of the negative dipole calculated as -1*Dipole Index such that larger values indicate a stronger negative anomaly.

Following these results, we tested if fish from specific habitats were differently affected during this period. There was a clear 3-way interaction (Type III Wald Chi-square tests: $x^2 = 14.685, \text{df} = 4, \text{p} = 0.005$) whereby the total catch from each habitat (pelagic, reef, demersal) increased in 2016 and decreased in 2017 and 2018. However, the magnitudes of change varied by habitat with the strongest shift in slopes occurring for demersal species (Figure 2). Catch from all habitats showed a similar pattern of increasing during 2016 as the dipole event intensified peaking in December two months after the IOD resolved (October) and finally falling between December and January of 2017. Catch declines continued for fish from all habitat types through 2017 and 2018, and the probability of structural zeroes (zero-inflation parameter) again increased over this period (2016 = $0.379 \pm 0.012\ (se), p = 7.3e^{-22}$; 2017 = $0.440 \pm 0.016\ (se)$, $p = 1.1e^{-4}$; $2018 = 0.546\ \pm 0.023\ (se), p = 5.4e^{-13}$).

Figure 2: Total catch varied across years and habitats. (A) Predictions of total catch generated from negative binomial mixed model indicating that total catch increased in 2016 as the IOD intensified and then began to decrease between December 2016 and January 2017 for taxa for each habitat type. Reductions continued into 2018. (B) The same predictions as in panel A separated by habitat shows that pelagic and reef fishes were similarly affected whereas demersal fish experienced a steeper increase in 2016. The shaded envelopes around model generated curves (A&B) depict 95% confidence intervals. (C) Means and boot strap confidence intervals of raw data for each habitat. Note: means of raw data are biased down relative to fitted curves because of zero-inflation.

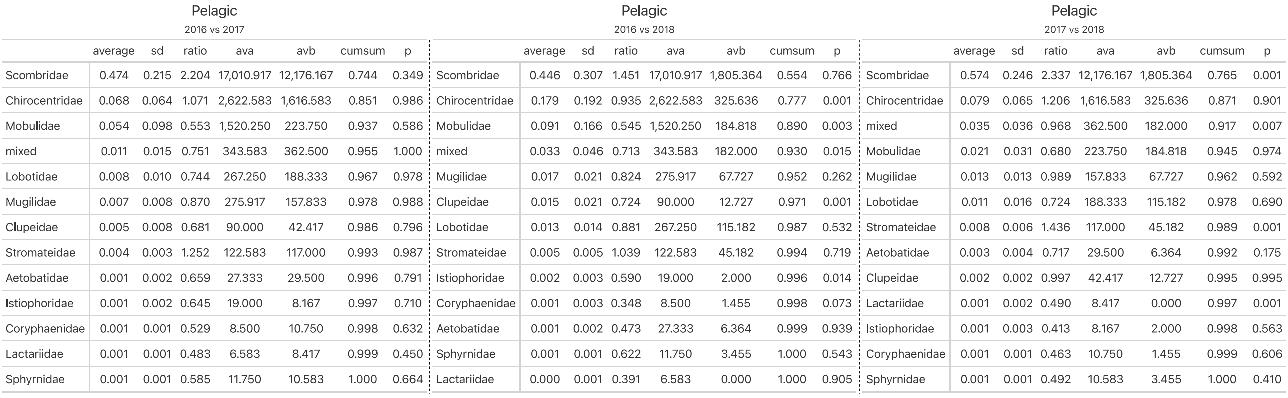
Next, we evaluated if there were any changes in the families fished in each habitat. For pelagic fishes there was a change in both the composition (PerMANOVA – df=2, Sums of Squares = 1.6918, F = 6.299, p = 0.001) and dispersion (Sums of Squares = 0.221, F = 5.782, df= 2, p = 0.007) of families captured in years 2016, 2017 and 2018. For pelagic fishes PCOA1 and 2 described approximately 39% and 22% of the variation in total weight caught of each group among years, and clear dissimilarity in taxonomic groups captured in each month across years (Figure 3).

Figure 3: Total catch of pelagic fish from different taxonomic groups was dissimilar across years.

A Simper analysis did not reveal any families that were contributing to the dissimilarity in the communities fished between 2016 and 2017. However, five pelagic families contributed strongly to the dissimilarity in the composition of catches between 2016 and 2018 (Chirocentidae, Mobulidae, mixed, Clupeidae, and

Istiophoridae) and four families drove the dissimilarities between 2017 and 2018 (Scombridae, mixed, Stomateidae, and Lactariidae) with only one group (mixed – consisting of a mix of small pelagic fish) maintaining statistical difference in both contrasts (Table 1, Fig. 4).

Table 1: Statistical results from the similarity percentage analyses to determine which pelagic taxa were contributing most to observed dissimilarities among years (Simper – Clarke 1993).



Pelagic
2016 vs 2017

	average	sd	ratio	ava	avb	cumsum	p
Scombridae	0.474	0.215	2.204	17,010.917	12,176.167	0.744	0.349
Chirocentridae	0.068	0.064	1.071	2,622.583	1,616.583	0.851	0.986
Mobulidae	0.054	0.098	0.553	1,520.250	223.750	0.937	0.586
mixed	0.011	0.015	0.751	343.583	362.500	0.955	1.000
Lobotidae	0.008	0.010	0.744	267.250	188.333	0.967	0.978
Mugilidae	0.007	0.008	0.870	275.917	157.833	0.978	0.988
Clupeidae	0.005	0.008	0.681	90.000	42.417	0.986	0.796
Stromateidae	0.004	0.003	1.252	122.583	117.000	0.993	0.987
Aetobatidae	0.001	0.002	0.659	27.333	29.500	0.996	0.791
Istiophoridae	0.001	0.002	0.645	19.000	8.167	0.997	0.710
Coryphaenidae	0.001	0.001	0.529	8.500	10.750	0.998	0.632
Lactariidae	0.001	0.001	0.483	6.583	8.417	0.999	0.450
Sphyrnidae	0.001	0.001	0.585	11.750	10.583	1.000	0.664

Pelagic
2016 vs 2018

	average	sd	ratio	ava	avb	cumsum	p
Scombridae	0.446	0.307	1.451	17,010.917	1,805.364	0.554	0.766
Chirocentridae	0.179	0.192	0.935	2,622.583	325.636	0.777	0.001
Mobulidae	0.091	0.166	0.545	1,520.250	184.818	0.890	0.003
mixed	0.033	0.046	0.713	343.583	182.000	0.930	0.015
Mugilidae	0.017	0.021	0.824	275.917	67.727	0.952	0.262
Clupeidae	0.015	0.021	0.724	90.000	12.727	0.971	0.001
Lobotidae	0.013	0.014	0.881	267.250	115.182	0.987	0.532
Stromateidae	0.005	0.005	1.039	122.583	45.182	0.994	0.719
Istiophoridae	0.002	0.003	0.590	19.000	2.000	0.996	0.014
Coryphaenidae	0.001	0.003	0.348	8.500	1.455	0.998	0.073
Aetobatidae	0.001	0.002	0.473	27.333	6.364	0.999	0.939
Sphyrnidae	0.001	0.001	0.622	11.750	3.455	1.000	0.543
Lactariidae	0.000	0.001	0.391	6.583	0.000	1.000	0.905

Pelagic
2017 vs 2018

	average	sd	ratio	ava	avb	cumsum	p
Scombridae	0.574	0.246	2.337	12,176.167	1,805.364	0.765	0.001
Chirocentridae	0.079	0.065	1.206	1,616.583	325.636	0.871	0.901
mixed	0.035	0.036	0.968	362.500	182.000	0.917	0.007
Mobulidae	0.021	0.031	0.680	223.750	184.818	0.945	0.974
Mugilidae	0.013	0.013	0.989	157.833	67.727	0.962	0.592
Lobotidae	0.011	0.016	0.724	188.333	115.182	0.978	0.690
Stromateidae	0.008	0.006	1.436	117.000	45.182	0.989	0.001
Aetobatidae	0.003	0.004	0.717	29.500	6.364	0.992	0.175
Clupeidae	0.002	0.002	0.997	42.417	12.727	0.995	0.995
Lactariidae	0.001	0.002	0.490	8.417	0.000	0.997	0.001
Istiophoridae	0.001	0.003	0.413	8.167	2.000	0.998	0.563
Coryphaenidae	0.001	0.001	0.463	10.750	1.455	0.999	0.606
Sphyrnidae	0.001	0.001	0.492	10.583	3.455	1.000	0.410

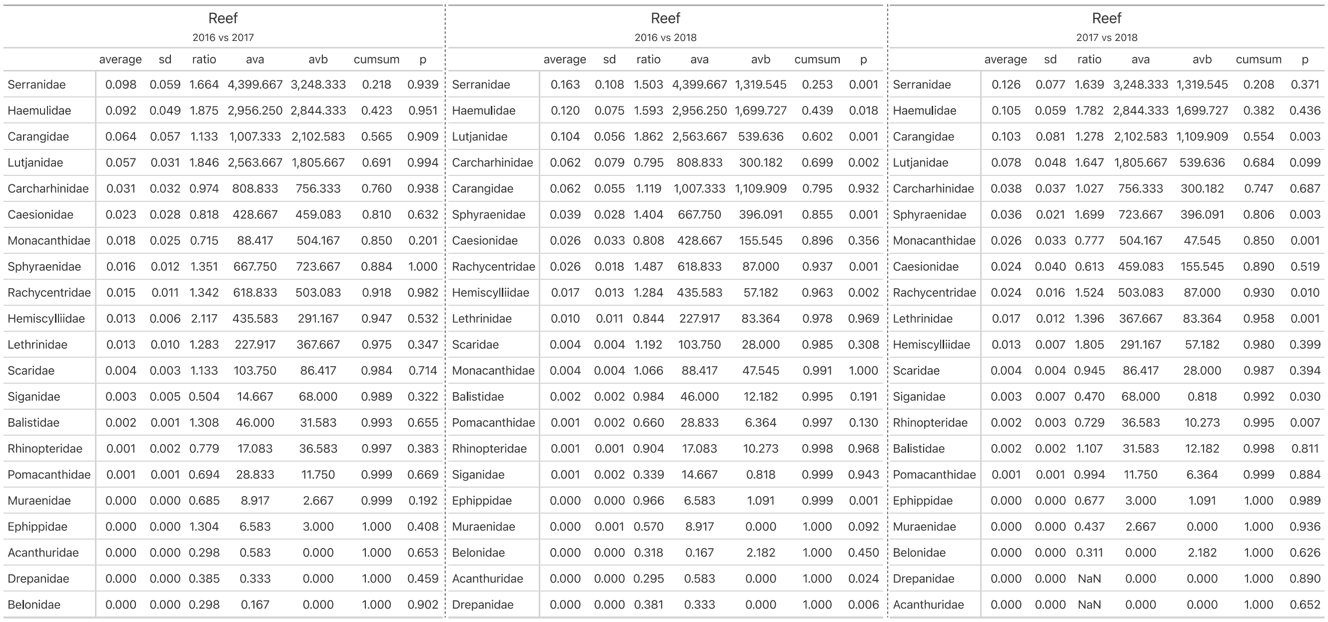
Figure 4: Total catch of pelagic fish from different taxonomic families was dissimilar across years. Some showed increases in 2016 (e.g., Chirocentridae, and Mobulidae) whereas others seemed unaffected across years (e.g., Coryphaenidae).

Like pelagic fishes, the reef fish families captured also varied in both the composition (PerMANOVA; df=2, Sums of Squares = 1.364, F = 5.228, p = 0.001) and dispersion (Permutation test; Sums of Squares = 0.229, F = 9.169, df= 2, p = 0.003) among years, with 2018 being the most dissimilar (Figure 5). The PCOA1 and 2 for reef fishes described approximately 49% and 19% of the variation in total weight caught of each group across years, respectively (Figure 5).

Figure 5: Total catch of reef fish from different taxonomic groups was dissimilar across years.

Like with pelagic fishes, the Simper analysis did not reveal any families strongly contributing to the dissimilarity in the communities fished between 2016 and 2017. However, total catch of 10 families differed statistically between 2016 and 2018 (Serranidae, Haemulidae, Lutjanidae, Carcharhinidae, Sphyraenidae, Rachycentridae, Hemiscylliidae, Ephippidae, Acanthuridae, and Drepanidae), and seven families contributed to the distances observed between 2017 and 2018 catches (Carangidae, Sphyraenidae, Monacanthidae, Rachycentridae, Lethrinidae, Siganidae, and Balistidae) with two groups contributing strongly in both contrasts (Sphyraenidae, Rachycentridae) (Table 2, Figure 6).

Table 2: Statistical results from the similarity percentage analyses to determine which reef associated taxa were contributing most to observed dissimilarities among years (Simper – Clarke 1993).



Reef 2016 vs 2017							
	average	sd	ratio	ava	avb	cumsum	p
Serranidae	0.098	0.059	1.664	4,399.667	3,248.333	0.218	0.939
Haemulidae	0.092	0.049	1.875	2,956.250	2,844.333	0.423	0.951
Carangidae	0.064	0.057	1.133	1,007.333	2,102.583	0.565	0.909
Lutjanidae	0.057	0.031	1.846	2,563.667	1,805.667	0.691	0.994
Carcharhinidae	0.031	0.032	0.974	808.833	756.333	0.760	0.938
Caesionidae	0.023	0.028	0.818	428.667	459.083	0.810	0.632
Monacanthidae	0.018	0.025	0.715	88.417	504.167	0.850	0.201
Sphyraenidae	0.016	0.012	1.351	667.750	723.667	0.884	1.000
Rachycentridae	0.015	0.011	1.342	618.833	503.083	0.918	0.982
Hemiscylliidae	0.013	0.006	2.117	435.583	291.167	0.947	0.532
Lethrinidae	0.013	0.010	1.283	227.917	367.667	0.975	0.347
Scaridae	0.004	0.003	1.133	103.750	86.417	0.984	0.714
Siganidae	0.003	0.005	0.504	14.667	68.000	0.989	0.322
Balistidae	0.002	0.001	1.308	46.000	31.583	0.993	0.655
Rhinopteridae	0.001	0.002	0.779	17.083	36.583	0.997	0.383
Pomacanthidae	0.001	0.001	0.694	28.833	11.750	0.999	0.669
Muraenidae	0.000	0.000	0.685	8.917	2.667	0.999	0.192
Ephippidae	0.000	0.000	1.304	6.583	3.000	1.000	0.408
Acanthuridae	0.000	0.000	0.298	0.583	0.000	1.000	0.653
Drepanidae	0.000	0.000	0.385	0.333	0.000	1.000	0.459
Belonidae	0.000	0.000	0.298	0.167	0.000	1.000	0.902

Reef 2016 vs 2018							
	average	sd	ratio	ava	avb	cumsum	p
Serranidae	0.163	0.108	1.503	4,399.667	1,319.545	0.253	0.001
Haemulidae	0.120	0.075	1.593	2,956.250	1,699.727	0.439	0.018
Lutjanidae	0.104	0.056	1.862	2,563.667	539.636	0.602	0.001
Carcharhinidae	0.062	0.079	0.795	808.833	300.182	0.699	0.002
Carangidae	0.062	0.055	1.119	1,007.333	1,109.909	0.795	0.932
Sphyraenidae	0.039	0.028	1.404	667.750	396.091	0.855	0.001
Caesionidae	0.026	0.033	0.808	428.667	155.545	0.896	0.356
Rachycentridae	0.026	0.018	1.487	618.833	87.000	0.937	0.001
Hemiscylliidae	0.017	0.013	1.284	435.583	57.182	0.963	0.002
Lethrinidae	0.010	0.011	0.844	227.917	83.364	0.978	0.969
Scaridae	0.004	0.004	1.192	103.750	28.000	0.985	0.308
Monacanthidae	0.004	0.004	1.066	88.417	47.545	0.991	1.000
Balistidae	0.002	0.002	0.984	46.000	12.182	0.995	0.191
Pomacanthidae	0.001	0.002	0.660	28.833	6.364	0.997	0.130
Rhinopteridae	0.001	0.001	0.904	17.083	10.273	0.998	0.968
Siganidae	0.001	0.002	0.339	14.667	0.818	0.999	0.943
Ephippidae	0.000	0.000	0.966	6.583	1.091	0.999	0.001
Muraenidae	0.000	0.001	0.570	8.917	0.000	1.000	0.092
Belonidae	0.000	0.000	0.318	0.167	2.182	1.000	0.450
Acanthuridae	0.000	0.000	0.295	0.583	0.000	1.000	0.024
Drepanidae	0.000	0.000	0.381	0.333	0.000	1.000	0.006

Reef 2017 vs 2018							
	average	sd	ratio	ava	avb	cumsum	p
Serranidae	0.126	0.077	1.639	3,248.333	1,319.545	0.208	0.371
Haemulidae	0.105	0.059	1.782	2,844.333	1,699.727	0.382	0.436
Carangidae	0.103	0.081	1.278	2,102.583	1,109.909	0.554	0.003
Lutjanidae	0.078	0.048	1.647	1,805.667	539.636	0.684	0.099
Carcharhinidae	0.038	0.037	1.027	756.333	300.182	0.747	0.687
Sphyraenidae	0.036	0.021	1.699	723.667	396.091	0.806	0.003
Monacanthidae	0.026	0.033	0.777	504.167	47.545	0.850	0.001
Caesionidae	0.024	0.040	0.613	459.083	155.545	0.890	0.519
Rachycentridae	0.024	0.016	1.524	503.083	87.000	0.930	0.010
Lethrinidae	0.017	0.012	1.396	367.667	83.364	0.958	0.001
Hemiscylliidae	0.013	0.007	1.805	291.167	57.182	0.980	0.399
Scaridae	0.004	0.004	0.945	86.417	28.000	0.987	0.394
Siganidae	0.003	0.007	0.470	68.000	0.818	0.992	0.030
Rhinopteridae	0.002	0.003	0.729	36.583	10.273	0.995	0.007
Balistidae	0.002	0.002	1.107	31.583	12.182	0.998	0.811
Pomacanthidae	0.001	0.001	0.994	11.750	6.364	0.999	0.884
Ephippidae	0.000	0.000	0.677	3.000	1.091	1.000	0.989
Muraenidae	0.000	0.000	0.437	2.667	0.000	1.000	0.936
Belonidae	0.000	0.000	0.311	0.000	2.182	1.000	0.626
Drepanidae	0.000	0.000	NaN	0.000	0.000	1.000	0.890
Acanthuridae	0.000	0.000	NaN	0.000	0.000	1.000	0.652

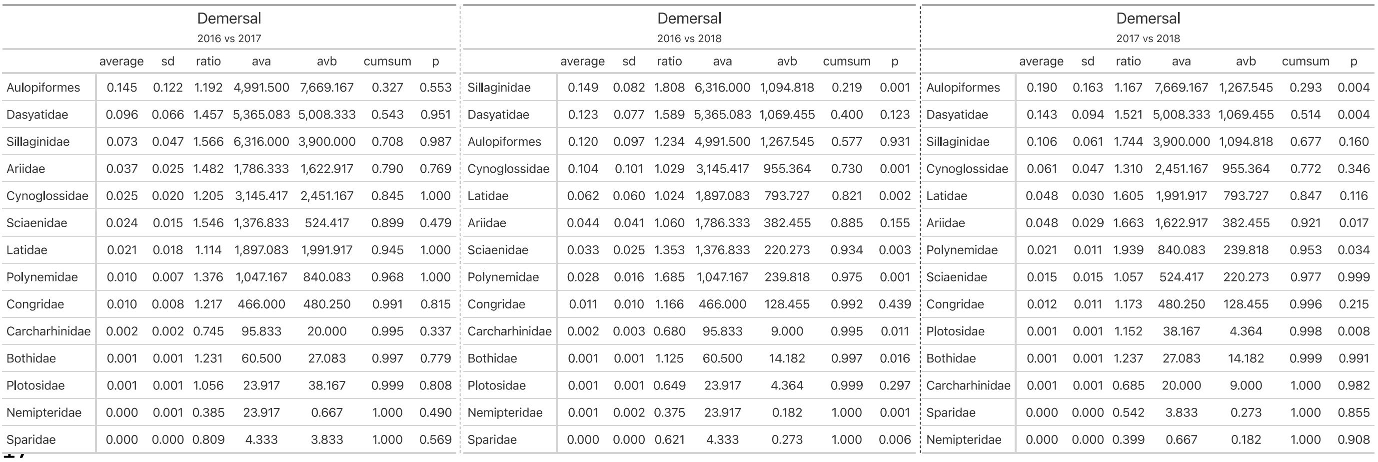
Figure 6: Total catch of reef fish from different taxonomic families was dissimilar across years. Some showed increases in 2016 and subsequent decreases (e.g., Lutjanidae and Hemiscyllidae) whereas others seemed unaffected by the 2016 negative dipole having yearly seasonal fluctuations (e.g.,Carcharhinidae).

Like pelagic and reef fishes, the demersal fish families captured also varied in both the composition (PerMANOVA; df=2, Sums of Squares = 1.692, F = 6.299, p = 0.001) and dispersion (Permutation test; Sums of Squares = 0.221, F = 5.781, df= 2, p = 0.006) among years. The composition of the catches over the year were again the most dissimilar in 2018 relative to 2016 and 2017 (Figure 6). PCoA1 and 2 described approximately 45% and 25% of the variation in total weight caught of each group across years, respectively (Figure 7).

Figure 7: Total catch of demersal fish from different taxonomic groups was dissimilar across years.

In contrast with the pelagic and reef fish, no demersal families were strongly dissimilar in total catch between 2016 and 2017 (Table 3). However, nine families (Sillaginidae, Cynoglossidae, Latidae, Sciaenidae, Polynemidae, Carcharhinidae, Bothidae, Nemipteridae, and Sparidae) were differentially represented in 2016 and 2018 and five families (Aulopiformes, Dasyatidae, Ariidae, Polynemidae, and Plotosidae) between 2017 and 2018 with only one group (Polynemidae) contributing to the dissimilarities in both contrasts (Figure 8).

Table 3: Statistical results from the similarity percentage analyses to determine which demersal taxa were contributing most to observed dissimilarities among years (Simper – Clarke 1993).



Demersal								Demersal								Demersal							
2016 vs 2017								2016 vs 2018								2017 vs 2018							
	average	sd	ratio	ava	avb	cumsum	p		average	sd	ratio	ava	avb	cumsum	p		average	sd	ratio	ava	avb	cumsum	p
Aulopiformes	0.145	0.122	1.192	4,991.500	7,669.167	0.327	0.553	Sillaginidae	0.149	0.082	1.808	6,316.000	1,094.818	0.219	0.001	Aulopiformes	0.190	0.163	1.167	7,669.167	1,267.545	0.293	0.004
Dasyatidae	0.096	0.066	1.457	5,365.083	5,008.333	0.543	0.951	Dasyatidae	0.123	0.077	1.589	5,365.083	1,069.455	0.400	0.123	Dasyatidae	0.143	0.094	1.521	5,008.333	1,069.455	0.514	0.004
Sillaginidae	0.073	0.047	1.566	6,316.000	3,900.000	0.708	0.987	Aulopiformes	0.120	0.097	1.234	4,991.500	1,267.545	0.577	0.931	Sillaginidae	0.106	0.061	1.744	3,900.000	1,094.818	0.677	0.160
Ariidae	0.037	0.025	1.482	1,786.333	1,622.917	0.790	0.769	Cynoglossidae	0.104	0.101	1.029	3,145.417	955.364	0.730	0.001	Cynoglossidae	0.061	0.047	1.310	2,451.167	955.364	0.772	0.346
Cynoglossidae	0.025	0.020	1.205	3,145.417	2,451.167	0.845	1.000	Latidae	0.062	0.060	1.024	1,897.083	793.727	0.821	0.002	Latidae	0.048	0.030	1.605	1,991.917	793.727	0.847	0.116
Sciaenidae	0.024	0.015	1.546	1,376.833	524.417	0.899	0.479	Ariidae	0.044	0.041	1.060	1,786.333	382.455	0.885	0.155	Ariidae	0.048	0.029	1.663	1,622.917	382.455	0.921	0.017
Latidae	0.021	0.018	1.114	1,897.083	1,991.917	0.945	1.000	Sciaenidae	0.033	0.025	1.353	1,376.833	220.273	0.934	0.003	Polynemidae	0.021	0.011	1.939	840.083	239.818	0.953	0.034
Polynemidae	0.010	0.007	1.376	1,047.167	840.083	0.968	1.000	Polynemidae	0.028	0.016	1.685	1,047.167	239.818	0.975	0.001	Sciaenidae	0.015	0.015	1.057	524.417	220.273	0.977	0.999
Congridae	0.010	0.008	1.217	466.000	480.250	0.991	0.815	Congridae	0.011	0.010	1.166	466.000	128.455	0.992	0.439	Congridae	0.012	0.011	1.173	480.250	128.455	0.996	0.215
Carcharhinidae	0.002	0.002	0.745	95.833	20.000	0.995	0.337	Carcharhinidae	0.002	0.003	0.680	95.833	9.000	0.995	0.011	Plotosidae	0.001	0.001	1.152	38.167	4.364	0.998	0.008
Bothidae	0.001	0.001	1.231	60.500	27.083	0.997	0.779	Bothidae	0.001	0.001	1.125	60.500	14.182	0.997	0.016	Bothidae	0.001	0.001	1.237	27.083	14.182	0.999	0.991
Plotosidae	0.001	0.001	1.056	23.917	38.167	0.999	0.808	Plotosidae	0.001	0.001	0.649	23.917	4.364	0.999	0.297	Carcharhinidae	0.001	0.001	0.685	20.000	9.000	1.000	0.982
Nemipteridae	0.000	0.001	0.385	23.917	0.667	1.000	0.490	Nemipteridae	0.001	0.002	0.375	23.917	0.182	1.000	0.001	Sparidae	0.000	0.000	0.542	3.833	0.273	1.000	0.855
Sparidae	0.000	0.000	0.809	4.333	3.833	1.000	0.569	Sparidae	0.000	0.000	0.621	4.333	0.273	1.000	0.006	Nemipteridae	0.000	0.000	0.399	0.667	0.182	1.000	0.908

Figure 8: Total catch of demersal fish from different taxonomic families was dissimilar across years. Almost all families showed increases in the later half 2016 and subsequent declines, whereas others (e.g., Latidae and Plotosidae) showed no pattern across years.

Discussion

Possibly the strongest negative IOD event in recorded history, but certainly within the last century took place in the tropical Indian Ocean during 2016 (Iskandar et al., 2018; Lu et al., 2018). Based on the Dipole Mode Index (DMI) which measures the gradient in the sea surface temperature anomaly between the western tropical Indian Ocean (near Java, Indonesia) and its eastern counterpart off the coast of Africa (north of Madagascar), the 2016 IOD event began in May, reached the first peak in July, weakened in August, then rebounded to a second higher peak in September and ended in November. During this event, the southeastern tropical Indian Ocean off the coast of Java saw robust sea surface temperature anomalies of up to nearly +2.5°C from July through September (Figure 9c-e).

Figure 9. Sea Surface Temperature anomalies (blue-red shading °C) and low-level wind vectors (m/s) during May-December 2016. Figure adapted from (Iskandar et al., 2018).

In addition, there was a strong downwelling event, an associated decrease in chlorophyll-a, and reductions in small pelagic fishes along the coasts of Sumatra and Java (Lumban-Gaol et al., 2021). Although the negative dipole event is thought to influence the entire Indonesian coast, farther north, the Myeik archipelago in the Tanintharyi Region in south Myanmar is more protected from the most intense sea surface temperature increases. However, in 2016 this region actually experienced its highest sea surface temperature anomaly just as the IOD began in May (Iskandar et al., 2018), and then remained much cooler than the southern Indonesian islands throughout the rest of the year (Figure 9) .

Using three years of continuous fish landing data (2016-2018) collected from the artisanal fishery in the Tanintharyi Region we found that total catch near Myeik archipelago increased dramatically during the 2016 IOD and subsequently decreased over the next two years, back to pre IOD levels (Figure 1). The small-scale fisheries in this region caught a wide range of pelagic, reef, and demersal taxa. Although patterns across time were similar across habitats, demersal families were the dominant catch in 2016 and 2017 and then coalesced to catch levels similar to other habitats by the end of 2018 (Figure 2). It is commonly believed and has been shown for the southwestern tropical Indian Ocean that negative dipole events cause downwelling, reduced productivity and decreased fishery catch (Lumban-Gaol et al., 2021). The counterintuitive effect of having higher fish populations (measured as fisheries catch) off the coast of Myanmar might be due to increased migration of fish from southern, hotter, more oligotrophic areas that were more strongly affected by the 2016 negative IOD (Jacox et al., 2020). Indeed, four of the five pelagic fish taxa that were dissimilar between 2016 and 2018 (Chirocentidae, Mobulidae, Clupeidae, and Istiophoridae) showed a higher total catch in the latter half of 2016 with subsequent declines in 2018 (Figure 4). Interestingly, these groups include predatory and prey fish, and it is possible these highly mobile taxa migrated north to more productive waters that were less affected by high temperature anomalies and then returned south, or elsewhere, after the negative dipole abated. Indeed, marine heatwaves are known to induce short term thermal displacements of marine species of up to thousands of kilometres (Jacox et al., 2020). Demersal fish taxa strongly followed this pattern with eight of the nine families that were dissimilar between 2016 and 2018 (Sillaginidae, Cynoglossidae, Sciaenidae, Polynemidae, Carcharhinidae, Bothidae, Nemipteridae, and Sparidae) showing increases in catches by the end of 2016 followed by subsequent decreases thereafter (Figure 8). Total catch of reef fish was relatively lower across all years but generally followed the same patterns as pelagic and demersal taxa (Figure 2). Catches of most families of reef fish (Figure 6), however, did not dramatically increase in 2016 in contrasts to pelagic and demersal fishes with most taxa exhibiting more seasonal patterns. However, catches of 3 families of reef fish (e.g., Haemulidae (grunts), Lutjanidae (snapper), and Hemiscyllidae (bamboo sharks)) did exhibit the sharp increase in 2016 with subsequent decreases, and interestingly all three are known to be migratory. Better understanding the migratory behaviour of fishes and fishers to climate shocks will help build more accurate predictions for the inevitable effects of global climate change on fisheries productivity (Abe et al., 2024; Cruz et al., 2024; Villaseñor-Derbez et al., 2024).

Another explanation for the yearly differences in total catch is that fishing activity and effort might have differed across years, due to the negative IOD. Fishing activity in the Tanintharyi Region, as in many other coastal fisheries, is weather dependant and opportunistic and therefore catch levels likely reflect relative availability of different species in addition to accessibility due to weather conditions throughout the year (Abe et al., 2024). In addition, fishing activities could be strongly influenced by weather events in mainland areas that affect other key food production industries, such as agriculture and livestock, as Myanmar's agricultural sector is vulnerable to the effects of extreme weather (Horton et al., 2017). For instance, the combined effects of a positive IOD, an El Nino, and a strong Madden-Julian Oscillation event caused unusually heavy monsoon rain fall that resulted in severe floods and landslides in July and August of 2015 (Brakenridge et al., 2017; Oo, 2021; Zhang et al., 2018). During these heavy rain events 1.4 million acres of farmland were flooded destroying more than 841,000 acres of crop land, and the loss of 242,000 livestock (Floodlist, 2015; Singh, Angad, 2015). Therefore, it is not unreasonable to assume that some portion of the increase in total fish was been driven by protein demands of local populations along with associated changes in economic pressures that are often coincident with extreme weather and climate change (World Economic Forum, 2023). However, the amount of Myanmar's GDP that is accounted for by agriculture has been declining since approximately 2013 and is coincident with growth in industry and service sectors (Htoo, 2022), so there is not a clear connection between failing agriculture and increased fishing practices. Future work should determine whether fish stocks change predictably in conjunction with IOD events and whether the increase in fisheries catches along the Myanmar coast is due to fishers responding to the redistribution of fisheries during negative dipole events (Abe et al., 2024; Cruz et al., 2024). Although frequent bad weather during the monsoon season (May to October) in Myanmar is broadly considered to provide a natural cessation of fishing that allows stocks to recover, our data suggest that this cessation of fishing pressures is not actualized (Segura-Garcia, I. et al., accepted). In fact, we did not observe any reductions in fishing pressure in any of the three marine habitats analysed here (Figure 2) with total catches increasing throughout the monsoon season of 2016 for all taxa including bycatch (Segura-Garcia, I. et al., accepted).

Ecosystem approaches to fisheries management (EAFM) is the current preferred option by most countries in Southeast Asia to ensure the long-term sustainability of fisheries and the ecosystem services they provide (e.g., food security, livelihoods, economic security, coastal protection, human health and wellbeing) (CTI-CFF, 2009; Heenan et al., 2015; Muawanah et al., 2018; Pomeroy et al., 2013, 2016). Although Myanmar's fishing industry is critically important for food security and employment, their fisheries are data-deficient and poorly regulated. Our findings provide pivotal baseline data on the diversity and biomass of fishes collected from different habitats, and how large scale regional climatic events might affect both the fish community and the harvests that can be anticipated by local communities. Specifically, our results suggest that changes in the strength of the IOD may drive predictable changes in the abundance and diversity of fishes utilizing the inshore waters of the Myiek archipelago and how these changes may impact local artisanal fisheries and local economies. Governance of coupled human and natural systems like the artisanal fisheries and coastal ecosystems of southern Myanmar must balance human well-being and the health of the ecosystem. Thus, gaining a better appreciation for how regional climate phenomenon like the IOD affects the redistribution of fish species can provide key insights for protecting threatened species like mobulids from fishing pressure (Segura-García et al., 2024), while also enhancing the livelihoods of local artisanal fishers.

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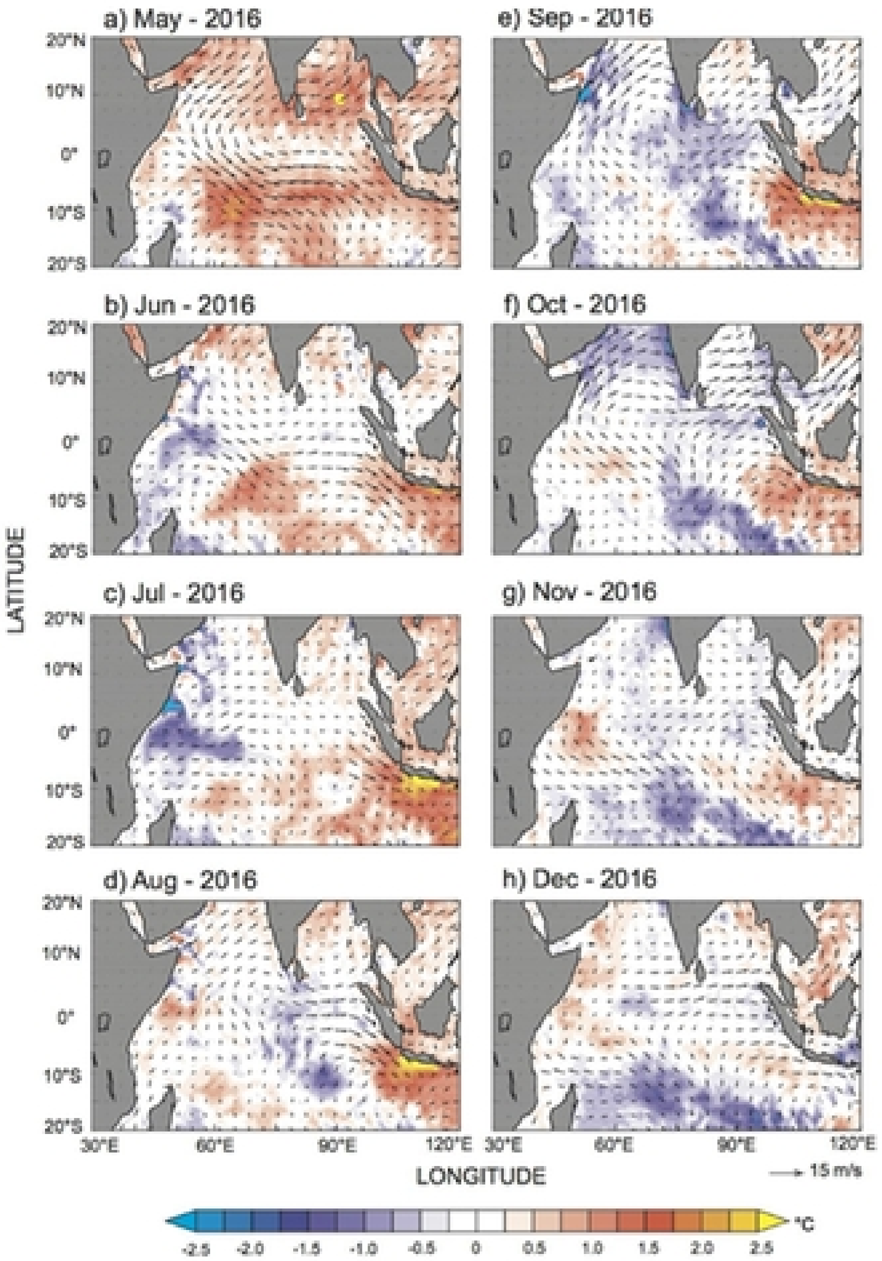

Fig. 9

Figure 9

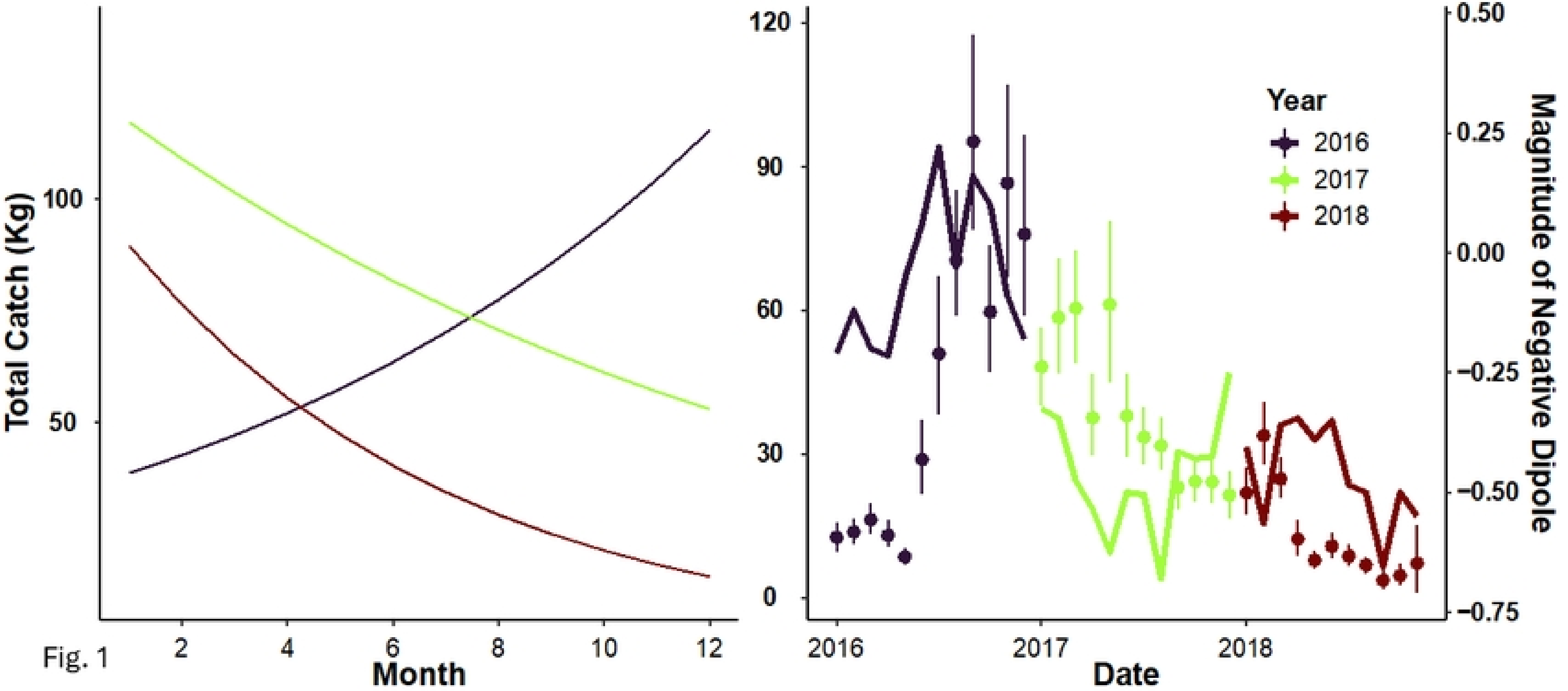

Fig. 1

Figure 1

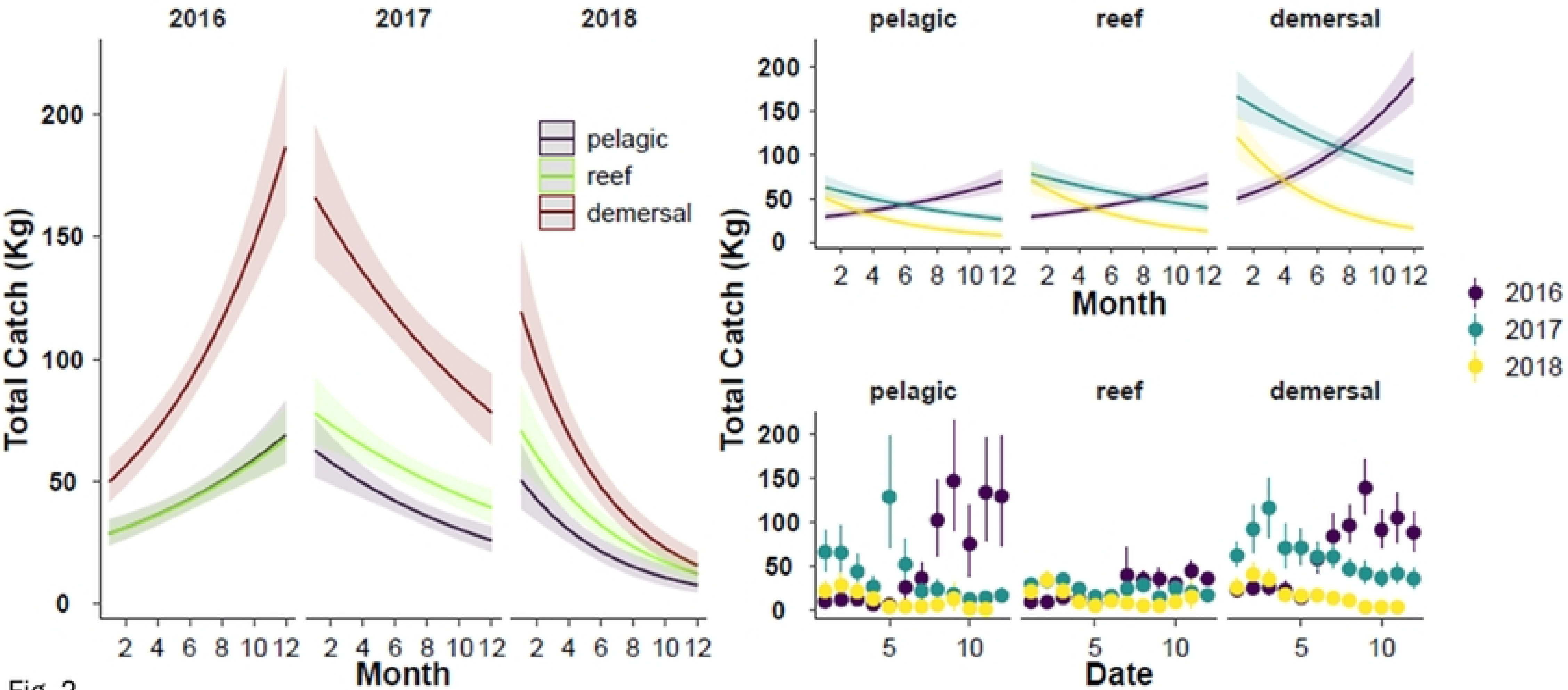

Fig. 2

Figure 2

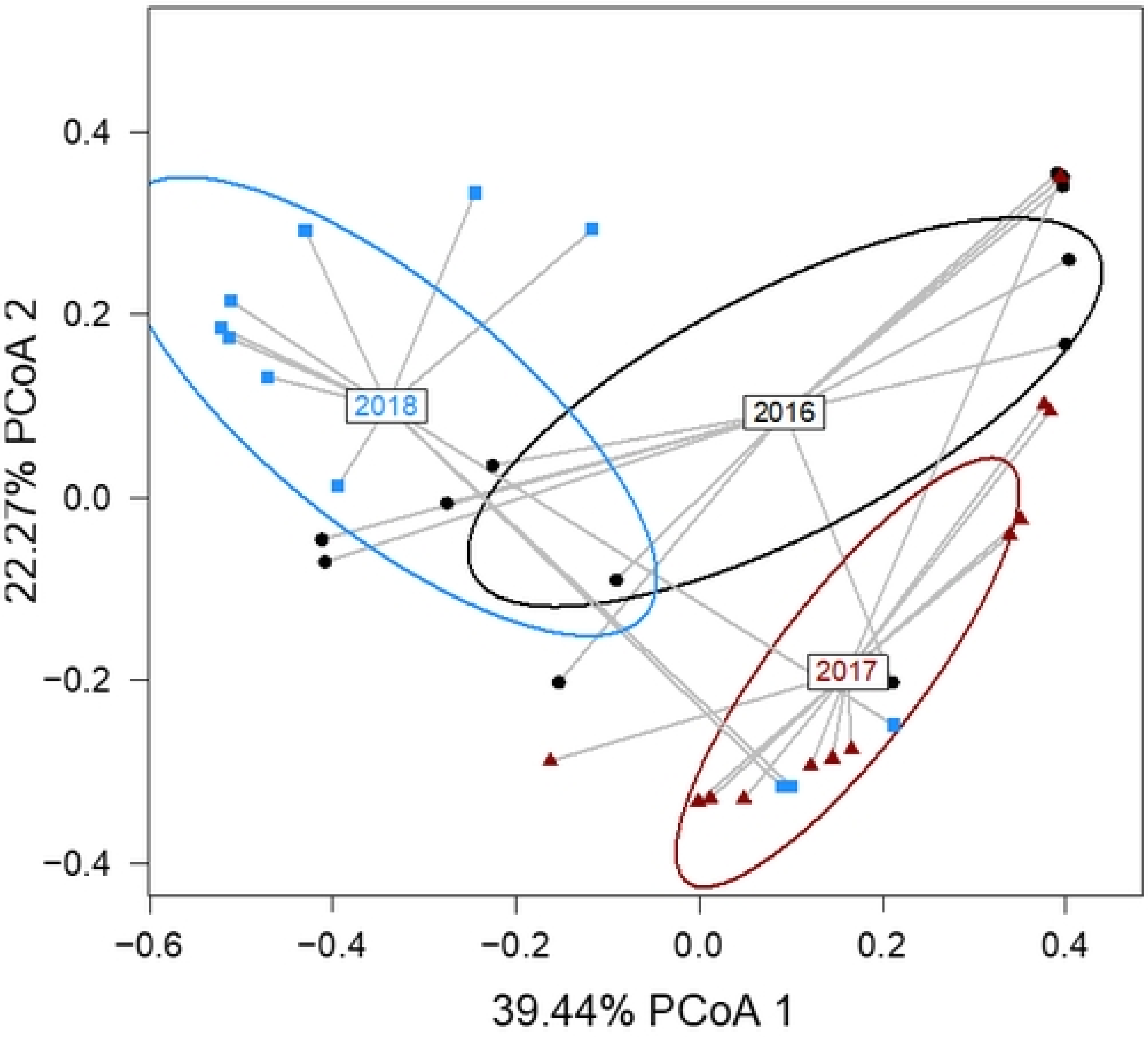

Fig. 3

Figure 3

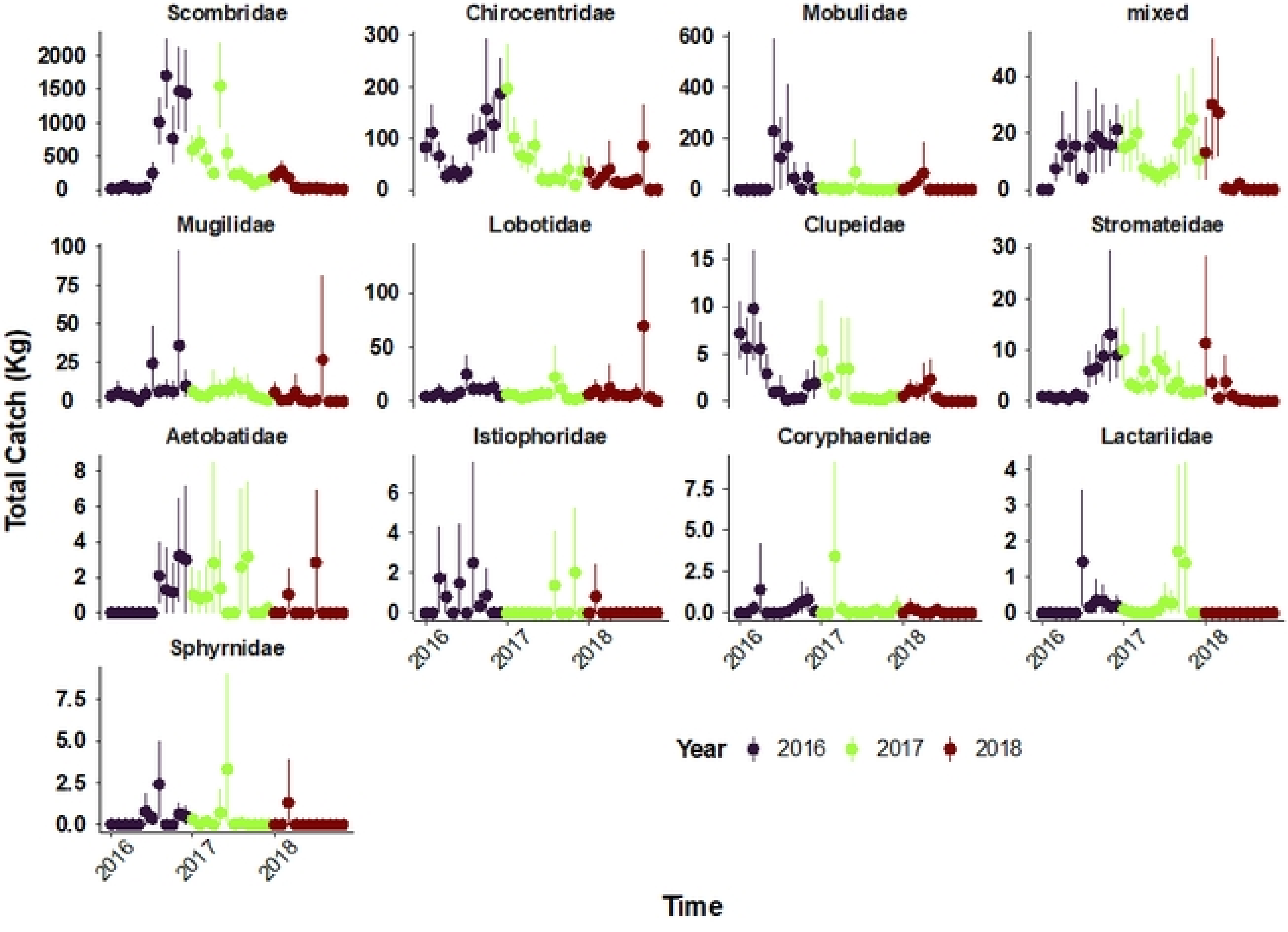

Fig. 4

Figure 4

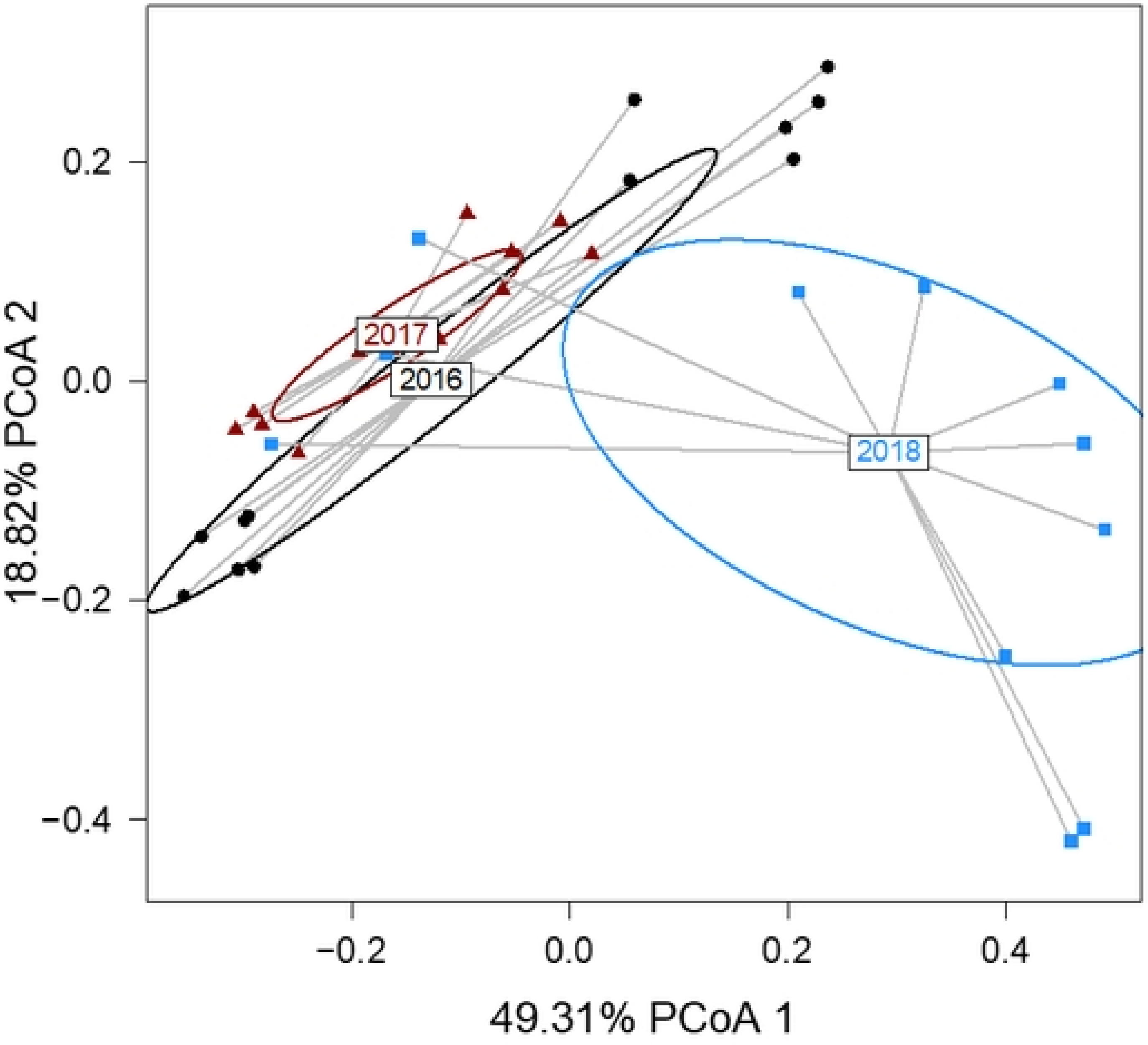

Fig. 5

Figure5

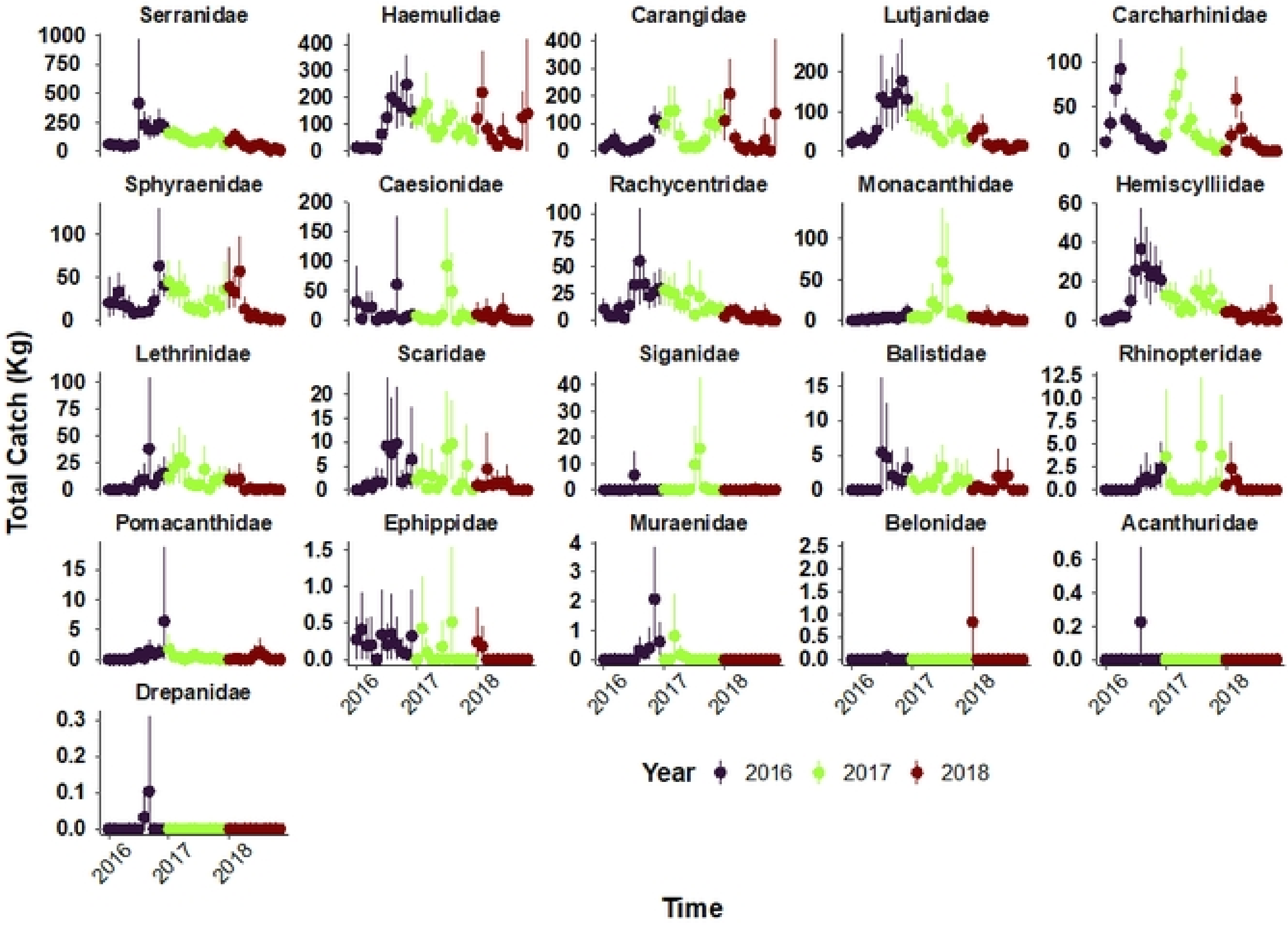

Fig. 6

Figure 6

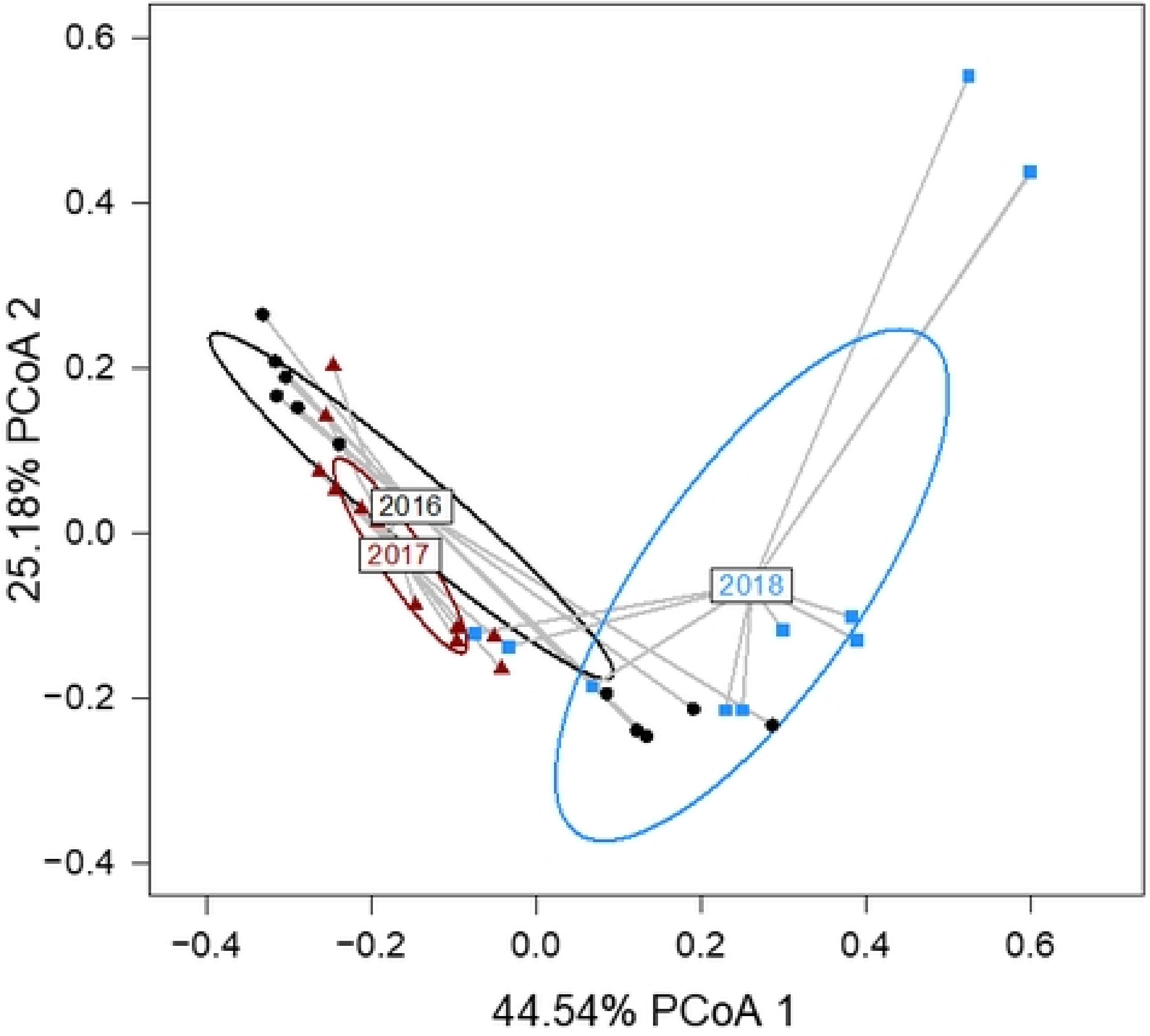

Fig. 7

Figure 7

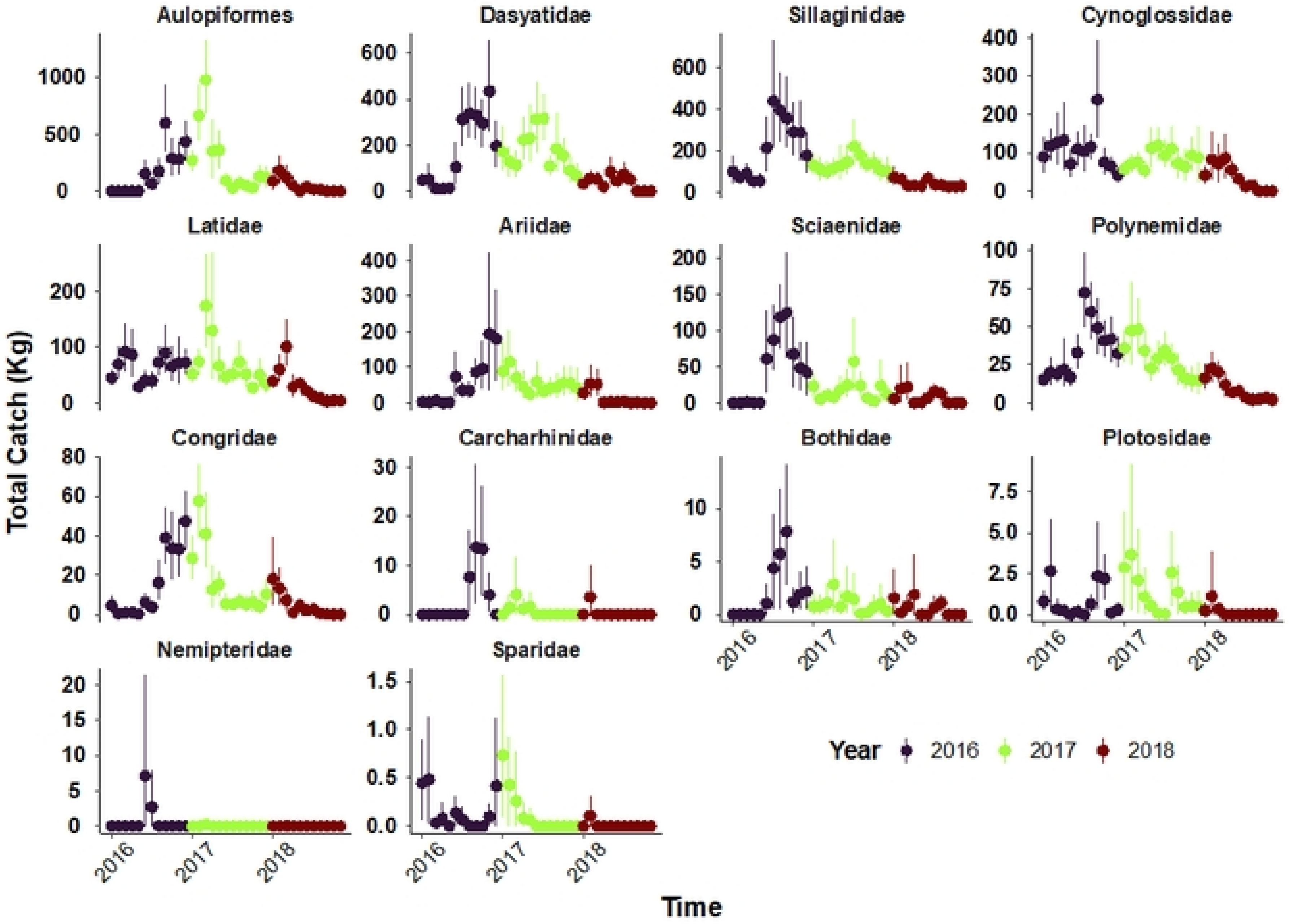

Fig. 8

Figure 8